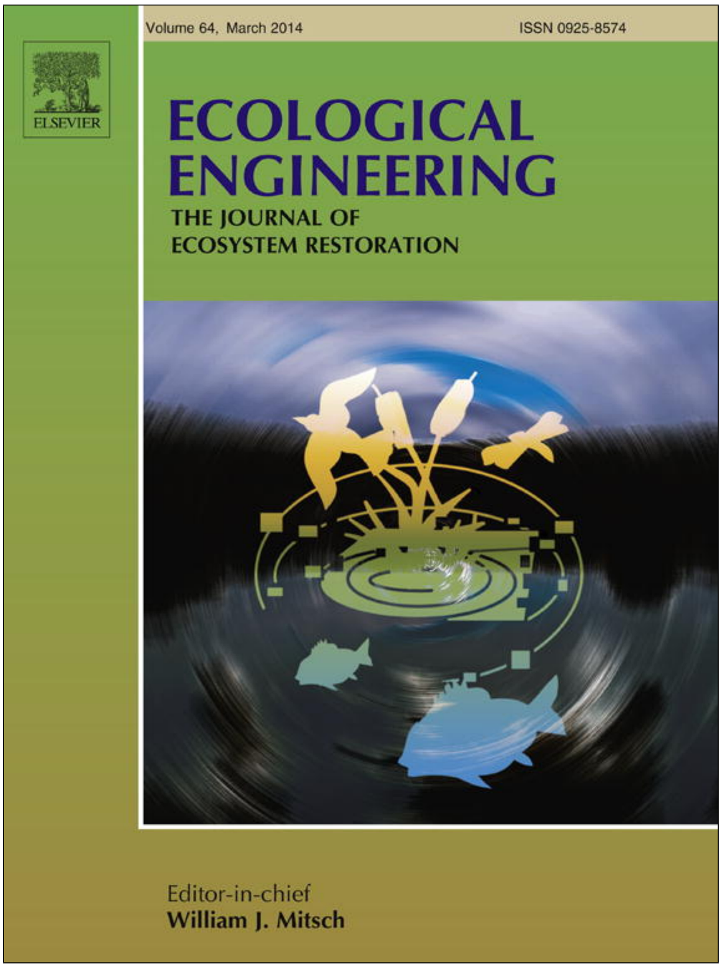
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An integrated treatment of domestic wastewater using sequencing batch biofilm reactor combined with vertical flow constructed wetland and its artificial neural network simulation study

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ABSTRACT

In this study, a sequencing batch biofilm reactor combined with a vertical flow constructed wetland (SBBR-VFCW) system was constructed and applied to the wastewater treatment. *Thalia dealbata*s were planted in the VFCW. The artificial neural network (ANN) was used to simulate and predict the performance of SBBR-VFCW. The results showed that when the concentrations of COD, NH_4^+-N, TN and TP in the wastewater were 200.22 mg/L, 48.11 mg/L, 48.11 mg/L and 6.11 mg/L respectively, the removal efficiencies were 97.0%, 98.5%, 91.5% and 88.5%, correspondingly, which indicated that the SBBR-VFCW system can treat the wastewater effectively. According to the results of the ANN simulation analysis, the correlation coefficients (R^2) were all higher than 0.99, and the root mean squared errors (RMSE) were lower than 0.0782. The concentrations of DO, NH_4^+-N and TP in the influent exhibited strong impacts on the effluent. This study reveals that the ANN can efficiently reflect the nonlinear function of each factor, and is suitable for the dynamic monitoring of SBBR-VFCW treatment for wastewater in various conditions.

1. Introduction

With the development of the economy, non-point pollution has become the main pollution source in many rural areas of China ever since 1999 (State Environment Protection Administration of China, 1999–2011). Decentralized domestic wastewater which includes all types of wastewater from rural living activities is considered to be one of the principal nonpoint sources of pollution (Feng et al., 2008; Li et al., 2009). Nowadays, in rural areas of China, more than 96% of domestic wastewater is discharged directly into aquatic environment without any treatment (Liang et al., 2010). With high levels of phosphorous and nitrogen, these effluents will cause eutrophication and potential toxicity to aquatic species (Ye and Li, 2009; Bilanovic et al., 1999). Therefore, it is quite necessary to explore a proper wastewater treatment technology.

Some conventional treatment methods are employed in domestic wastewater treatment such as sequencing batch biofilm reactor (SBBR) and vertical-flow constructed wetland (VFCW). To date, SBBR is used widely in wastewater treatment. Compared with a sequencing batch reactor (SBR), SBBR has many advantages, such as more biomass and higher removal efficiency, less sludge and sludge conglomeration, greater volumetric loads and increased process stability toward shock loadings (Venkata Mohan et al., 2007; Gonzalez and Wilderer, 1991; Chiou and Yang, 2008; Ding et al., 2011). VFCW has gained popularity in China owing to its compact size and enhanced pollutant removal capacity (Brix and Arias, 2005). However, there are still limitations for them needing to be dealt with. For example, water quality varies with operating conditions, the uncertainty operation mode for SBBR; strict requirements for the influent water quality, clogging of packing medium, non-uniformity of hydraulic load, maintenance problems for VFCW (Andrade do Canto et al., 2008; Hua et al., 2010; Knight et al., 2000).

Considering the resource-scarce, economic developing rural areas in China, an integrated SBBR-VFCW system was constructed and applied to wastewater treatment. Though both SBBR and VFCW are well-known systems for wastewater treatment, their combination in an integrated installation has not been verified experimentally yet. During the wastewater treatment process, SBBR was applied to cope with the high hydraulic load of

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Table 1
Detail parameters of three reactors used in the designed experiments.

