Environ Earth Sci (2016) 75:1327
DOI 10.1007/s12665-016-6134-z

THEMATIC ISSUE

Raw water quality assessment for the treatment of drinking water

Dongsheng Wang[1]

Received: 24 January 2016 / Accepted: 19 July 2016 / Published online: 7 October 2016

Abstract Changes in the quality of raw water can significantly affect the treatments necessary for drinking water. Generally, raw water quality assessments are carried out to classify the pollution level of raw waters and cannot be used directly as a control for drinking water treatments. In order to improve the adaptability of drinking water treatments and to stabilize the overall quality of treated water, a raw water quality assessment technique that is specifically related to drinking water treatments is developed in this study. First, a drinking water treatment-oriented raw water quality assessment standard is proposed, based on historical environmental information and an analysis of operational data from drinking water treatments. A raw water quality assessment model is then set up to assess the raw water quality in real time. Finally, the results from this assessment are used to compute feedforward compensation for real-time control of the chemical dosing process, including both alum and ozone in the drinking water treatment. In this way, drinking water treatment can be adjusted according to the temporal changes in raw water quality, thereby stabilizing the quality of treated waters. Experimental implementation of this technique has been carried out in the chemical dosing process control systems of a drinking water treatment plant in China, and the results obtained demonstrate the effectiveness of the raw water quality assessment method proposed herein. This development will be helpful in satisfying the basic requirement of safe drinking water under a worsening global water environment.

Keywords Raw water quality assessment · Chemical dosing process · Drinking water treatment

This article is part of a Topical Collection in Environmental Earth Sciences on "Environment and Health in China II", guest edited by Tian-Xiang Yue, Cui Chen, Bing Xu and Olaf Kolditz.

✉ Dongsheng Wang
wangdongsheng@njupt.edu.cn

[1] School of Automation, Nanjing University of Posts and Telecommunication, Nanjing 210003, People's Republic of China

Introduction

Drinking water is made suitable for human consumption by a series of treatment processes. The specific treatment processes that are necessary to produce safe drinking water are largely governed by the raw water quality of a region, which is determined by temporally variable natural influences, including precipitation rate, soil erosion, and season, as well as anthropogenic influences such as urban, industrial, and agricultural activities (Symons and Robeck 1975; Slavik and Uhl 2009; Santana et al. 2014; Gao et al. 2014). Thus, it is very important to acquire reliable information on raw water quality for the effective production of safe drinking water, especially under the prevailing widespread pollution of water sources. In a drinking water treatment plant, important water quality parameters such as temperature, pH, turbidity, chemical oxygen demand (COD_{Mn}), ammoniacal nitrogen (NH_4^+-N) are generally monitored online and are also measured off-line in the laboratory to provide relatively real-time and accurate information (Zamyadi et al. 2012).

Raw water quality assessments have been widely used to classify the pollution levels of raw waters (Vega et al. 1998; Singh et al. 2005; Zhou et al. 2007; Chu et al. 2013). However, to our knowledge, there have not yet been any reports of such assessments being used to guide drinking water treatment. This is mainly due to the fact that drinking water treatment processes are not only related to the levels of raw water quality, but are also linked to factors such as weather, climate, and the discharge of raw sewage (Delpla et al. 2011; Stepien et al. 2014). As a result, conventional raw water quality assessment techniques can only be used for off-line operator support and cannot be directly employed for the real-time control of drinking water treatment processes. Additionally, the raw water quality of developed countries is generally superior, and changes of raw water quality are considered to be relatively mild. In contrast, the safety of drinking water in many developing countries is not assured, due to the potentially serious pollution of water sources, which may not be considered during drinking water production (Schulz et al. 1992; Gadgil 1998; Sobsey et al. 2008). The changes in raw water quality are becoming more frequent, especially in adverse weather conditions such as strong winds and heavy rains, as well as discharge of wastewater. Suspended material often becomes higher after strong winds, heavy rains, and discharge of wastewater. Therefore, a drinking water treatment-oriented raw water quality assessment is urgently needed, in order to stabilize the quality of treated water.

Artificial neural networks (ANNs) are effective nonlinear modeling tools, due to their great ability in mapping input-output data. In particular, radial basis function (RBF) neural networks have been shown outstanding approximations and have been widely used in terms of environmental pollutants (Lu et al. 2003; Lu 2004; Tarek 2012; Iliyas et al. 2013). In RBF neural networks, a number of parameters, including the centers and widths of radial basis functions and the weights between the hidden and output layers, can have significant effects on the performance of the model (Chen et al. 1992; Knopf and Sangole 2004). Traditional training algorithm based on gradient descent (GD) method has the disadvantages of slow convergence precision and easy trapping into local minimum. Particle swarm optimization (PSO) is a swarm intelligence metaheuristic behavior of decentralized systems obtained from the simulation of flocking birds or schooling fish (Liu et al. 2004). It conducts an intelligent search for the solution space through 'cooperative' strategy of individuals (called particles), in contrast to the 'competitive' strategy of genetic algorithm (GA). Suboptimal solutions in the PSO algorithm can therefore survive and contribute to the search process at later stages of iteration. It has been proved that RBF neural networks with parameters optimized by PSO algorithm have excellent performance in the applications of water quality prediction and water quality evaluation (Xu et al. 2011; Shen and He 2012).

