

Research on soft measurement model of sewage treatment based on case-based reasoning approach

Jiayan Zhang, Cuicui Du and Xugang Feng

ABSTRACT

In this paper, the measurement of biochemical oxygen demand (BOD) in wastewater treatment process is analyzed and an intelligent integrated prediction method based on case-based reasoning (CBR) is proposed in order to overcome the difficulty. Due to the fact that there are many factors influence the accuracy of prediction model, the radial basis function, which is a neural network with 3 layers feedforward network, is employed to reduce the dimension of input values. Under this circumstance, the back propagation neural network combining with nearest neighbor retrieval strategy is adopted to match case. Then, the measurement of BOD in wastewater treatment process is analyzed. Finally, the validity of the improved CBR in sewage treatment is demonstrated by using numerical results.

Key words | case-based reasoning (CBR), intelligent integrated prediction, sewage treatment, soft-sensing

Jiayan Zhang
Cuicui Du
Xugang Feng (corresponding author)
School of electrical and information engineering,
Anhui University of Technology,
Maanshan,
Anhui 243002,
China
E-mail: fxg773@ahut.edu.cn

INTRODUCTION

Wastewater and sewage threatens human safety and development, as well as impeding the sustainable development of the economy and society (Zhang *et al.* 2016). In order to curb the adverse effects of environmental pollution due to the uncontrolled discharge of sewage, effective measurements must be taken to ensure that the discharge of sewage meets the required standards (Izady *et al.* 2016).

Activated sludge is the most widely adopted method in wastewater treatment process, which utilizes the organic compounds in wastewater as the culture medium (Mjalli *et al.* 2007). To achieve the purpose of removing organic substances, the microbial population are co-cultured under the condition of oxygen, and finish the operation of the adsorption, condensation, oxidation, decomposition and precipitation.

There are several quality indexes of sewage treatment such as biochemical oxygen demand (BOD), total nitrogen (TN)-containing, total phosphorus (TP)-containing, chemical

oxygen demand (COD) (Liu & Zhang 2015). However, the examination of these parameters of sewage treatment mainly depends on artificial sampling to test and analyze. It has large errors and fails to control automatically in real time. Take for example the examination of BOD. The steps for the examination of BOD are as follows. Use water sample to fill the totally enclosed bottle with dissolved oxygen. The BOD is assessed by iodometric method. Especially, the testing cycle of BOD is longer relatively (Ren *et al.* 2014), which enormously lags in the process of sewage disposal. Therefore, when the nonconforming outlet water quality of BOD is detected, a large amount of water with exceeding hygienic standard has been emitted. Soft sensor can be used to estimate variables that can not be measured real-time. Based on the optimal rule, it determines a set of indirect variables which not only have a significant association with the variables under test, but also are measured easily. The mathematical models to be measured are established to realize the measurement for the variable under test (Ben *et al.* 2017). Therefore, in order to realize real-time monitoring and forecasting of sewage treatment process, the soft-sensing method is applied to measure quality indexes parameters, construct a model of measuring the parameters such as BOD, develop the system

This is an Open Access article distributed under the terms of the Creative Commons Attribution Licence (CC BY-NC-ND 4.0), which permits copying and redistribution for non-commercial purposes with no derivatives, provided the original work is properly cited (<http://creativecommons.org/licenses/by-nc-nd/4.0/>)

for on-line monitoring and predict the quality indexes parameters in sewage disposal process. It can not only control the quality of effluent, but also has great theoretical significance and engineering application value (Tang & Guan 2017).

The soft-sensing technique in wastewater treatment process has been widely researched and exploited by many groups. Liu *et al.* (2017) proposed a soft-sensing model of water quality parameter under multiple loading conditions based on multiple models, which aims at the characteristic parameters analysis of water quality in wastewater treatment process. What's more, inspired by the idea of multi-model modeling of soft hand off, Qiao *et al.* (2016) proposed a new soft-sensing method of controlling effluent quality. They use the recursive least square algorithm to learn the linear auto regressive exogenous (ARX) model. By analyzing the coupling relationship among the key effluent quality parameters (COD, BOD, TN, TP), Yoo *et al.* (2016) presented a soft-sensing model based on feedforward neural networks. In this model, the soft-sensing approach based on improved particle swarm optimization algorithm is adopted (Struijs *et al.* 2016), and the performance of the algorithm is demonstrated by using the simulation results. Aiming at the characteristics of strong-nonlinearity and coupling in wastewater treatment process, Dąbrowski *et al.* (2017) proposed a soft-sensing approach of multi-model modeling based on fuzzy kernel clustering. According to different wear conditions, the input parameters are used to get cluster partition using the fuzzy kernel clustering algorithm. Furthermore, build sub-models for every subset of clusters based on least squares support vector machines (Yang *et al.* 2016). Finally, the system output is obtained by using the sub-models switching strategy. However, due to the characteristics of bad production circumstances, the drastic working condition changes, strong coupling and large delay in wastewater treatment process (Kumar *et al.* 2016), these soft sensor modeling methods have the poor global generalization ability and low estimation precision. Therefore, in this paper, a case-based reasoning (CBR) method on soft sensors model of wastewater treatment process control parameters is proposed by combing radial basis function (RBF) neural network and CBR. Experimental results show that the measuring accuracy of the approach is high.