Reactor	DO (mg/L)	Aeration/non-aeration ratio		Wet/Dry ratio	Packing (pieces)	Number of *T. dealbata*
		First 6 h	Second 6 h			
1st	1.5	2/1	3/1	1/2	32	50
2nd	2.0	2/2	2/1	1/3	32	50
3rd	2.5	2/2	3/1	1/4	32	50

pollutants firstly, and then the VFCW is used to achieve deep purification. Compared with the single-use, the combined-use of SBBR and VFCW has many advantages, such as small space-occupying, cost-effectiveness, a lower energy demand, and the capability of meeting effluent discharge standards.

Artificial neural network (ANN) is widely used in solving complex and nonlinear problems (Punal, 2001; Du and Taygi, 1999; Naz et al., 2009). An ANN is composed of many single elements called neurons. These neurons are connected to each other in different ways therefore forming different types of ANN. Back propagation neural network (BPN) is a type of ANN that can effectively solve non-linear problems. It has the abilities of self-learning, self-adapting and self-management. It can map a set of input patterns onto a corresponding set of output patterns after learning, by processing data from a given system (Huang et al., 2009). Delnavaz et al. (2010) have used ANN to predict the moving bed biofilm reactor (MBBR) performance for the treatment of aniline. Sadrzadeh et al. (2009) utilized ANN to predict separation of lead ions from wastewater using electro-dialysis. Sahinkaya (2009) studied the use of ANN modeling for bio-treatment of zinc-containing wastewater in a sulfidogenic continuous stirred-tank reactor. All those ANN-based models were found to perform as efficient and robust tools, in predicting each specific process. However, few studies evaluating the wastewater treatment efficiency of SBBR-VFCW by ANN have been reported. For the wastewater treatment process, it is difficult to use a precise mathematical model to describe its characteristics of complexity, nonlinearity, time-variation and indeterminability (Anderson and McNeill, 1992). Therefore, to conquer the limitations of conventional mathematical models, ANN was used to simulate the process of SBBR-VFCW.

The objectives of this study were to: (1) assess the feasibility and efficiency of SBBR-VFCW for the treatment of domestic wastewater; (2) evaluate the resistance of SBBR-VFCW to shock loading; (3) realize the simulation of SBBR-VFCW by using ANN system.

2. Materials and methods

2.1. Experimental set-up

The cylindrical SBBR-VFCW apparatus (Fig. 1) consists of SBBR (Part A) and VFCW (Part B). The SBBR was filled with the fibrous packing made from materials such as PVC, soft polyethylene and porous aggregates (Fig. 2). The fibrous packing can protect the biofilm and ensure an optimal environment for the bacteria to thrive. The biofilm carrier forms a robust system to protect the bacterial cultures from the effects of operating excursions. The filling ratio of the SBBR was 30%, while the working volume was 40 L. The activated sludge inoculated for SBBR was gained from the second pond of oxidation ditch process in Jin-Xia wastewater treatment plant in Changsha. The values of pH, mixed liquid suspended solids (MLSS), sludge volume index (SVI) and specific gravity (SG) of this activated sludge were 7.04, 3.59 g/L, 91.00 mL/g and 1.02 g/m^3, respectively. The feeding solution and effluent were added and removed from the reactor by using peristaltic pumps, respectively. Oxygen was supplied by means of air gasification through the liquid phase by using a diffuser, to obtain small air bubbles. To keep the DO level constant, the air-flow was controlled by the rotameter. By using the heating system, the temperature was maintained at 30 ± 2 °C.

The VFCW with a working volume of 60 L was filled, from the bottom up, with a layer of large sized gravel, a mixed layer of coarse and fine sand, a layer of clinoptilolite layer, a layer of small sized gravel, and an emergent plant layer with 52 *Thalia dealbatas* (*T. dealbata*). The plant height of *T. dealbata* was in the range of 30–35 cm. The distribution of wastewater was achieved via pumping, piping and valves.

2.2. Experimental procedures

Three reactors were designed to investigate their wastewater treatment efficiencies under different experiment conditions. The exact values of all parameters were shown in Table 1. The operate cycle of SBBR was 12 h, which were divided into intermittent aeration/non-aeration periods. All the reactors were filled with synthetic wastewater within a period of 10 min. The initial period of 2 h aeration started after influent recharged. This phase was followed by a break of 1 or 2 h, without aeration. Sequences of aerated and non-aerated periods were repeated, right up to the end of the 12 h cycle. The water exchange period of VFCW was 12 h and the wet/dry ratio (the ratio of the feed time to the idle time) was controlled by regulating the velocity of the sprinkler. To a large extent, the proper wet/dry ratio in VFCW promoted the hydraulic load, the removal efficiency and its performance (Song et al., 2006).

The influent and effluent samples were collected mainly from the water inlet and outlet at 10 a.m. every day, and the average value of 3 samples was adopted. SBBR did not run in the entire drainage pattern. Influent data was the mixed values which combines the value of domestic wastewater and the remaining water in the reactor after drainage. Meanwhile, the influent parameters of SBBR-VFCW were chosen as input variables of ANN. Three reactors were run under different influent conditions (the 1st reactor, 20 L; the 2nd reactor, 22 L; the 3rd reactor, 24 L).

2.3. Feeding solutions

The synthetic wastewater used in this study was simulated to represent the domestic wastewater, so the influent concentration of TN equals to NH_4^+-N. Detailed components of the synthetic wastewater are shown in Table 2.

Table 2
Components of the synthetic domestic wastewater.

