Journal of Urban and Environmental Engineering
E-ISSN: 1982-3932
celso@ct.ufpb.br
Universidade Federal da Paraíba
Brasil

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Journal of Urban and Environmental Engineering, vol. 9, núm. 1, 2015, pp. 54-65
Universidade Federal da Paraíba
Paraíba, Brasil

Journal of Urban and Environmental Engineering, v.9, n.1, p.54-65

ISSN 1982-3932
doi: 10.4090/juee.2015.v9n1.054065

Journal of Urban and Environmental Engineering

www.journal-uee.org

MODELING OF MIXED LIQUOR VOLATILE SUSPENDED SOLIDS AND PERFORMANCE EVALUATION FOR A SEQUENCING BATCH REACTOR

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Received 22 January 2015; received in revised form 6 June 2015; accepted 12 June 2015

Abstract: This study examined carbon, nitrogen and phosphorous removal from municipal wastewater in a sequencing batch reactor and biokinetic coefficients were evaluated according to results of BOD and COD. Furthermore, the MLVSS in the aeration reactor was modeled by using multilayer perceptron and radial basis function artificial neural networks (MLPANN and RBFANN). The experiments were performed so that the cell retention time, filling time and intensity of aeration were (5, 10 and 15 d), (1, 2 and 3 h) and (weak, medium and strong) respectively. The result indicated that with cell retention time of 15 d, filling time of 1 h, aeration time of 6 h and settling time of 3 h the HRT is optimized at 10 h. The BOD_5, COD, TP, TN and NH_4^+-N removal efficiencies were 97.13%, 94.58%, 94.27%, 89.7% and 92.75% respectively. The yield coefficient (Y), decay coefficient (K_d), maximum specific growth rate (K) and saturation constant (Ks) were 6.22 mgVSS/mgCOD, 0.002 1/d, 0.029 1/d and 20 mg COD/L according to COD experimental data. The values of the biokinetic coefficients were found to be as follows: Y = 10.45 mgVSS/mgBOD, K_d = 0.01 1/d, 0.014 1/d and 3.38 mgBOD/L according to BOD_5 experimental data. The training procedures for simulation of MLVSS were highly collaborated for both RBFANN and MLPANN. The train and test models for both MLPANN and RBFANN demonstrated perfectly matched results between the experimental and the simulated values of MLVSS. The values of RMSE for train and test (verification) models obtained by MLPANN were 31.82 and 40.25 mg/L respectively, and the value of R^2 was 0.99 for both models. The values of RMSE for train and test models obtained by RBFANN were 69.04 and 43.87 mg/L respectively, and the value of R^2 was 0.99 for both models. It was observed that the MLPANN has stronger approximation and generalization ability than the RBFANN with regard to our experimental data for MLVSS.

Keywords: Performance evaluation; artificial neural network; MLVSS; biokinetic coefficients

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INTRODUCTION

The selection of wastewater treatment process is based on the qualities of effluent and influent volume and type of influent, investment and operating costs and so on (Elmolla & Chaudhuri, 2011, Ruiz *et al.*, 1997). Sequencing batch reactor (SBR) is a wastewater treatment process based on the principles of the activated sludge process. SBR has been successfully employed in the treatment of both municipal and industrial wastewater (Mace & Mata-Alvarez, 2002).

The discharge of effluents containing high concentrations of nitrogen is undesirable because it causes excessive oxygen demand in receiving waters, has a toxic effect on fish and other organisms, causes Eutrophication in rivers and lakes and increases the formation of nitrosamines which are carcinogenic (Dapena-Mora *et al.*, 2004, Dapena-Mora *et al.*, 2006) Biological nitrification–denitrification is the most frequently used process for removing nitrogen in wastewater as it occurs in nature as part of the biogeochemical nitrogen cycle (Andrew, 2005, Bernet *et al.*, 2000). SBR systems, applied to nitrification and denitrification, offer various advantages including: minimal space requirements, ease of management and possibility of modifications during trial phases through on-line control of the treatment strategy. Increasing interest towards on-line control of biological processes allowed the development of techniques and operation strategies able to optimize treatment plants, both in terms of removal efficiencies and in terms of costs (Andreottola *et al.*, 2001, Fu *et al.*, 2001).