FACTOR ANALYSIS AND STRUCTURE DESIGN FOR AFFECTING THE FORECASTING MODEL

There are mainly five factors that influence the BOD parameters in wastewater treatment process, namely: water,

carbon and inorganic salts, growth factors and energy (De Soto *et al.* 2016). By analyzing the technological mechanism of biological wastewater treatment, the concrete parameters for influencing BOD have been basically defined, including MLSS, temperature, PH value, effluent COD/DO, electric currents of n pump motors, NH_4^+-N and hydraulic retention time (HRT). If these parameters were used as the input variable of the forecasting model, it would cause excessive input variable and reduce the forecasting effect of model (Lee & Oh 2016). Therefore, in this paper, we put the electric currents of pump motors as the input variable of RBF neural network and calculate the total water inflow Q . Then the aforesaid variable parameters and Q are used as the input variable to calculate the BOD through the improved CBR approach. The structure of the intelligent integration of the forecasting model for BOD is shown in Figure 1.

CONSTRUCTION OF FORECASTING MODEL OF THE TOTAL WATER INFLOW BASED ON RBF

RBF neural network is one of the local approximation neural networks. In theory, it can approximate any continuous function if there is enough neuron. It not only has fast learning rate, but also can avoid local minimums (De Sousa *et al.* 2016). Thus, it can satisfy the requirement of real-time control. In this paper, 250 groups of data samples in wastewater treatment process are selected to carry on modeling and the selected data samples are processed abnormally. The first 150 groups are used as the training samples of the model, and then the remaining 100 groups are used to test the forecasting effect of the model. After normalization processing for the original data, a three-layer RBF neural network is used to carry on modeling. The basic principle is setting

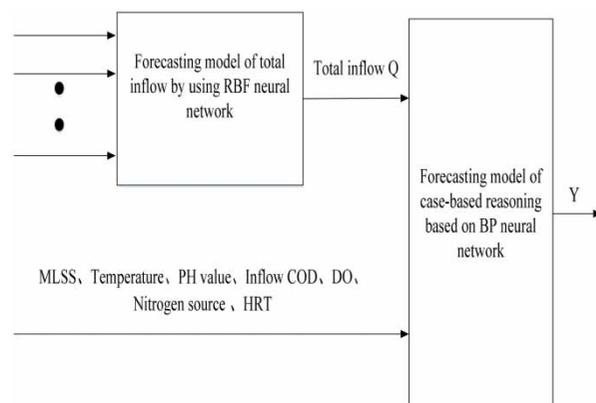


Figure 1 | Forecasting model of BOD.

RBF as the ‘base’ of the hidden units to construct the hidden layer. It can avoid using the weights to connect between the input layer and hidden layer.

When the center point of RBF is determined, the structure of the net can be confirmed. The electric currents of pump motors are selected as the input variable of model and the output variable is the total water inflow Q . In addition, the hidden layer nodes are confirmed by the orthogonal least square. In this paper, the hidden layer nodes are 17 and the Gauss function is used as the function of hidden layer nodes. The output of the i hidden layer node can be expressed by an equation (Barber 2016)

$$\varphi_i(x) = \exp\left(-\frac{\|V - c_i\|^2}{2\sigma_i^2}\right); i = 1, 2, \dots, m \quad (1)$$

Where,

V is the input vector, m is the number of hidden nodes

$\varphi_i(x)$ is the output of the i hidden layer node

σ_i is the width of the center point for the action function

c_i is the data center of the i node in the hidden layer

$\|V - c_i\|^2$ is the Euclidean distance between input vector V and the data center c_i

The forecasting model of the total water inflow Q is denoted by

$$Q_{total} = \sum_{i=1}^m \omega_{ik} \varphi_i(x), k = 1, 2, \dots, p \quad (2)$$