Practical drinking water treatment processes are severely affected by changes in raw water quality and exhibit clear nonlinearity with a considerable time delay (Helm 2007; Wang et al. 2013). Under the conventional feedback control scheme based on processing error, it is difficult to achieve satisfactory real-time control performances, especially when raw water quality underdoes frequent changes (Cromphout et al. 2005; Courtois 2005; Elovitz et al. 2000). In contrast to such error-based controls, feedforward control system is based on estimations or measurements of disturbances to the process. The controlling action of feedforward system occurs at the same time as the disturbance, and the process response is faster than under feedback control. In practical applications, it is usually employed to overcome major disturbance to the process and is combined with feedback control to optimize performance (Xu and Ouyang 2012; Zheng and Fu 2013).

The main aim of this study is to develop a raw water quality assessment method that is specially oriented toward the drinking water treatment process. We first study the influence of various raw water quality parameters on drinking water treatment and propose a raw water quality assessment standard for drinking water treatment. An RBF neural network trained by a PSO algorithm is then established as a model or on-line raw water quality assessment. Following this, a composite feedforward and feedback control scheme is developed to guide chemical dosing during drinking water production. In the feedforward control loop, the control action is based upon on-line assessment of raw water quality, while an internal model controller (IMC) is designed for the feedback control loop. One of the unique aspects of this work is that the assessment method is oriented specifically toward drinking water treatment and can be utilized directly for the real-time control of practical chemical dosing processes. Additionally, a feedforward and feedback composite control scheme based on the assessment of raw water quality is developed here for the first time. Finally, this work has been experimentally implemented in the chemical dosing control systems of the Xiangcheng water treatment plant (XWTP) in Suzhou, China.

Material and methods

Raw water quality assessment standard

The XWTP (capacity of $300,000\,m^3$/day) was originally put into service in 2007, and the raw water is captured from Taihu Lake at Jinsu station. Taihu lake is the third largest freshwater lake in China, with a surface area of $2338\,km^2$. It is shallow, with an average depth of around 2.0 m, and eutrophic, with wind-induced sediment resuspension occurring frequently. Owing to variations in wind speeds and directions, in addition to differences in the growth of animals and plant in different seasons, the amount of suspended material in the lake water is seen to change throughout the year. Thus, the water quality in the lake is seriously affected by such seasonal changes (Blindow et al. 2002). In general, the concentrations of total nitrogen (TN) and total phosphorus (TP) in the water are higher in the summer, whereas the concentrations of ammoniacal nitrogen are higher in the winter. Statistical analysis of the time series of daily values of water quality parameters of Xiangcheng water treatment plant during 2012–2014 is summarized in Table 1, while the time series of monthly averages of water quality parameters are illustrated in Fig. 1. As can be seen, the average concentrations of temperature, turbidity, NH_4^+-N, and COD_{Mn} are 16.7°C, 25.3 NTU, 0.22 mg/L, 2.6 mg/L, respectively, and the standard deviation is 5.2°C, 2.3 NTU, 0.06 mg/L, 0.11 mg/L, respectively.

In order to evaluate the influence of these raw water quality parameters on the chemical dosing process, including alum and ozone, we study the daily operating data of chemical dosage under different conditions of raw water quality using statistical analysis methods. Moreover, we refer to operators with rich experience and select those parameters that have a significant influence on the chemical dosing process, namely temperature, turbidity, $NH_4^+ - \mathrm{N}$, and COD_{Mn}, as the factors for raw water quality assessment. Based on the statistical analysis of historical data of raw water quality parameters, ideal process output and corresponding chemical dosage during 2012–2014, which is collected from the online measuring system of Xiangcheng water treatment plant, the raw water quality assessment standard oriented to the control of chemical dosing process is established in Table 2. The water quality grades and the desired output defined herein refer to the optimum chemical dosage for reference.

Table 1 Raw water quality of Xiangcheng water treatment plant during 2012-2014

Parameter	Max	Min	Average	SD
pH	9.3	6.9	8.4	0.17
Temperature/°C	33.9	1.5	16.7	5.2
Turbidity/NTU	197.4	9.2	25.3	2.3
NH_4^+-N/mg L^{-1}	2.21	0.03	0.22	0.06
COD_{Mn}/mg L^{-1}	5.2	1.7	2.6	0.11
TOC/mg L^{-1}	6.27	3.58	4.17	0.12
TP/mg L^{-1}	0.527	0.003	0.052	0.011
TN/mg L^{-1}	4.62	0.079	1.22	0.17
Bromide/mg L^{-1}	0.378	0.182	0.272	0.026