Components	Concentration (g/L)
Glucose	0.186
CH_3COONa	0.238
NH_4Cl	0.024
Soluble starch	0.158
Peptone	0.174
Beef extract	0.045
$(NH_4)_2SO_4$	0.479
KH_2PO_3	0.067
Na_2CO_3	0.057

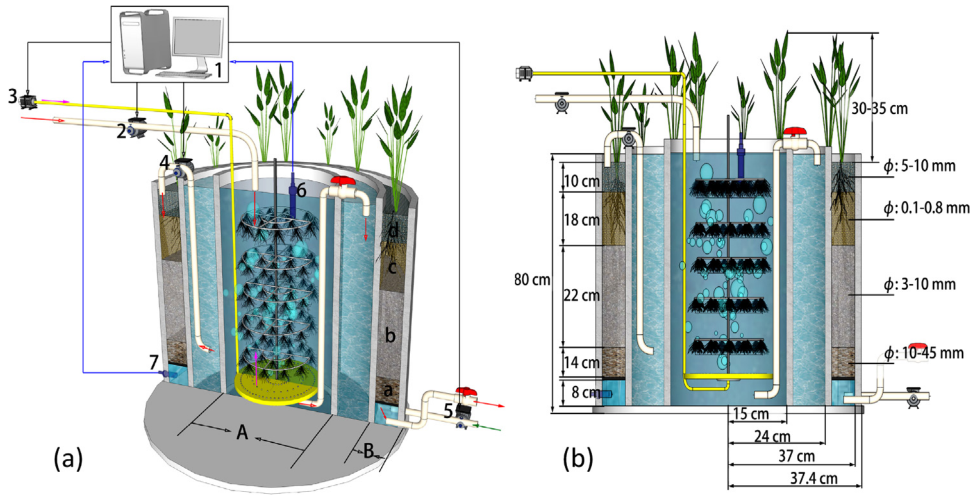

Fig. 1. Schematic (a) and dimensions (b) diagram of the SBBR-VFCW. A: SBBR; B: VFCW; a: large size gravel layer; b: coarse and finer sand mixed layer; c: clinoptilolite layer; d: small size gravel and emergent plant layer; 1: control system; 2: influent pump; 3: air compressor; 4: thermostatic pump; 5: back-washing pump; 6: influent probes (pH, DO, T); 7: effluent probes (pH, DO, T); ϕ: particle size of each matrix.

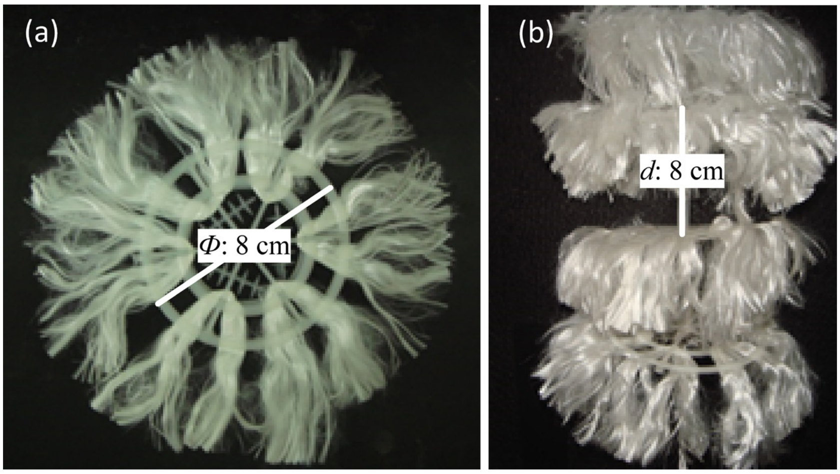

Fig. 2. Schematic diagram of the fibrous packing used in SBBR.

2.4. Chemical analysis

Ammonium nitrogen (NH_4^+-N), total nitrogen (TN), chemical oxygen demand (COD) and total phosphorus (TP) were analyzed according to the Standard Methods for the examination of water and wastewater (APHA, 1995). DO and pH were measured by a DO meter (HI9143, Hanna, Italy) and a pH meter (pH meter pen, Lida, China), respectively. All experiments were conducted in duplicate and the average values were used for data analysis.

3. Neural network model

3.1. Principle and algorithm of ANN

Back-Error Propagation Network (BPN) is the most representative learning model for ANN (Delnavaz et al., 2010). The main principle of neural computing is the decomposition of the input–output relationship into a series of linear separable steps, using hidden layers (Delnavaz et al., 2010; Ráduly et al., 2007). As shown in Fig. 3, the BPN consists of the input layer, the hidden layer, and the output layer. The learning process is divided into forward-propagation and back-propagation. The input signal is propagated to the output layer through the hidden layer. The state of each neuron can only affect the next neural network. The gradient descent method is utilized in BPN to calculate the weight of the network, and adjust the weight of interconnections, to minimize the output

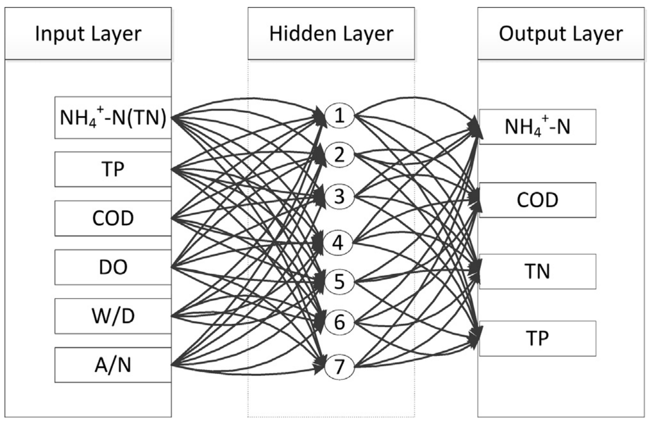

Fig. 3. Architecture of ANN model. W/D is wet/dry ratio, A/N is aeration/non-aeration ratio. This experiment use synthetic wastewater to simulate actual wastewater, so influent concentration of TN was equal to NH_4^+-N.

error (Lee, 2004). This easily solves the interaction of processing elements, by adding hidden layers. In the learning process of BPN, the interconnection weights were adjusted by using an error convergence technique, to obtain a desired output for a given input. In general, the error of the output layer in the BPN model propagates backward to the input layer, through the hidden layer, to obtain the final desired output.