Where,

Q_{total} is the output value of the net

ω_{ik} is the value of the connection between the hidden layer node i and the output node k

$\varphi_i(x)$ is the output of the i hidden layer node

There are 3 parameters to be dealt with in RBF neural network, namely c_i , σ_i and ω_{ik} . Because the mapping between the hidden layer and output layer is linear, so ω_{ik} is obtained by using the least square method. Denote

$$\sigma_i = \frac{d_i}{\sqrt{2M}}; i = 1, 2, \dots, m \quad (3)$$

Where,

M means the number of the selected data center

d_i means maximum center distance between the i data and other data.

DESIGN OF FORECASTING MODEL OF BOD BASED ON CBR

CBR has been widely applied in various fields (Singh et al. 2016). It is one kind of reasoning methods based on the specific knowledge according to the past experience. Comparing with conventional expert system, it has some advantages. According to the present problem, CBR will find some similar problems which have been solved in the past memory by comparing the attribute characteristics. Then make some adjustment and modification accordingly so as to assist in solving the problem.

The CBR is used to carry on soft-sensor modeling, and it can realize simple and easily train the new neural network (Xu et al. 2016). In CBR, one or more related cases are retrieved in the case base so as to solve a new problem. And then use the solution which is obtained through case matching to verify the application effect. If the matching degree of the solution is high, the solution is adopted. Otherwise, it will go on adjusting to get a preserved and matching case. At present, there is no one universal CBR which is suitable for all fields. The main cause is that different fields and problems generally require different method, and it can reflect the validity of the system through case representation, case matching, case adaption, case learning and maintenance. The main flowchart of the forecasting model based on CBR is shown in Figure 2.

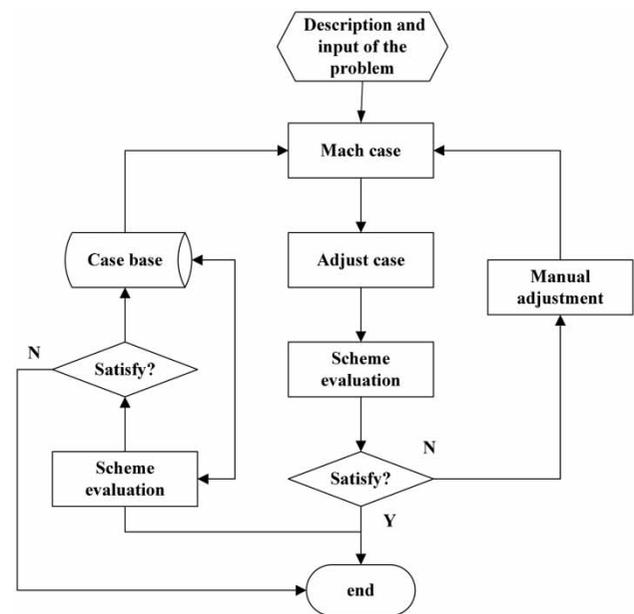


Figure 2 | Prediction model of CBR.

Case representation

Since the case includes a description of the problem and its solution, the representation of the case should contain at least 2 aspects. So it can be expressed as one ordered pair <problem, solution>. In addition, it adds the generation time of the case in the forecasting model of the BOD. Therefore, the case of the forecasting model for the qualitative index of the sewage is composed of time, case description and the solution. Case description is the selected auxiliary variable, and the solution is the predictive value of the BOD. The operating mode features include MLSS (activated sludge concentration), temperature, PH value, effluent COD/DO, Water inflow Q, $\text{NH}_4^+\text{-N}$ and HRT, which are selected as the auxiliary variable. It can be represented as x_1, x_2, \dots, x_8 , and the solution is expressed as Y. The storage mechanism of individuating information is shown in Table 1.