Raw water quality assessment modeling

Raw water quality assessment modeling is a crucial part of raw water quality assessment. Here, an RBF neural network model is established to enable real-time assessment of raw water quality. RBF neural networks are effective feedforward neural networks with one hidden layer, which have excellent nonlinear mapping capabilities. As shown in Fig. 2, the structure of a basic RBF neural network comprises one input layer, one hidden layer, and one output layer. The output of a single-output RBF neural network can be described as

$$y = \sum_{k=1}^{q} \omega_k \phi_k(\mathbf{X}) \quad (1)$$

where $\mathbf{X}$ the input vector, including temperature, turbidity, $NH_4^+ - \mathrm{N}$, and COD_{Mn}, q the number of hidden nodes, ω_k the neural network weight that connects the kth hidden node and output, and ϕ_k the output of the kth hidden node, which is often defined by a Gaussian function shown as follows

$$\phi_k(\mathbf{X}) = e^{-\frac{||\mathbf{X}-\mu_k||^2}{\delta_k{}^2}} \quad k = (1, 2, \ldots, q) \quad (2)$$

where μ_k the center of the kth hidden node and δ_k the variance of the kth hidden node.

The number of hidden nodes q is a key factor affecting the prediction performance of the neural network. If it is excessively large, the generalization capability of neural network may decrease, possibly even resulting in problematic over-learning phenomena. If it is too small, however, the desired prediction performance may be not achieved. For determining the number of hidden nodes, RBF neural networks with different hidden nodes have been tried, and three hidden nodes are selected by considering the tradeoff between generalization capability and modeling accuracy.

The model parameters of the RBF neural network, such as the centers and widths of the hidden RBF functions and the weightings associating the hidden nodes with the output nodes, have a strong influence on the performance of an RBF neural network model. Particle swarms explore the search space through a population of particles. Each particle tries to find the best global solution, by adjusting its trajectory toward its own best position p_i and the best particle of the swarm p_g at each iteration. The velocity and position are updated according to the following equations:

$$v_i{}^{(k+1)} = h^{(k)} v_i{}^{(k)} + c_1 r_1 (p_i{}^{(k)} - x_i{}^{(k)}) + c_2 r_2 (p_g{}^{(k)} - x_i{}^{(k)}) \quad (3)$$