3.2. Network performance and weight analysis

To evaluate the performance of the neuron network, four evaluation criteria were used. These indicators are mean average error rate (MAER), root mean squared error (RMSE), standard error of prediction (SEP) and correlation coefficient (R^2):

Mean average error rate (MAER)

$$\text{MAER} = \frac{1}{n}\sum_{k=1}^{n}\frac{|y_k - \hat{y}_k|}{|y_k|} \tag{1}$$

Root mean squared error (RMSE)

$$\text{RMS} = \sqrt{\sum_{k=1}^{n}(y_k - \hat{y}_k)^2 \Big/ \sum_{k=1}^{n}\hat{y}_k^2} \tag{2}$$

Standard error of prediction (SEP)

$$\text{SEP} = \frac{100}{\bar{y}_k}\sqrt{\frac{\sum_{k=1}^{n}(y_k - \hat{y}_k)^2}{n}} \tag{3}$$

Correlation coefficient (R^2)

$$R^2 = \frac{\sum_{k=1}^{n}(y_k - \bar{y}_k)(\hat{y}_k - \bar{\hat{y}}_k)}{\sqrt{\sum_{k=1}^{n}(y_k - \bar{y}_k)^2 \sum_{k=1}^{n}(\hat{y}_k - \bar{\hat{y}}_k)^2}} \tag{4}$$

Average values of $y_k(\hat{y}_k)$

$$\bar{y}_k = \frac{1}{n}\sum_{k=1}^{n} y_k \tag{5}$$

Average values of $\hat{y}_k(\bar{\hat{y}}_k)$

$$\bar{\hat{y}}_k = \frac{1}{n}\sum_{k=1}^{n}\hat{y}_k \tag{6}$$

where y_k is the actual value, $\hat{y}_k$ is the predicted value, n is the number of training or testing samples.

Weight is an important factor of ANN. Connection weights can be obtained through the network program, and the effect of input factors on output factors can be analyzed, as according to the formula (7) (Olden et al., 2004).

$$Input_x = \sum_{Y=1}^{7} HiddenX \cdot HiddenY \tag{7}$$

where $Input_x$ is the weight of the input layer, *HiddenX* is the connection weight between the input and the hidden layer, *HiddenY* is the connection weight between the output and the hidden layer. It can be inferred from the values of the connection weights what kind of role, positive or negative, the influential factors play in the whole process.

3.3. Sample data

The supernatant was discharged after the fresh sludge had settled. Then the fresh sludge was put into the SBBR with packing. Meanwhile, the SBBR was continuously aerated with synthetic wastewater for two days. The synthetic wastewater was used to domesticate the biofilm, after the two-day aeration. Thirty days later, the biofilm matured gradually and its color became brown. Furthermore, zoogloea, filamentous bacteria and rotifers could be observed, and the water quality became stable. Data, from the continuous operation of 20 days, were taken as samples.

3.4. Network topology

BPN contains one or more hidden layers, which normally uses the logarithmic function or tangent sigmoid transfer function, while the output layer neurons adopt the linear transfer function. It is commonly believed that increasing the hidden layers has the effect of reducing the network error. This improves the precision, which also makes the network complicated. When training time for the network increases, the network will become over-fitted. Three layers (6-n-4) were employed in the neuron network (Fig. 3). The input layer contains NH_4^+-N, COD and TP of the influent, DO, wet/dry ratio and aeration/non-aeration ratio. The output layer contains NH_4^+-N, COD, TN and TP of effluent.

3.5. Determination of optimum operating parameters

Learning rate (LR), learning time (LT) and momentum constant (MC) are the main parameters of the network. Among these network parameters, MC and LR affect the velocity of the network directly. In order to improve the learning velocity, a large LR should be used. If the LR is too large, it can cause vibration tend to the stable points, and even non-convergence. For the model of specific structure and learning sample, there exist optimum LR and MC (range from 0 to 1). LT is the indicator evaluating the learning efficiency. The optimal LT can be obtained by regulating the number of network trainings. Within the scope of the above conditions, the optimum operating parameters of this network model were set as follows: $n = 7$, LR = 0.14, MC = 0.6, LT = 8000.

4. Results and discussion

4.1. Performance of the SBBR-VFCW

Fig. 4 shows the removal efficiencies of COD, TP, NH_4^+-N and TN in SBBR-VFCW. High removal efficiencies of COD and NH_4^+-N were presented in the three reactors. In the 1st reactor, the removal efficiency of NH_4^+-N reached 98.5%, while the removal efficiency of COD reached 97.0%. The removal efficiencies of TN and TP changed with the operating conditions and the maximum removal efficiencies occurred in the 1st reactor too (TN 91.5%, TP 88.5%). The results showed that the effluent quality of SBBR-VFCW could meet the first class standard of integrated wastewater discharge standards of the People's Republic of China (GB8978-1996) under the optimum conditions.