Case matching based on back propagation neural network

Case matching

Case matching is the key technique in CBR system. In order to find out as few as possible revisable case which is similar with the description of the problem quickly and accurately, the powerful indexing and case base are needed to control the direction of search. Among, the nearest-neighbor strategy is the simplest, most convenient and the most widely adopted method. Based on the geometric model method of 'distance', this paper carries on the measurement of the similarity. According to the definition of the Euclidean distance, the similarity function can be denoted by

$$\begin{aligned} \text{sim}(X_0, X_i) &= 1 - \text{dist}(X_0, X_i) \\ &= 1 - \sqrt{\sum_{k=1}^n \omega_k^2 \text{dist}^2(x_{i0}, x_{ik})} \end{aligned} \quad (4)$$

Where,

X_0, X_i represent the current working condition vector and the case description of the case i

Table 1 | Storage mechanism of individuating information

Time	Case description	Solution
T	x_1, x_2, \dots, x_8	Y

ω_k is the weighted coefficient of the descriptive characteristics of the working condition

Case matching based on back propagation

There are various factors which have the coupling and the complicated nonlinearity in the soft sensors model of wastewater treatment process control parameters. The nearest neighbor algorithm can be used to solve the problems which are sample and determine the weight of the attribute easily. For the complex problem like the soft sensors in wastewater treatment process, it is difficult to determine the weight of each attribute reasonably owing to the complicated relationship among the attributes. So, the nearest neighbor algorithm will lose its meaning. Therefore, the technology of back propagation (BP) neural network is applied to the case matching. Train the previous input/output samples until the convergence, and then save the data of the link weight in order to be called by the case matching. Finally, it is compared with the samples in the base case, so as to improve the efficiency and accuracy of the case matching.

The implement step of BP neural network

Step 1: The initialization of the BP neural network. According to the randomized principle, the connection weight ω_{ij} between the input layer and hidden layer, the connection weight v_i , the threshold $\theta_{i,\gamma}$ between the hidden layer and output layer will be given the random value among the interval $(-1, 1)$. Because the nonlinear self-response term is sensitive to the initial conditions, so each initial state corresponds to one motion trajectory.

Step 2: Provide one input-output model (A_K, Y_K) randomly.

Step 3: Determine the input and output value between the hidden layer and output layer. We denote

$$S_j = \sum_{i=1}^{2n} \omega_{ij} a_i - \theta_j \quad (5)$$

$$b_j = f(S_j) \quad (6)$$

$$I = \sum_{j=1}^q v_j b_j - \gamma \quad (7)$$

$$c = f(I) \quad (8)$$

Where,

$$f(x) = 1/(1 + \exp(-x))$$

$$i = 1, 2, L, 2n; j = 1, 2, L, q$$

Step 4: Construct the random movement mechanism of the connection weight parameter value. The (9) and (10) are the calibration error of the connection weight of the input and output layer respectively. Adjust the connection weight between the hidden and output layer. Firstly, generate the random ε value among the interval (0, 1).

$P[v_j(t) - v_j(t-1)] - v_j(t+1)$ means a probability, which brought by the nonlinear self-feedback.

When $\varepsilon > P[v_j(t) - v_j(t-1)]$ making the adjustment according to the formula (11).

When $\varepsilon < P[v_j(t) - v_j(t-1)]$ making the adjustment according to the formula (12).

Where, t is the times of learning.

Furthermore, adjust the threshold of the neural unit of the output layer. In the same way, adjust the connection weight ω_{ij} between the input and hidden layer. Denote

$$d^k = (y^k - c)c(1 - c) \quad (9)$$

$$e_j^k = d^k v_j b_j (1 - b_j) \quad (10)$$

$$v_j(t+1) = v_j(t) + \alpha d^k(t) b_j(t) \quad (11)$$

$$v_j(t+1) = v_j(t) + \alpha d^k(t) b_j(t) + \varphi [v_j(t) - v_j(t-1)] \quad (12)$$

$$\gamma(t+1) = \gamma(t) + \alpha d^k(t) \quad (13)$$

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \beta e_j^k(t) a_i^k(t) \quad (14)$$

$$\omega_{ij}(t+1) = \omega_{ij}(t) + \beta e_j^k(t) a_i^k(t) + \varphi [\omega_{ij}(t) - \omega_{ij}(t-1)] \quad (15)$$

$$\theta_j(t+1) = \theta_j(t) + \beta e_j^k(t) \quad (16)$$

Case adaption

Because the process of case retrieval is to look for the most similar case in case base, it is difficult to identify the past cases which match well the current problem. So the past cases need to be adjusted appropriately. The adaption of the

cases includes the selection of the content, the transformation and evaluation of the solution. If the adjusted cases pass the quality estimation of the case evaluation, it will be put into practice. Meanwhile, it will be deposited in the case base after the evaluation of the learning technology. In order to eliminate the inconsistency of time and prevent the time of the case failing, the old cases need to be deleted.