$$x_i{}^{(k+1)} = x_i{}^{(k)} + v_i{}^{(k)} \quad (4)$$

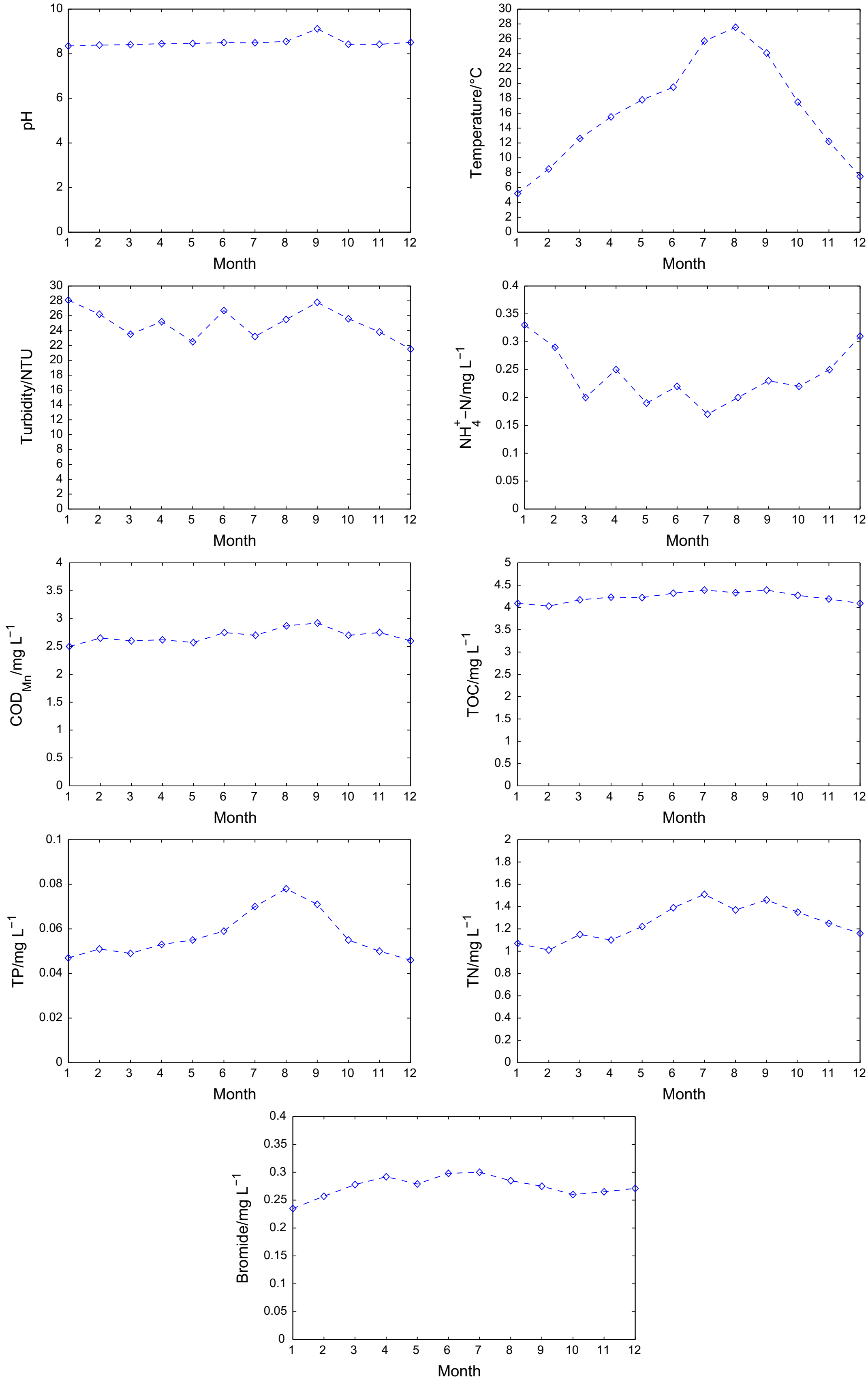

Fig. 1 Time series of monthly averages of water quality parameters during 2012–2014

Table 2 Raw water quality assessment standard oriented to the control of chemical dosing process

Water quality grade	Temperature (°C)	Turbidity (NTU)	NH_4^+-N (mg L^{-1})	COD_{Mn} (mg L^{-1})	Desired output	Optimum alum dosage (mg L^{-1})	Optimum ozone dosage (mg L^{-1})
I	10	20	0.5	2	0.1	9	0.7
II	10	40	1	2	0.2	11	0.8
III	10	80	2	2.5	0.3	14	0.9
IV	20	20	0.5	2.5	0.4	8	0.8
V	20	40	1	3	0.5	10	0.9
VI	20	80	1.5	3.5	0.6	13	1
VII	30	20	0.5	4	0.7	7	0.9
VIII	30	40	1	4.5	0.8	9	1
IX	30	80	2	5	0.9	12	1.2

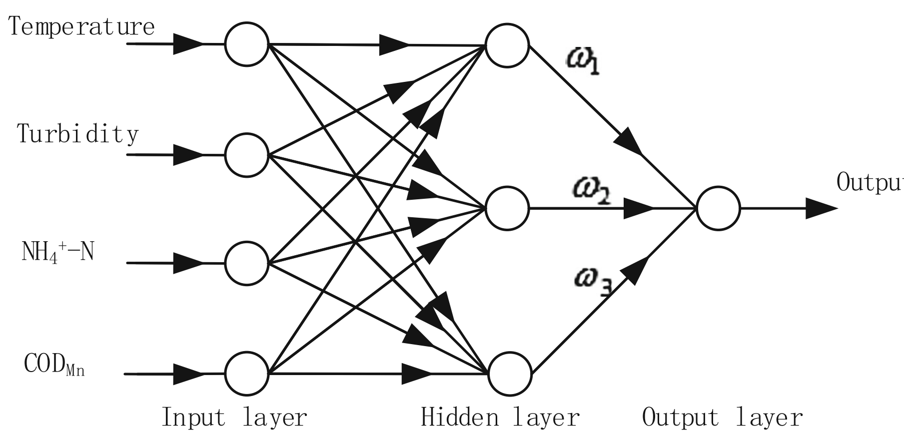

Fig. 2 Structure of the RBF neural network

where $i = 1, 2, \ldots, n$, $n$is the number of the particle 50 in this study, $v_i{}^k$ the present velocity of the particle i, $x_i{}^k$ the present position of the particle i, k the inertia number, c_1 and c_2 the acceleration constants, r_1 and r_2 the random numbers selected between [0,1], h^k the inertia weight, which can be described as follows:

$$h^{(k)} = (h_1 - h_2)(k_{\max} - k)/k_{\max} + h_2 \tag{5}$$

where $k_{\max}$ is the max inertia number, h_1 and h_2 the initial inertia weight and final inertia weight, respectively.

The fitness function of particle is shown in the following equation:

$$\text{Fitness} = \frac{1}{N}\sum_{i=1}^{N}(y_i - y_t)^2 \tag{6}$$

where N is the number of training samples, y_i the ideal output, and y_t the actual output.

Therefore, since PSO algorithms have been shown to produce superior training results compared with conventional algorithms, we use the PSO approach to train the parameters of our RBF neural network model.

3000 groups of historical data for the sampling frequency of three times a day from XWTP during 2012–2014 are collected and divided into two parts. The first 2000 groups are used to train the RBF neural model, and the remaining 1000 groups are used to test the performance of the model. It is noted that the abnormal data have been eliminated and smooth processing for the 3000 groups of historical data has been conducted to deal with noise or missing values in the dataset.