As seen in Fig. 4, all the influent parameters of the 3rd reactor were significantly higher than those of the other two. Looking at the variation of the 3rd reactor, the concentration of each parameter (COD, influent 276.20 mg/L, effluent 15.37 mg/L; NH_4^+-N, influent 79.25 mg/L, effluent 1.85 mg/L; TN, influent 79.25 mg/L, effluent 9.90 mg/L; TP, influent 11.15 mg/L, effluent 2.35 mg/L) could steadily reach the discharge standard. That proved the SBBR-VFCW could run normally, operate in a stable manner, and resist impact load efficiently. When this finding was compared with the research of Lu et al. (2010), it indicated that the SBBR-VFCW could achieve better purification and deal with a higher hydraulic load, while occupying lesser space.

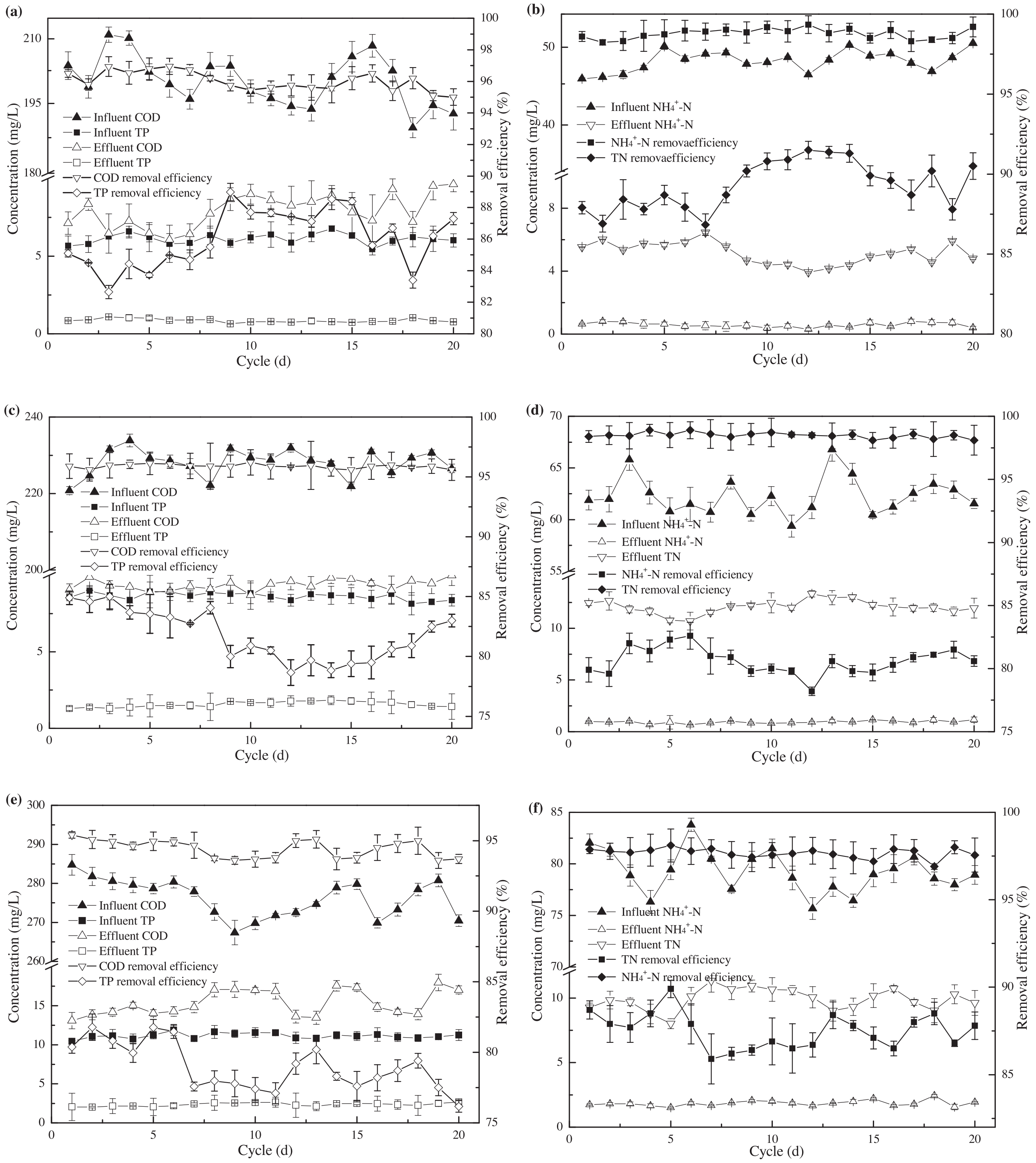

Fig. 4. (a) COD and TP removal efficiencies of the 1st reactor; (b) NH_4^+-N and TN removal efficiencies of the 1st reactor; (c) COD and TP removal efficiencies of the 2nd reactor; (d) NH_4^+-N and TN removal efficiencies of the 2nd reactor; (e) COD and TP removal efficiencies of the 3rd reactor; (f) NH_4^+-N and TN removal efficiencies of the 3rd reactor.