The required adjusted cases are assumed to be n cases, respectively $[X_1, Y_1], [X_2, Y_2], \dots [X_n, Y_n]$ and the estimated value of the current condition information is denoted by

$$Y_0 = \frac{\sum_{i=1}^n Y_i \text{sim}(X_0, X_i)}{\sum_{i=1}^n \text{sim}(X_0, X_i)} \quad (17)$$

Where,

$\text{sim}(X_0, X_i)$ is the similarity between the current condition information and the cases in case base, which calculated according to the (4).

After the adjustment of the case, the system exports the results and records the time, case description and case solution.

Case learning and maintenance

The process of case learning is to make the adjusted cases deposit the case base. If there are existing the cases which are the same as the target case in the case base, the target case will be abandoned directly. Otherwise, the adjusted cases will be saved in the case base. Case learning is an incremental learning method, and the system with high academic ability can alleviate the problem of the retrieval time and the increased number of cases effectively. The increase of the number of the case-base can improve the accuracy of the system, but slow down the operating speed of the system. Therefore, the prompt case maintenance is an important step for the case reasoning. In order to make the cases have high typicality, timeliness, consistency and non-redundancy, the case maintenance generally uses some methods to keep the features, such as fluctuate the number of the case samples, prune the interferential case samples and adjust the structure of the case-base and the index device and so on.

THE MODEL TRAINING AND VALIDATION BASED ON ACTUAL OPERATION DATA

In order to verify the reliability of the forecasting model, the MLSS (activated sludge concentration), temperature, PH

value, effluent COD/DO, Water inflow Q, NH₄⁺-N and HRT, which are selected as the auxiliary variable are collected in wastewater treatment plants. The corresponding detection values of BOD parameter are collected as the primary variable. Where, the abnormal sample and data are carried out the normalization processing, so as to make the indexes be located on the same number order and obtain 250 groups sample points. The first 150 groups are used to make the initial modeling, and then the remaining 100 groups are used to test the forecasting effect of the model. The simulation diagrams are as follows.

- (1) The prediction effect of the soft-sensing model of the sewage treatment based on RBF neural network is shown in Figure 3.
- (2) The prediction effect of the soft-sensing model of the sewage treatment based on conventional CBR is shown in Figure 4.
- (3) The prediction effect of the soft-sensing model of the sewage treatment based on improved CBR is shown in Figure 5.

In order to evaluate the model, the following three performance indexes are used to evaluating the forecasting results. The smaller the error, the better the forecasting results. These performance indexes are given by

- (1) Root mean-square error

$$MSE = \sqrt{\frac{1}{n} \sum_{i=1}^n (y_i - \hat{y}_i)^2} \quad (18)$$

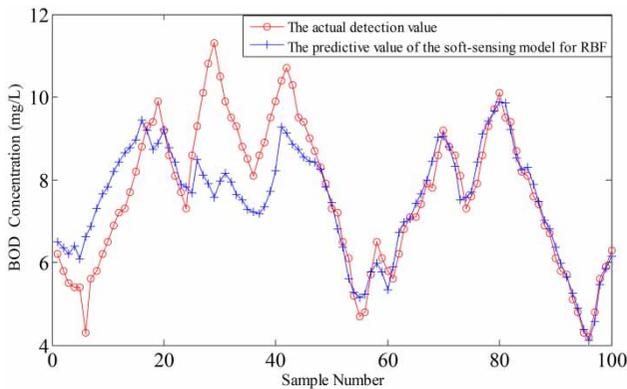


Figure 3 | Soft sensor model predictions curve of sewage treatment. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH₄⁺-N: 25~60 mg/L (average value), PH: 6~9.

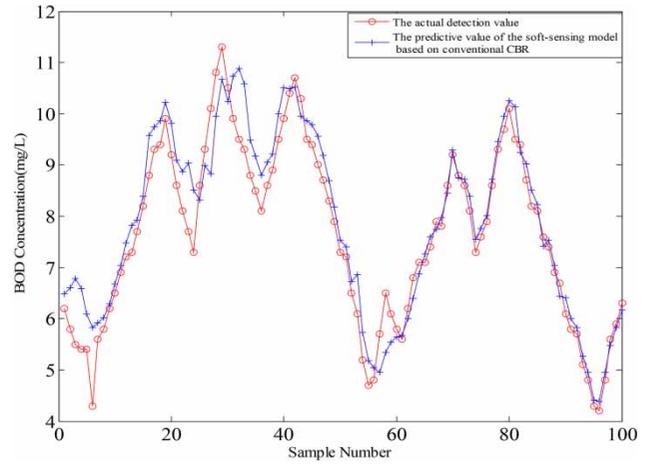


Figure 4 | Soft sensor model predictions curve of sewage treatment based on conventional CBR. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH₄⁺-N: 25~60 mg/L (average value), PH: 6~9.