The Theil's inequality coefficient (TIC) value represents the goodness-of-fit between model output and desired output:

$$TIC = \frac{\sqrt{\sum_i (\hat{y}_i - y_i)^2}}{\sqrt{\sum_i \hat{y}_i^2} + \sqrt{\sum_i y_i^2}} \tag{7}$$

where $\hat{y}_i$ the model output, y_i the desired output.

Feedforward–feedback composite control scheme

Owing to the reactivity of the substances involved, the chemical dosing processes of drinking water treatment are seriously affected by the factors, such as water flow, water quality, and chemical dosage. It is therefore difficult to stabilize the quality of treated waters using the traditional

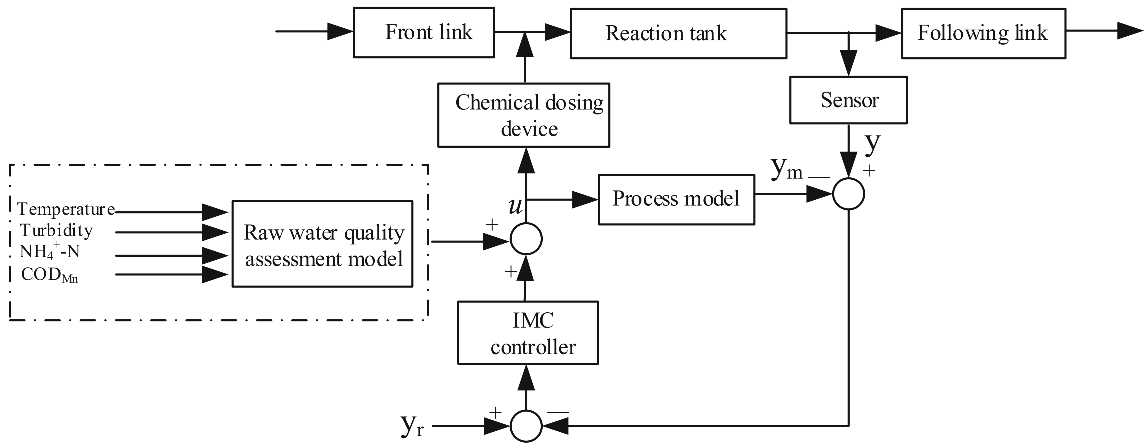

Fig. 3 Feedforward–feedback composite control scheme

feedback control scheme, especially during periods of rapid change in raw water quality. Thus, we propose a feedforward–feedback composite control scheme, as illustrated in Fig. 3.

For the alum dosing process, the process model is the model of alum dosing process, the front link is the pre-ozonation, and the following link is the sand filtration. For the ozone dosing process, the process model is the model of ozone dosing process, the front link is the sand filtration and the following link is the biological activated carbon filtration. It is noted that turbidity is the output of alum dosing process and dissolved ozone residual ($resO_3$) is the output of ozone dosing process. y is the actual value of process output (turbidity or $resO_3$). y_r is the reference value of process output (turbidity or $resO_3$). y_m is the process model output (turbidity or $resO_3$). u is the control input (alum dosage or ozone dosage). Within this composite control scheme, the feedforward compensation is based upon the raw water quality assessment, while an IMC is used for the feedback control loop.

The integral of absolute error (IAE) is chosen as the quantitative index to evaluate the closed-loop control performance:

$$IAE(t) = \frac{1}{N}\sum_{t=1}^{N} |y_r(t) - y(t)| \tag{8}$$

where $y_r(t)$ is the reference value of process output, $y(t)$ the actual value of process output.

Results and discussion

Raw Water Quality Assessment Results.

The results of our testing of the RBF neural network model are presented in Fig. 4. It can be seen from this that the assessment model performs well in predicting the relevant desired output given by the assessment standard in Table 2. The TIC values of 0.06 are much lower than 0.3, indicating

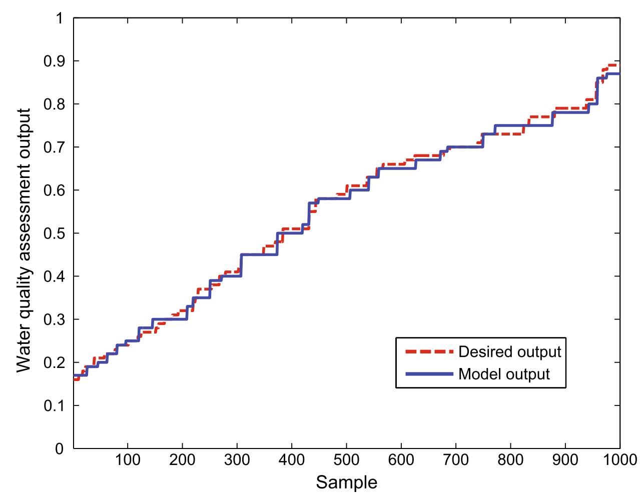

Fig. 4 Testing results of RBF neural network model

good model performance (Zhou 1993). On the basis of this, we can assume that the RBF neural network model is able to give an acceptable raw water quality assessments.