4.2. Performance comparison between SBBR and VFCW

In this experiment, the 3rd reactor with the highest influent concentration of pollutants was chosen to compare performance between SBBR and VFCW in the integrated installation. Fig. 5 shows the comparison of COD, NH_4^+-N, TN and TP removal efficiencies of SBBR and VFCW. The result showed that the concentration variation of each parameter in SBBR was as follows: COD from 276.20 mg/L to 50.89 mg/L; NH_4^+-N from 79.25 mg/L to 13.10 mg/L; TN from 79.25 mg/L to 24.76 mg/L; TP from 11.15 mg/L to 3.69 mg/L. The results indicate that the system has a great capacity to resist the impact load, which was in accordance with the observation of Ding et al. (2011). SBBR could cope well with the high hydraulic load, which is due to the following reasons. Firstly, with an optimal microenvironment supplied by the biofilm carrier, a large number of microorganisms thrived. Secondly, metabolism of attached microorganisms over COD, NH_4^+-N, TN and TP, was enhanced, with their growing density. Thirdly, the growth rate and activity

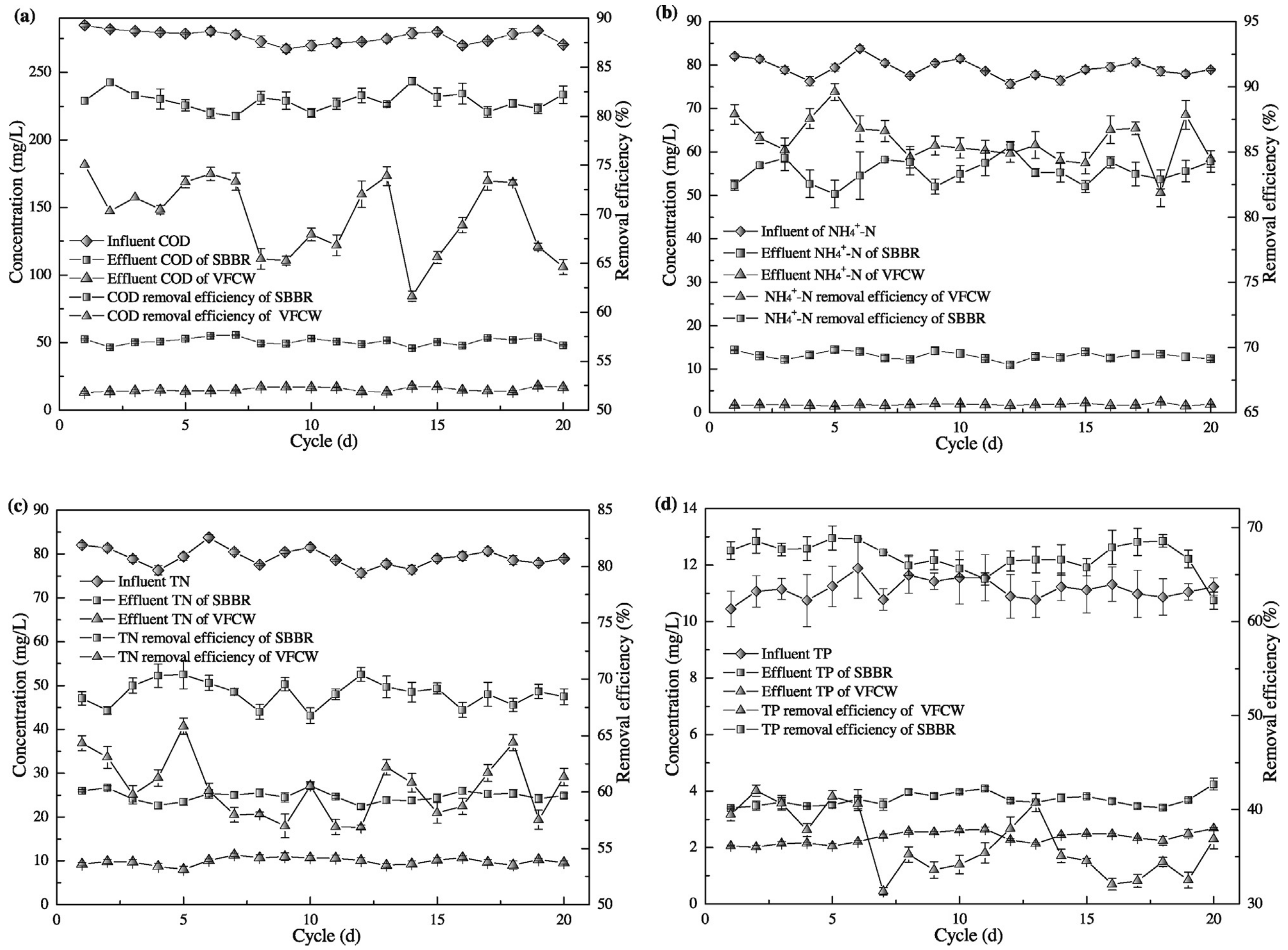

Fig. 5. (a) Comparisons of COD removal efficiencies in SBBR and VFCW; (b) Comparisons of NH_4^+-N removal efficiencies in SBBR and VFCW; (c) Comparisons of TN removal efficiencies in SBBR and VFCW; (d) Comparisons of TP removal efficiencies in SBBR and VFCW.

of microorganisms in the biofilm could be promoted by the intermittent aeration/non-aeration process (Ding et al., 2011; Chiou and Yang, 2008).

For further study of the performance of the integrated system, the effluent of SBBR was chosen as the influent of VFCW. The concentrations of COD, NH_4^+-N, TN and TP of VFCW effluent were 15.37 mg/L, 1.85 mg/L, 9.90 mg/L and 2.35 mg/L, respectively. The results indicate that the VFCW can achieve deep purification efficiently. This fact has been independently proved by Chang et al. (2012).

VFCW is a complex assemblage of wastewater, matrix, vegetation and an array of microorganisms. *T. dealbata* used in the emergent plants layer plays a vital role in the VFCW, as it provides a suitable environment for microbial growth and filtration. Pollutants could be removed by several complex physical, chemical and biological processes in the VFCW such as sedimentation, UV irradiation, filtration, ammonification, nitrification/denitrification, plant uptake and matrix sorption (Dzikus et al., 2008). Specifically, a biofilm with high activity and stability on the matrix surface would accelerate the metabolism of COD, NH_4^+-N, TN and TP. Meanwhile, filtration and absorption of the matrix and plant root systems could also facilitate the purification of VFCW. Besides, clinoptilolite can absorb NH_4^+ greatly via ion-exchange, and also offers the additional function of the total removal of TP and organic matter (Dzikus et al., 2008; Georgios and Vassilios, 2012). Therefore, nutrients, which are not completely removed in the SBBR, could be further removed in the VFCW by the above mechanisms.