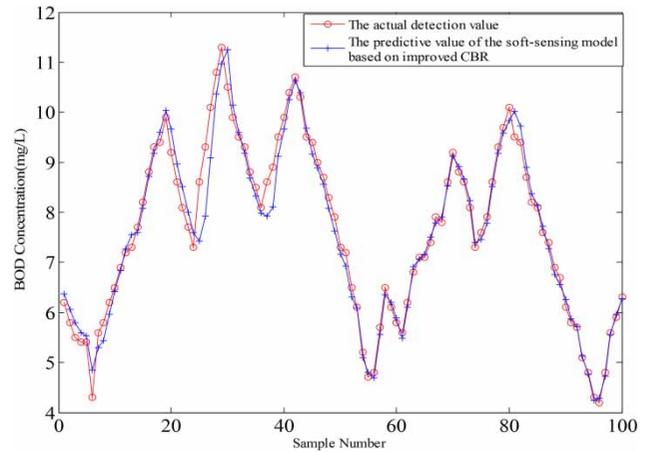


Figure 5 | Soft sensor model predictions curve of sewage treatment based on improved CBR. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH₄⁺-N: 25~60 mg/L (average value), PH: 6~9.

- (2) Mean-absolute relatively error

$$EAE = \frac{1}{n} \sum_{i=1}^n \left| \frac{y - \hat{y}_i}{y} \right| \quad (19)$$

- (3) Maximize-absolute relatively error

$$EME = \text{Max} \left| \frac{y - \hat{y}_i}{y} \right| \quad (20)$$

Where,

n is the number of the testing sample

y_i is the actual value of the data
 \hat{y}_i is the forecasting value of the model

The prediction performance is shown in Table 2.

As can be seen in Figures 3, 4 and 5, the training results of the model are close to the actual results. Furthermore, it gives the comparison of the performances of the forecasting model in Table 2. Results show that the control precision of the soft-sensing model based on improved CBR is greatly improved. Thus it can be seen that the soft-sensing model of sewage treatment based on CBR approach, which can effectively solve the real-time estimation problem of the performance indexes in wastewater treatment process.

ENGINEERING APPLICATION

In order to validate the application effect of the proposed predictive model in industrial field, the MLSS (activated sludge concentration), temperature, PH value, effluent COD/DO, Water inflow Q, NH_4^+-N and HRT, which are selected as the auxiliary variable are collected in wastewater treatment plants. The corresponding detection values of BOD parameter are collected as the primary variable. The selected 150 groups are used to make the initial modeling, and then the established model is carried out the measurement for the BOD. The following parts show the simulation diagrams for comparing results of the three results of measurement with the actual value.

It can be seen from the Figure 6 that the predictive value of the soft-sensing model based on RBF shows more stability, but it gets low accuracy. Furthermore, compared with other estimations, there is a relatively huge difference between the predicted and actual values from May to June. This result indicates that the soft-sensing model based on RBF is influenced by the time for training sample. As shown in Figures 7 and 8, the forecasting value of the soft-sensing model based on CBR becomes more and more close to the actual value over time. This is because the CBR improves the rules of the case base until it achieves

Table 2 | Evaluating indicators

Index	Soft-sensing model based on RBF neural network	Soft-sensing model based on conventional CBR	Soft-sensing model based on improved CBR
MSE	0.384	0.326	0.282
EAE	2.158%	2.138%	1.814%
EME	0.18	0.146	0.115

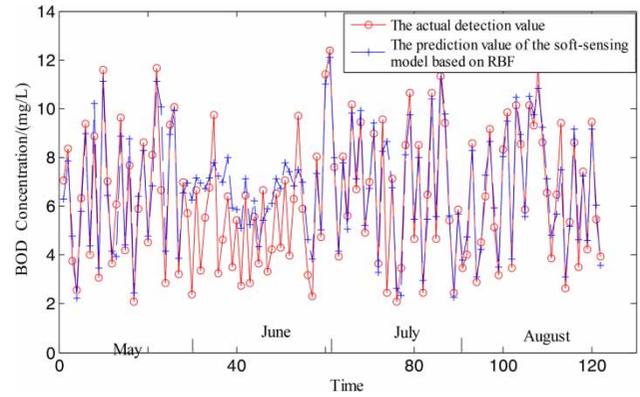


Figure 6 | Comparison of actual value and soft sensor model predictions value of sewage treatment based on RBF neural network. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH_4^+-N : 25~60 mg/L (average value), PH: 6~9.