The RBF neural network model is thus used to provide real-time assessments of raw water quality in the XWTP, on the basis of on-line measurements of various raw water quality parameters, including water temperature, turbidity, COD_{Mn}, and $NH_4^+ - N$. Table 3 shows real-time raw water quality assessment results of 12 May 2015 at XWTP. It is clear from this that raw water quality undergoes an abrupt change at 10:00 following heavy rains and the optimum chemical dosage becomes greater according to the assessment output.

It should be noted that the parameters of raw water quality typically vary simultaneously and cannot be controlled artificially. It is therefore difficult to address all of the chemical conditions of raw water quality during the production of drinking water. As a result, further real-time assessments with a different range of raw water qualities are necessary to more thoroughly validate the proposed assessment method.

Table 3 Real-time assessment results of raw water quality of 12 May 2015 at XWTP

Time	Temperature (°C)	Turbidity (NTU)	NH_4^+-N (mg L^{-1})	COD_{Mn} (mg L^{-1})	Assessment output	Optimum alum dosage (mg L^{-1})	Optimum ozone dosage (mg L^{-1})	Water quality grade
6:00	17.1	76	0.62	2.2	0.49	9.8	0.89	V
7:00	17.3	79	0.63	2.3	0.51	10.3	0.91	V
8:00	17.5	89	0.69	2.5	0.53	10.9	0.93	V
9:00	17.6	85	0.65	2.3	0.52	10.6	0.92	V
10:00	18.1	101	0.73	2.7	0.58	12.4	0.98	VI
11:00	18.6	107	0.77	2.8	0.59	12.7	0.99	VI
12:00	18.5	122	0.81	2.7	0.63	11.2	0.97	VI
13:00	18.3	125	0.92	2.5	0.67	8.8	0.93	VII
14:00	18.9	130	0.91	2.9	0.69	7.6	0.91	VII
15:00	19.1	131	0.96	3.1	0.69	7.6	0.91	VII

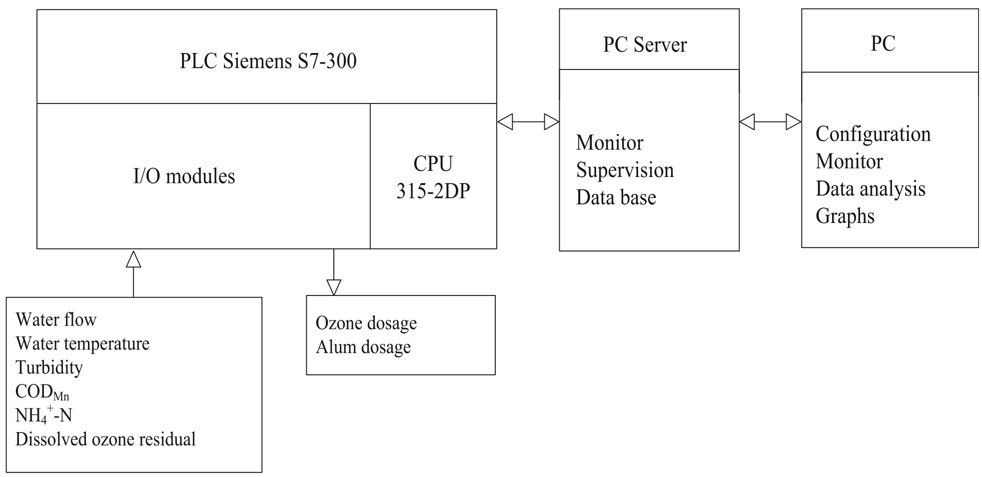

Fig. 5 DCS for the chemical dosing process

Experimental results of the feedforward–feedback composite control scheme

In order to test the practical capability of the proposed raw water quality assessment method, the feedforward–feedback composite control scheme developed in this study has been experimentally implemented at the XWTP. All of the on-line signals delivered to and from the chemical dosing process are interconnected by a distributed control system (DCS) as shown in Fig. 5. Process data are saved in the database of a computer server, and the control schemes are programmed on the computer and executed through a programmable logic controller (PLC).

Results from this experimental implementation of the proposed feedforward–feedback composite control scheme are shown in Fig. 6 and are compared with the IMC feedback control alone, under the abrupt changes of raw water quality seen in 12 May 2015. The corresponding performance indices are shown in Table 4. It can be seen that the feedforward–feedback composite control scheme gives more steady output (solid line). This is very important especially in the conditions of big and frequent changes of raw water quality. The experimental results are basically consistent with the theoretical analysis in the preceding sections, which determined that the chemical dosage supplied by the feedforward–feedback composite control scheme can be adjusted over time to address changes in raw water quality. In order to provide more reliable feedforward–feedback composite control of the chemical dosing process, the proposed control scheme should be tested for at least one year to cover all the typical conditions of abrupt changes of raw water quality and the modifications of control parameter adaptation might be required.