The process of denitrification is the reduction of nitrate to nitrite and subsequently the reduction of nitrite to nitric oxide (NO), then to nitrous oxide (N_2O) and finally to molecular nitrogen (N_2), which is released into the atmosphere (Knowles, 2005). In the biological nitrogen removal system, nitrite appears as an intermediate in the course of nitrification and denitrification. Generally, the accumulation of nitrite is known to cause severe problems in the biological process (Mardani *et al.*, 2011, Wang *et al.*, 2007). Biological denitrification is a reliable method for nitrogen removal from wastewater (Abufayed & Schroeder, 1986). Heterotrophic bacteria use the available carbon source. Since nitrified liquor is usually deficient in organic carbon and the low carbon source level limits the biological denitrification process, sufficient organic carbon sources must be provided for proper denitrification. In addition, for proper biological phosphorus removal, an easily biodegradable carbon source is needed at the P release stage (Obaja *et al.*, 2005). In recent years, simultaneous nitrification and denitrification (SND) has gained significant attention (Chiu *et al.*, 2007, Rene *et al.*, 2008). The SND process represents a significant advantage over the separated biological nitrogen removal process (Guo *et al.*, 2011).

In the current research, hydraulic retention time was optimized for biological carbon, nitrogen and phosphorous removal from the municipal wastewater in a sequencing batch reactor. The biokinetic coefficients were evaluated according to the experimental measured data for BOD and COD. Furthermore, the MLVSS in the aeration reactor was modeled by using multilayer perceptron and radial basis function artificial neural networks with regard to our experimental data.

MATERIAL AND METHODS

Wastewater characteristics

The pilot was located in Ekbatan wastewater treatment plant of Tehran, which has been operating since 1988. Chemical and biological analyses of the wastewater treatment plant influent was performed for four months. Regarding the results obtained from raw wastewater analysis, the maximum values were selected as critical design parameters. The critical values of the influent characteristics are shown in (**Table 1**).

Sequencing batch reactor

The pilot plant was composed of feeding tank, aeration tank and air compressors as its three main components (**Fig. 1**). Feeding tank was cylindrical and made of plastic with a dimension of 0.95 by 0.66 m and total volume of 0.3 m^3. Moreover, feeding tank was located 1.5 m above the ground level to establish a continuous flow. Complete mixing of the aeration tank was the effective factor in the selection of geometrical shape of the diffusers. To achieve this and because of the high volume of experiments, two plastic tanks of rectangular shape were utilized with a dimension of 0.76 by 0.65 m, and a height of 0.69 m, a free board of 0.1 m and thickness of 6 mm. Two air compressors were used to supply oxygen with air volume flow of 0.45 m^3/min and 0.88 m^3/min. In addition, a settling tank was applied as the last process unit in wastewater treatment by SBR. The settling tank consisted of a cylindrical part with a height of 1.1 m, a diameter of 0.8 m and cone shaped part with a height of 0.5 m, 0.80 m and 75 mm in diameter. The settling tank was made of plastic with a thickness of 6 mm and total volume of 0.42 m^3.

Table 1. Wastewater characteristics in the critical conditions

Parameter	Value	Parameter	Value
Temperature (^oC)	25.14	Org-N (mg/L)	16.8
DO (mg/L)	0	TKN (mg/L)	39.6
BOD_5 (mg/L)	145	TS (mg/L)	780
COD (mg/L)	288	TDS (mg/L)	630
$NO_3^- - N$ (mg/L)	0.92	TSS (mg/L)	150
$NH_3^+ - N$ (mg/L)	22.8	TP (mg/L)	16.15