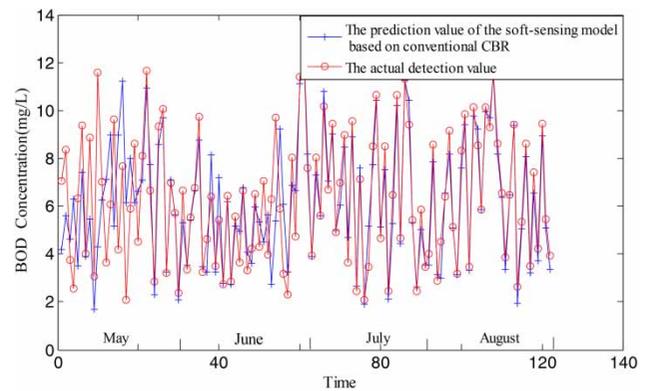


Figure 7 | Comparison of actual value and soft sensor model prediction value of sewage treatment based on conventional CBR. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH_4^+-N : 25~60 mg/L (average value), PH: 6~9.

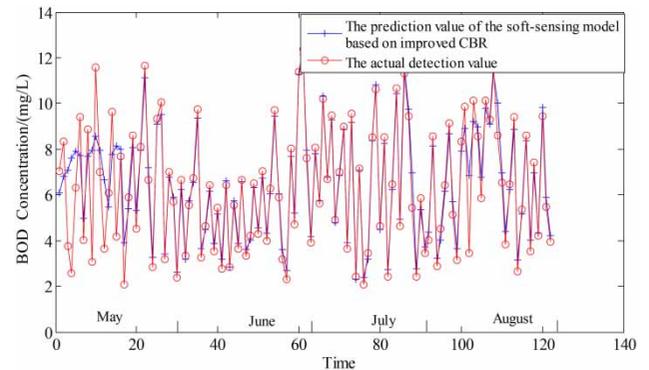


Figure 8 | Comparison of actual value and soft sensor model predictions value of sewage treatment based on improved CBR. Experimental conditions: MATLAB simulation tool, DO concentration: approximately 2.6 mg/L, COD: 30~120 mg/L (average value), NH_4^+-N : 25~60 mg/L (average value), PH: 6~9.

the best effect. Comparing the three prediction effect, it can be seen that the forecasting effect of the soft-sensing model based on the conventional CBR is similar to the RBF. However, the forecasting effect of the improved soft-sensing model based on CBR is the closest to the actual value. It also indicates that the validity of the improved soft-sensing model based on CBR in the prediction of wastewater BOD. Han et al. (2016) proposed a soft-sensing approach of sewage treatment based on RBF neural network. However, the proposed method has shortcomings such as slow speed of convergence, poor capability of fitting, low accuracy of prediction and indefiniteness of the training results. An et al. (2016) adopts the soft measurement of BP neural network to establish the prediction model of dissolved oxygen concentration. The simulation results show that, using genetic algorithm to optimize BP neural network weight and threshold value and the training data is normalized, effectively solve the dissolved oxygen concentration in BP soft measurement model accuracy. However, the measurement accuracy of the dissolved oxygen in the soft measurement model is lower than the proposed CBR approach in my paper.

CONCLUSION

This paper proposed the predictive method by applying of intelligent integrated modeling which is integrated by the RBF neural network and the improved CBR. Comparing the single forecasting methods based on RBF, the intelligent integrated modeling method presented in this paper can enhance the prediction accuracy and robustness of the model. This method can effectively solve the forecast problems of BOD in wastewater treatment process and it also has some engineering significance and practical value.

ACKNOWLEDGEMENTS

We greatly appreciate the Natural Science Foundation of Anhui Higher Education Institutions of China [grant number: KJ2013A054].