Conclusions

Raw water quality assessment for the drinking water treatment has been conducted in this paper. A feedforward–feedback composite control scheme based on the raw water quality assessment is designed for the chemical dosing process control of drinking water treatment to cope with the changes of raw water quality and to stabilize the quality of treated water. Thus, the consumer's health is protected from chemical and

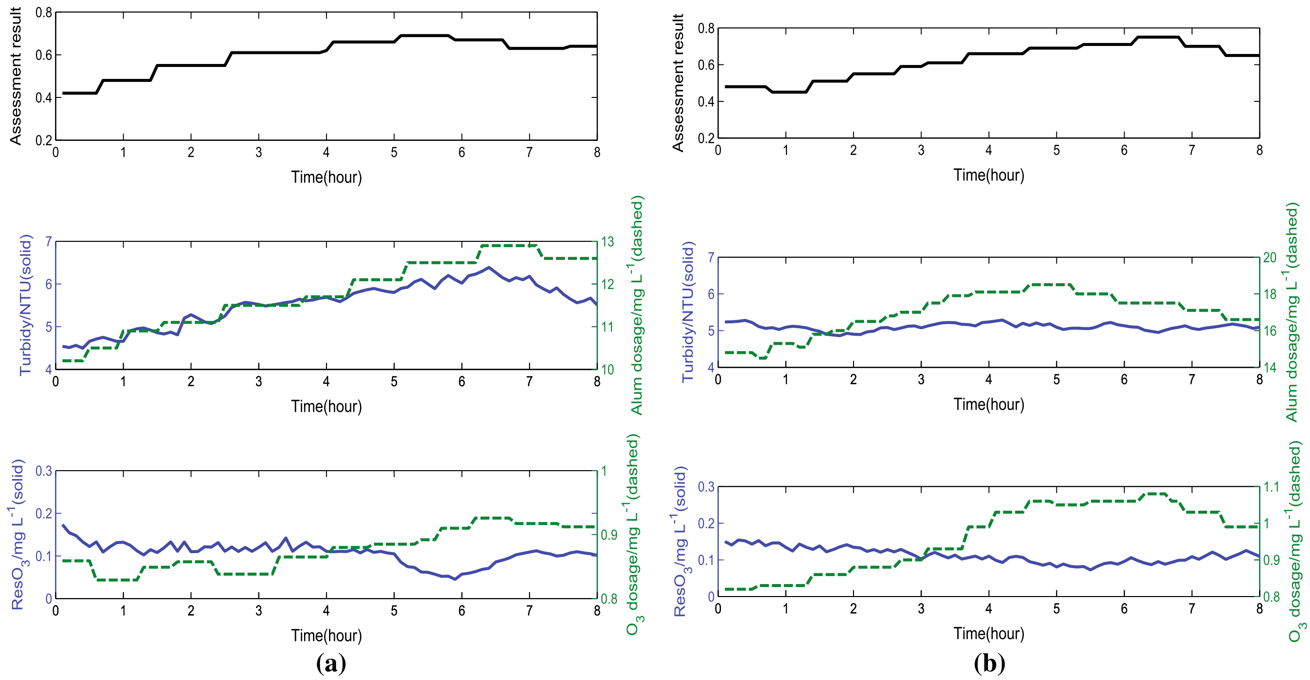

Fig. 6 Experimental results of chemical dosing process control: **a** IMC feedback control; **b** Feedforward–feedback control

Table 4 Performance index of experimental results of chemical dosing process control

Method	Control objective	IAE /mg L^{-1}
IMC feedback	Turbidity	0.17
	ResO$_3$	0.045
Feedforward–feedback	Turbidity	0.06
	ResO$_3$	0.016

microbiological risks. Meanwhile, the proposed feedforward–feedback composite control scheme makes the operation of drinking water treatment more efficient and brings great improvements in plant management. To realize wider application, further research of real-time assessment for different water sources should be developed and further stability evaluations of feedforward–feedback composite control scheme should be conducted.

Acknowledgments The work is supported in part by Natural Science Foundation of Jiangsu Province (Grant No. SBK2015041829), NUPTSF (Grant No. NY214019) and NUPTSF (Grant No. NY214078).

References

Blindow I, Hargeby A, Andersson G (2002) Seasonal changes of mechanisms maintaining clear water in a shallow lake with abundant Chara vegetation. Aquat Bot 72(3–4):315–334

Chen S, Grant PM, Cowan CFN (1992) Orthogonal least-squares algorithm for training multioutput radial basis function networks. IEEE Trans Neural Netw 6:378–384

Chu H, Lu W, Zhang L (2013) Application of artificial neural network in environmental water quality assessment. J Agr Sci Tech 15(2):343–356

Courtois S (2005) Utilisation de l'ozone dans le traitement des eaux de surface: l'exemple de l'usine de Tailfer. Tribune de leau. 58(633):3–8

Cromphout J, Walraevens E, Vanhoucke R (2005) Improvement of water quality in the drinking water plant of Kluzen by the use of ozone in combination with GAC. Tribune de L'Eau. 58(1):15–18