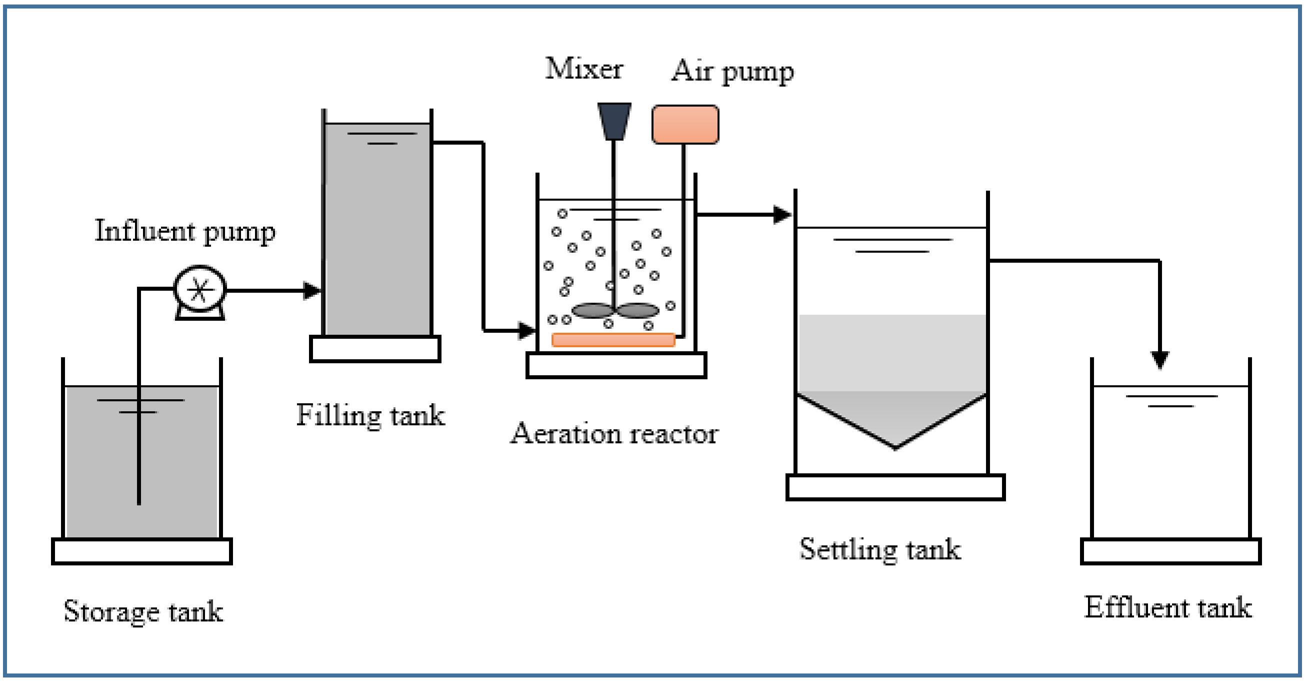

Fig. 1 Schematic of sequencing batch reactor used in this study.

Operation conditions

The continuous flow was stabilized by some preparations for the pilot. The sampling and experiments were started to determine the characteristics of wastewater after pilot was reached to steady state conditions and bacteria had adopted to the environmental conditions. In this study we used aeration time of 6 h and settling time of 3 h for all of experiments. Cell retention time, filling time and intensity of the aeration were considered as variable parameters in the experiments. Each parameter had been sorted into three classes including cell retention times of (5, 10 and 15 d), filling times of (1, 2 and 3 h) and intensities of the aeration (weak, medium and strong). The effects of each parameter were investigated by three samples. Then, the effects of variable parameters were examined on BOD, COD, MLSS and MLVSS. Moreover, after reaching to optimal conditions, other parameters such as TP, TN, $NH_4^+ - N$ and $NO_3^- - N$ were examined at the optimal conditions.

Analytical methods

Temperature, pH, DO, BOD_5, COD, TSS, MLSS and MLVSS concentration as well as, $NH_4^+ - N$ and TP were measured in this study. The pH and temperature were measured by using a digital pH meter. A dissolved oxygen meter (YSI 5000) was utilized to determine dissolved oxygen (DO) in the SBR system. Biodegradability was measured by 5-day biochemical oxygen demand (BOD_5) test according to the Standard Methods (Andrew, 2005). The seed for BOD_5 test was obtained from a municipal wastewater treatment plant (Elmolla & Chaudhuri, 2011). Chemical oxygen demand (COD) was determined according to the Standard Methods (Andrew, 2005). Weekly analyses included MLVSS, MLSS in reactor (Fu *et al.*, 2001). MLSS and MLVSS were determined in Ekbatan wastewater treatment plant laboratory at the temperature of 550°C (Metcalf *et al.*, 2010). TP and $NH_4^+ - N$ were measured with aid of a spectrophotometer (The Hach DR 5000 UV-Vis Laboratory Spectrophotometer) at wastewater treatment plant laboratory.