4.3. Simulation results of testing samples

The adaptive learning ability of the neuron network is important for the simulation process. Generally speaking, when more information that is given, the network model will be more accurately fitted. There will be increased precision in the mapping relation of the data. The training data were shown in Fig. 4, 6 out of 60 sets were stochastically chosen as the testing sample groups. As shown in Fig. 6, the mapping relationship between the actual and predict values was accurate by ANN.

4.4. Results and analysis of ANN simulation

The data were simulated for adaptive learning, and the simulation results are presented in Tables 3 and 4. The ANN simulation results showed that the minimum relative error was 0.48% in group A8 (simulation for NH_4^+-N), and the maximum relative error was 13.35% in group A4 (simulation for TP). In the 6 tested groups of simulation data, the MAER of NH_4^+-N, TN, COD and TP were 7.22%, 6.64%, 6.37% and 5.93%, respectively. Therefore, all MAER values were below 13.5%, which indicated that ANN had excellent simulation ability for the whole process.

4.5. Evaluation of network performance

Table 5 shows that ANN has superior performance in terms of RMS, SEP and R^2 values. The error between the concentration value

Table 3
The ANN simulation results of NH_4^+-N and TN.

Testing groups	NH_4^+-N			TN		
	Actual value	Simulation value	Relative error (%)	Actual value	Simulation value	Relative error (%)
A4	0.64	0.67	5.43	5.75	5.96	3.65
A8	0.48	0.52	8.46	5.57	5.85	5.08
B5	0.90	0.82	8.55	10.76	9.85	8.49
B7	0.85	0.90	5.89	11.54	10.30	10.78
C5	1.51	1.64	8.53	8.02	7.40	7.67
C9	2.06	1.93	6.45	10.94	10.49	4.15
		MAER = 7.22			MAER = 6.64	

Table 4
The ANN simulation results of COD and TP.

Testing Groups	COD			TP		
	Actual value	Simulation value	Relative error (%)	Actual value	Simulation value	Relative error (%)
A4	7.27	8.00	10.05	1.03	1.17	13.35
A8	7.74	8.29	7.15	0.92	0.98	6.63
B5	8.88	9.36	5.37	1.47	1.50	2.25
B7	9.27	10.13	9.25	1.49	1.59	6.97
C5	14.06	14.36	2.12	2.05	2.06	0.62
C9	17.09	16.36	4.25	2.54	2.39	5.74
		MAER = 6.37			MAER = 5.93	

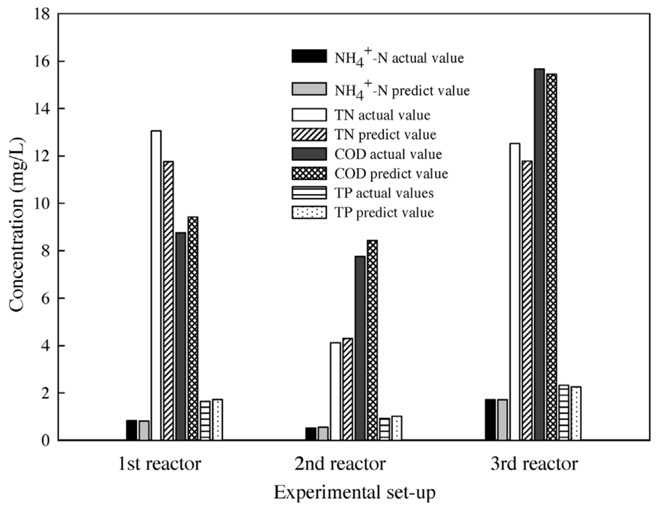

Fig. 6. Relation between actual and predict value by ANN based on testing samples.

predicted by ANN, and the actual value, is considerably less than 13.5%. When researchers did comparisons of the predicted values by the SEP, with experimental data, it indicated that the maximum deviation from the experimental data was 9.5178. All the results obtained by ANN were in excellent agreement, with the experimental data.

Table 5
Testing results of the ANN model.

Parameters	RMS	SEP	R^2
NH_4^+-N	0.0718	9.5178	0.9948
TN	0.0782	6.9872	0.9995
COD	0.0568	7.5291	0.9972
TP	0.0565	4.7045	0.9982

4.6. *Analysis of weight*

Table 6 describes the connection weights among the input layer, hidden layer and the output layer. Through observation of the value of connection weights, the product of the raw input-hidden and output-hidden connection weights between each input and output neuron can be calculated. The products across all hidden neurons can be summed up. Based on those values, the input layer, hidden layer and the output layer should be adjusted in order to obtain optimal results. The value of weights can be obtained according to the connection weights.