Delpla I, Baures E, Jung AV, Clement M, Thomas O (2011) Issues of drinking water quality of small scale water services towards climate change. Water Sci Technol 63(2):227–232

Elovitz MS, von Gunten U, Kaiser H (2000) Hydroxyl radical/ozone ratios during ozonation processes. II. The effect of temperature, pH, alkalinity, and DOM properties. Ozone Sci Eng 22(2):123–150

Gadgil A (1998) Drinking water in developing countries. Annu Rev Energy Environ 23:253–286

Gao J, Jia J, Kettner A, Xing F, Wang Y, Xu X, Yang Y, Zou X, Gao S, Qi S, Liao F (2014) Changes in water and sediment exchange between the Changjiang River and Poyang Lake under natural and anthropogenic conditions. China Sci Total Environ 481(2):542–553

Iliyas SA, Elshafei M, Habib MA, Adeniran AA (2013) RBF neural network inferential sensor for process emission monitoring. Control Eng Prac 21:962–970

Knopf GK, Sangole A (2004) Interpolating scattered data using 2D self-organizing feature maps. Graph Models 66:50–69

Liu Y, Zheng Q, Shi Z, Chen J (2004) Training, networks radial basis function, with particle swarms. In: Advances in Neural Networks—ISNN, Springer, Berlin Heidelberg, pp. 317–322

Lu WZ, Wang WJ, Wang XK, Xu ZB, Leung AYT (2003) Using improved neural network to analyze RSP, NOX and NO2 levels

in urban air in Mong Kok, Hong Kong. Environ Monit Assess 87(3):235–254
Lu W (2004) Potential assessment of a neural network model with pca/rbf approach for forecasting pollutant trends in Mong Kok Urban Air, Hong Kong. Environ Res 96(1):79–87
Santana MVE, Zhang Q, Mihelcic JR (2014) Influence of water quality on the embodied energy of drinking water treatment. Environ Sci Technol 48(5):3084–3091
Schulz CR, Okun DA, Donaldson D, Austin J (1992) Surface water treatment for communities in developing countries. Wiley, New York
Shen XQ, He TD (2012) Water quality evaluation based on RBF neural network with parameters optimized by PSO algorithm. Eng Technol 1–4
Singh KP, Malik A, Sinha S (2005) Water quality assessment and apportionment of pollution sources of Gomti river (India) using multivariate statistical techniques - a case study. Anal Chim Acta 538(1):355–374
Slavik I, Uhl W (2009) Analysing water quality changes due to reservoir management and climate change for optimization of drinking water treatment. Water Sci. Technol. Water Supply. 9(1):99–105
Sobsey MD, Stauber CE, Casanova LM, Brown JM, Elliott MA (2008) Point of use household drinking water filtration: a practical, effective solution for providing sustained access to safe drinking water in the developing word. Environ Sci Technol 42(12):4261–4267
Stepien DK, Diehl P, Helm J, Thorns A, Puttmann W (2014) Fate of 1,4-dioxane in the aquatic environment: from sewage to drinking water. Water Res 48(1):406–419
Symons JM, Robeck GG (1975) Treatment processes for coping with variation in raw-water quality. J Am Water Works Assoc 67(3):142–145
Tarek GSKM (2012) Combination of artificial neural network models for air quality predictions for the region of Annaba. Algeria Int J Environ Stud 69(1):79–89
van der Helm AWC (2007) Integrated modeling and optimization for operation of drinking water treatment plants. Ph.D. Faculty of Civil Engineering and Geosciences, Delft University of Technology, Delft, Netherlands
Vega M, Pardo R, Barrado E, Deban L (1998) Assessment of seasonal and polluting effects on the quality of river water by exploratory data analysis. Water Res 32(12):3581–3592
Wang D, Li S, Zhou X (2013) Control-oriented modeling and real-time control for the ozone dosing process of drinking water treatment. Environ Sci Technol 47(5):2197–2203
Xu X, Hu N, Liu BX (2011) Water quality prediction of Changjiang of Jingdezhen through particle swarm optimization algorithm. In: International Conference on Management and Service Science (MASS 2011), pp. 1–4
Xu X, Ouyang Y (2012) Smith-immune predictive control for steel uncertain time-delay system. J Comput Appl 32:2956–2959
Zamyadi A, Mcquaid N, Prvost M, Dorner S (2012) Monitoring of potentially toxic cyanobacteria using an online multi-probe in drinking water sources. J Environ Monit 14(2):579–588
Zheng J, Fu M (2013) Saturation control of a piezoelectric actuator for fast settling-time performance. IEEE Trans Control Syst Technol 21(1):220–228
Zhou X (1993) A new method with high confidence for validation of computer simulation models for flight systems. Chin J Syst Eng Electron 4(4):43–52
Zhou F, Liu Y, Guo H (2007) Application of multivariate statistical methods to water quality assessment of the watercourses in northwestern new territories, hong kong. Environ Monit Assess 132(1–3):1–13