REFERENCES

- An, A. M., Qi, L. C., Chou, Y. X., Zhang, H. S. & Song, H. B. 2016 The study on soft sensor with BP neural network and its application to dissolved oxygen concentration. *Computers and Applied Chemistry* **33** (01), 117–121.
- Barber, W. P. F. 2016 Thermal hydrolysis for sewage treatment: a critical review. *Water Research* **104**, 53–71.
- Ben, W. W., Wang, J., Cao, R. K., Yang, M., Zhang, Y. & Qiang, Z. M. 2017 Distribution of antibiotic resistance in the effluents of ten municipal wastewater treatment plants in China and the effect of treatment processes. *Chemosphere* **172**, 392–398.
- Dąbrowski, W., Żyłka, R. & Malinowski, P. 2017 Evaluation of energy consumption during aerobic sewage sludge treatment in dairy wastewater treatment plant. *Environmental Research* **153**, 135–139.
- De Soto, B. G. & Adey, B. T. 2016 Preliminary resource-based estimates combining artificial intelligence approaches and traditional techniques. *Procedia Engineering* **164**, 261–268.
- De Sousa, R. V., Canata, T. F., Leme, P. R. & Martello, L. S. 2016 Development and evaluation of a fuzzy logic classifier for assessing beef cattle thermal stress using weather and physiological variables. *Computers and Electronics in Agriculture* **127**, 176–183.
- Han, H. G., Zhang, S. & Qiao, J. F. 2016 Soft-sensing measurement of permeability of MBR membrane based on recurrent RBF neural network. *2016 Chinese Conference on Process Control* **107**.
- Izady, A., Abdalla, O., Sadeghi, M., Majidi, M., Karimi, A. & Chen, M. 2016 A novel approach to modeling wastewater evaporation based on dimensional analysis. *Water Resources Management* **8** (30), 2801–2814.
- Kumar, J., Singh, A., Panda, M. K. & Bhadauria, H. S. 2016 Study and performance analysis of routing protocol based on CBR. *Procedia Computer Science* **85**, 23–30.
- Lee, J. H. & Oh, J. E. 2016 A comprehensive survey on the occurrence and fate of nitrosamines in sewage treatment plants and water environment. *Science of the Total Environment* **556**, 330–337.
- Liu, S. J. & Zhang, S. Y. 2015 Design of automatic door monitoring system based on the MCGS. *Foreign Electronic Measurement Technology* (9), 48–51.
- Liu, P., Gernjak, W. & Keller, J. 2017 Long-term performance of enhanced-zero valent iron for drinking water treatment: a lab-scale study. *Chemical Engineering Journal* **315**, 124–131.
- Mjalli, F. S., Al-Asheh, S. & Alfadala, H. E. 2007 Use of artificial neural network black-box modeling for the prediction of wastewater treatment plants performance. *Journal of Environmental Management* **3** (83), 329–338.
- Qiao, J. F., Li, R. X., Chai, W. & Han, H. G. 2016 Prediction of BOD based on PSO-ESN neural network. *Control Engineering of China* (4), 463–467.
- Ren, D. H., Han, H. G. & Qiao, J. F. 2014 Hierarchically neural network soft measurement modeling based on IHPSO algorithm for wastewater treatment process. *Information and Control* (1), 123–128.
- Singh, P., Kansal, A. & Carliell-Marquet, C. 2016 Energy and carbon footprints of sewage treatment methods. *Journal of Environmental Management* **165**, 22–30.
- Struijs, J., Van de Meent, D., Schowanek, D., Buchholz, H., Patoux, R., Wolf, T., Austin, T., Tolls, J., Van Leeuwen, K. & Galay-Burgos, M. 2016 Adapting simple treat for simulating

- behaviour of chemical substances during industrial sewage treatment. *Chemosphere* **159**, 619–627.
- Tang, C. & Guan, J. J. 2017 Treatment technology on polymer flooding wastewater in Henan oilfield. *Key Engineering Materials* **719**, 74–78.
- Xu, D. G., Chen, Y. W., Chen, X., Xie, Y. F., Yang, C. H. & Gui, W. H. 2016 Multi-model soft measurement method of the froth layer thickness based on visual features. *Chemometrics and Intelligent Laboratory Systems* **154**, 112–121.
- Yang, R., Er, P. V., Wang, Z. D. & Tan, K. K. 2016 An RBF neural network approach towards precision motion system with selective sensor fusion. *Neurocomputing* **199**, 31–39.
- Yoo, K., Shukla, S. K., Ahn, J. J., Oh, K. & Park, J. 2016 Decision tree-based data mining and rule induction for identifying hydrogeological parameters that influence groundwater pollution sensitivity. *Journal of Cleaner Production* **122**, 277–286.
- Zhang, Q. H., Yang, W. N., Ngo, H. H., Guo, W. S., Jin, P. K., Dzakpasu, M., Yang, S. J., Wang, Q., Wang, X. C. & Ao, D. 2016 Current status of urban wastewater treatment plants in China. *Environment International* **92–93**, 11–22.

First received 15 March 2017; accepted in revised form 27 June 2017. Available online 22 July 2017