Fig. 7 depicts the effects of different weights, as factors, on the output parameters. It can be seen that influent NH_4^+-N is more important than TN since free ammonia (FA) had a potent inhibitory effect upon the ammonia oxidizing bacteria (AOB) and nitrite oxidizing bacteria (NOB). FA was used as the substrate of AOB during the ammonia oxidation reaction. AOB and NOB were inhibited when the FA concentration was up to 0.1–1.0 mg/L. Consequently, the nitration reaction was restrained and the NH_4^+-N conversion

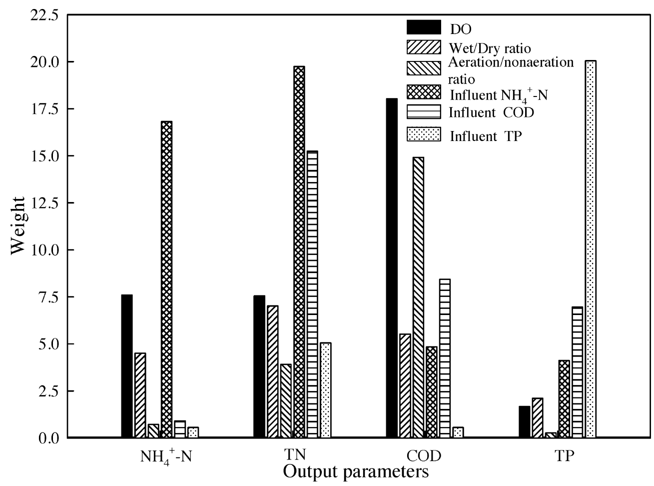

Fig. 7. The weights of the effect factors on the output parameters.

Table 6
Connection weights of the optimal ANN[a]

Parameters	Connection weights						
	H1	H2	H3	H4	H5	H6	H7
DO	1.6883	−1.0372	−0.6328	0.7224	0.4507	−0.4513	0.2742
Wet/dry ratio	−0.2960	0.8702	0.8027	−0.8321	1.7963	2.7650	−0.1355
Aeration/non-aeration ratio	−3.2410	−0.8677	1.9475	−0.2410	−2.0705	−1.6524	−4.1674
Influent NH_4^+-N	−1.8514	2.2596	−1.4987	2.5926	1.1897	−0.3824	1.0360
Influent COD	−2.6028	−0.7308	1.1344	1.1507	1.6927	2.1819	−0.7698
Influent TP	0.3411	−0.8442	−1.5591	0.7870	−3.5905	2.3718	−2.0715
Effluent NH_4^+-N	−0.9913	0.4532	−2.2732	2.0068	−2.1509	0.7875	0.0830
Effluent TN	−4.9649	1.2086	−0.8974	0.8471	1.5606	1.2667	2.8016
Effluent COD	0.7690	−1.7638	−0.1427	2.6072	−2.3454	0.8327	−3.1901
Effluent TP	−1.2494	−2.2569	−0.5935	0.5974	−3.0306	3.7206	1.2227

[a] H stands for hidden nodes.

ratio was also affected (Xu et al., 2008; Anthonisen et al., 1976). The FA concentration would influence the NH_4^+-N conversion directly. This formula, for the concentration of FA, can be described as follows (Yu et al., 2003):

$$FA = \frac{17}{14} \times \frac{[NH_4^+\text{-N}] \times 10^{pH}}{K_b/K_w + 10^{pH}} = \frac{1.214[NH_4^+\text{-N}] \times 10^{pH}}{\exp[6324/(273+t)] + 10^{pH}} \quad (8)$$

where K_b is the dissociation constant of ammonia, K_w is the dissociation constant of water.

In this experiment, FA concentration was positively correlated with the concentration of influent NH_4^+-N because of constant values of pH and temperature. Therefore, the influent NH_4^+-N was the most important parameter for the effluent NH_4^+-N and TN. DO was the most significant parameter for the COD removal process. COD was depleted by microbial degradation. As the final electron acceptor, DO has an erosion effect on the biofilm. The rate of microbial degradation was largely decided by dissolved oxygen concentrations present in the fluids. Therefore, DO was the most important factor for the COD analysis of weight. The concentration of TP in the influent had great influence on it. Phosphorus was released during the anaerobic period, and then absorbed during the aerobic period. Limited by biomass, the capacity of the phosphorus-accumulating organisms (PAOs) might unable to cope with varied concentrations of influent phosphorus, which would result in great changes in effluent TP concentrations (Sun et al., 2010).

Among the effluent parameters, the concentration of NH_4^+-N was mainly affected by the wet/dry ratio, which was shown in Fig. 7. The wet/dry ratio and re-oxygenation by VFCW were in a negative correlation. Nitrobacterium is a kind of aerobic bacteria whose growth and metabolism need oxygen. The process of denitrification, done by the denitrifying bacteria, required an anaerobic environment. Different wet/dry ratios provided alternating aerobic/anaerobic environments, and played an important role in the removal of NH_4^+-N. In the experiment, VFCW performed well in NH_4^+-N removal. On the one hand, commutative aerobic/anaerobic environments, formed by different wet/dry ratios, contributed to the NH_4^+-N removal. On the other hand, clinoptilolite and plants in the VFCW showed good absorption of NH_4^+-N (Edwards et al., 2006).

5. Conclusions

The following conclusions can be drawn from the present study:

(1) As an advanced biological process, the SBBR-VFCW has an efficient performance in the treatment of high concentration domestic wastewater and good resistance to shock loading. The removal efficiencies of COD, NH_4^+-N, TN and TP were 97.0%, 98.5%, 91.5% and 88.5%, respectively.
(2) The ANN model demonstrated its ability to predict performance of SBBR-VFCW, with sufficient accuracy. In the sample data simulation, the ANN had good generation ability, with RMSE lower than 0.0782, and correlation coefficients all higher than 0.99. Therefore, the ANN has a good potential to simulate nonlinear and multi-variable wastewater treatment.
(3) SBBR-VFCW can be a very promising technology for domestic wastewater purification in rural areas. The ANN simulation of SBBR-VFCW lays the foundation for its automatic control and application in the near future.

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Appendix A. Supplementary data

Supplementary data associated with this article can be found, in the online version, at http://dx.doi.org/10.1016/j.ecoleng.2013.12.040.

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