Modification of biokinetic coefficients

In the past, designs of biological wastewater treatment processes were based on the empirical parameters developed by experience, which included hydraulic loading, organic loading and retention time. Nowadays, the design utilizes empirical as well as rational parameters based on biological kinetic equations. Theses equations describe growth of biological solids, substrate utilization rates, food-to-microorganisms ratio, and the mean cell residence time (Mardani *et al.*, 2011). Our ability to predict the performance of wastewater treatment systems depends on accurate kinetic models and reliable methods for determining the model parameters. Current models for the prediction of effluent quality from activated sludge wastewater systems can successfully predict their performance with respect to organic matter oxidation, nitrification, denitrification, and even phosphorus removal (Henze *et al.*, 1987, Wentzel *et al.*, 1989). Biokinetic coefficients were determined by collecting data from pilot-scale experiments and under equations (Mardani *et al.*, 2011). The biokinetic coefficients were determined by **Eq. (1)** and **(2)**, respectively.

$$\frac{1}{SRT} = YU - K_d = Y\frac{S_0 - S}{X\theta} - K_d \qquad (1)$$

$$\frac{X\theta}{S_0 - S} = (\frac{Ks}{K})\frac{1}{S} + \frac{1}{K} = \frac{1}{U} \qquad (2)$$

where SRT is solids retention time (d), Y is biomass yield, mg biomass formed/ mg substrate utilized (mg VSS/ mg BOD or COD), U is substrate utilization rate (mg as BOD or COD/mg VSS.d), K_d is endogenous decay coefficient (1/d), S0 is influent substrate concentration (mg/L as BOD or COD), S is soluble substrate concentration in bioreactor (mg/L as BOD or COD), X is biomass concentration (mg VSS/L), θ is hydraulic retention time (d), Ks is half saturation coefficient (mg/L), K is a done substrate utilization rate (mg as COD/mg VSS.d).

The values for biokinetic coefficients such as K_d, K_s, Y and K for municipal wastewater have been reported in references. The wastewater characteristics for each society are different because of people's culture, economic climate and other issues. It can be perceived that these coefficients differ significantly for each society, so they were computed to compare with current values.

Artificial neural network modeling processes

Modeling and simulation are a do to achieve these objectives. However, modeling of a process covers a broad spectrum (Shokrian *et al.*, 2010). At one extreme, lie theoretical (or parametric) models a done fundamental knowledge of the process. These models are also called knowledge-based models. At the other end lie empirical (or non-parametric) models which do not rely on the fundamental principles which governing the process (Vaca Mier *et al.*, 2001, Vecchio *et al.*, 1998). Usually the evaluation of the time dependent processes is done by using the conceptual models which present good results (Sha & Edwards, 2007). However, conceptual models are difficult to develop and the calibration of the model parameters is subjective. Alternatives are empirical models which connect inputs and output by means of a mathematical function without an explicit relationship with the process characteristics. An artificial neural network (ANN) is an example of an empirical model. ANN is a computing method which mimics the human brain and nervous system (Sha & Edwards, 2007, Singh *et al.*, 2012). It is a mathematical structure, which is capable of approximating arbitrarily complex nonlinear processes that relate the inputs and output of any system. ANN models have been used successfully for modeling complex nonlinear input/output time series relationships, classification, pattern recognition and other problems in a wide variety of fields (Singh *et al.*, 2012).

So far, different types of neural network architectures and their performances have been studied for the purpose of neuroidentification (Azmy *et al.*, 2004, Park *et al.*, 2005, Singh & Venayagamoorthy, 2002, Venayagamoorthy, 2007). It includes Multilayer Perceptrons (MLPs), Radial Basis Functions (RBFs), Recurrent Neural Networks (RNNs), and Echo-State Networks (ESNs). In order to achieve the objective, it was decided to employ two types of feed forward artificial neural networks (FANNs), which are most commonly used in classification problems, namely multilayer perceptron and radial basis function (Suchacz & Wesołowski, 2006). Operational parameters were simulated a done the theory of FANN, namely RBF and MLP using the mathematical software program MATLAB. Experimental data over 90 d were used in ANN modeling processes in the current research. Statistical characteristics of the measured process variables are presented in **(Table 2)**.

The RBFANN consisted of one input layer, one output layer, and one hidden layer **(Fig. 2)**. Radially symmetric basis function is used as activation functions of hidden nodes. The transformation from the input nodes to the hidden nodes is a non-linear one, and training of this portion of the network is generally accomplished by an unsupervised fashion. The training of the network parameters (weight) between the hidden and output layers occurs in a supervised fashion a done target outputs (Kashaninejad *et al.*, 2009). In this study, the RBFANN applied network function of NEWRBE to the input data, which the NEWRBE created a two-layer network with biases for the both layers.

MLP normal feedforward artificial neural networks were used to simulate the biokinetic coefficients and MLVSS of the municipal wastewater treatment by a SBR **(Fig. 2)**. The MLPANNs were trained by different learning algorithms including incremental back propagation, batch back propagation, Levenberg–Marquardt algorithm and quickprob. The developed networks consisted of three layers including an input layer, a hidden layer and an output layer. For modeling of MLVSS the input layer comprised four nodes including HRT, influent COD, TSS and SRT. And the hidden layer consisted of several nodes, which varied to obtain the best model and he output layer a done output node. Another important factor in ANN design is the type of transfer (activation) functions (Kashani & Shahhosseini, 2010). The transfer function determines the input/output behavior and adds nonlinearity and stability to the network (Lipták, 2010).

Table 2. Wastewater characteristics in the critical conditions

Input variable NO.	Input variable	Value	Output variable	Value
1	HRT (h)	4–8	MLVSS (mg/L)	1670–3300
2	TSS (mg/L)	150–250		
3	COD_{in} (mg/L)	250–300		
4	SRT (d)	5–15		

To select the most suitable transfer function for the system, different kinds of activation functions were iteratively examined including sigmoid, hyperbolic tangent function, hyperbolic tangent sigmoid, Gaussian, linear, threshold linear and bipolar linear by developing several networks.

Prior to training of artificial neural networks, the data sets were normalized by using the zero-mean normalization method (Lee & Park, 1999). The data sets were normalized by **Eq. (3)** and **(4)**, respectively and represented as normalized variables, $X_{i,\,norm}$:

$$X_{i,norm} = \frac{X_i - X_{i,avg}}{R_{i,max}} \tag{3}$$

$$R_{i,max} = \max[X_{i,max} - X_{i,avg}, X_{i,avg} - X_{i,min}] \tag{4}$$

where X_i is an input or output variable, $X_{i,avg}$ is the average value of the variable over the data set, $X_{i,min}$ is the minimum value of the variable, $X_{i,max}$ is the maximum value of the variable, and $R_{i,max}$ is the maximum range between the average value and minimum/maximum value.

Each network was trained until the network average root mean squared error (RMSE) was minimum and coefficient of determination (R^2) was equal to 1. Other parameters for network were chosen as the default values of the software (Pendashteh *et al.*, 2011). The performances of the ANN models were measured by R^2 and RMSE between the predicted values of the network and the experimental values, which were calculated by **Eq. (5)** and **(6)**, respectively (Pendashteh *et al.*, 2011).

$$R^2 = 1 - \frac{\sum_{i=1}^{n} (y_i^* - y_p^{(i)})^2}{\sum_{i=1}^{n} (y_i^* - \bar{y})^2} \tag{5}$$

$$RMSE = 1 - \sqrt{\frac{1}{n} \sum_{i=1}^{n} (y_p^{(i)} - y_i^*)^2} \tag{6}$$

where $\bar{y}$ is the average of y over the n data, y_i^* and $y_p^{(i)}$ are the ith target and predicted responses, respectively.

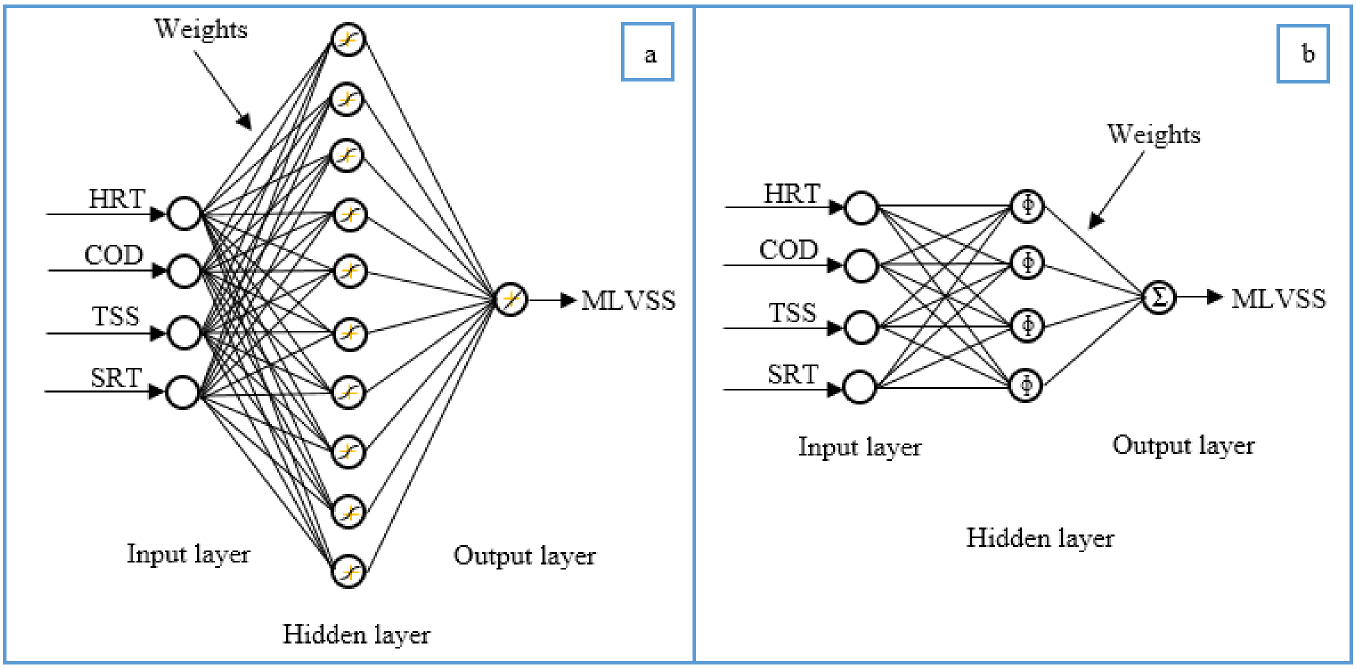

Fig. 2 Topological architectures of the artificial neural networks used in this study: (a) MLP (b) RBF.

RESULTS AND DISCUSSION

BOD removal efficiency

Experiments were begun with three different cell retention times of 5, 10 and 15 d to examine the BOD removal efficiency. It should be noted that all other operational conditions were constant during three experiments. The results showed that the BOD removal efficiency is improved by increasing cell retention time. The BOD removal efficiencies at three cell retention times of 5, 10 and 15 d were 86.46%, 95.98% and 97.32% respectively. The BOD concentration decreased from 161 mg/L to 4.3 mg/L at the cell retention time of 15 d (**Fig. 3**).

Therefore, the cell retention time of 15 d was chosen and experiments were continued to examine the effects of filling time on the BOD removal efficiency. Then the experiments were executed with three filling times of 1, 2 and 3 h, and other parameters were the same for three samples. The results indicated that with the increase of filling time changes of the BOD removal efficiency is not significant. At filling time of 2 h the BOD removal efficiency was 98.33% in comparison to filling time of 1 and 3 h with the BOD removal efficiencies of 97.13% and 97.54% respectively (**Fig. 3**). The BOD concentration after filling phase was low in comparison to the influent BOD. The influent BOD concentration decreased after filling phase because the organics were adsorbed to the suspended flocs and microorganisms instantaneously. It denotes that the BOD was reduced by PAO and denitrifiers within filling phase. There was no significant difference between filling time of 1 and 2 h in the BOD removal efficiency so their changes almost overlapped each other.

Because the optimization of hydraulic retention was one of the main purposes in this research, filling time of 1 h was chosen as the best result to continue experiments. Moreover, the effects of intensity of aeration were in such a way that BOD removal efficiency increased by enhancing the intensity of aeration. In addition, the BOD removal efficiencies for the aeration intensity of weak, medium and strong were 83.8%, 97.13% and 97.44% with cell retention time of 15 d and filling time of 1 h (**Fig. 3**). It was observed that there is no noticeable difference between medium and strong aeration in the BOD removal efficiency. We observed that air bubbles escaped from wastewater surface after strong aeration and therefore, small portion of the given oxygen were absorbed into the wastewater (**Fig. 4**). The result of medium and strong aeration were the same in spite of the fact that in strong intensity of aeration the energy had consumed twice as much as medium intensity of aeration. The optimal results were obtained by cell retention time of 15 d, filling time of 1 h and medium aeration intensity.

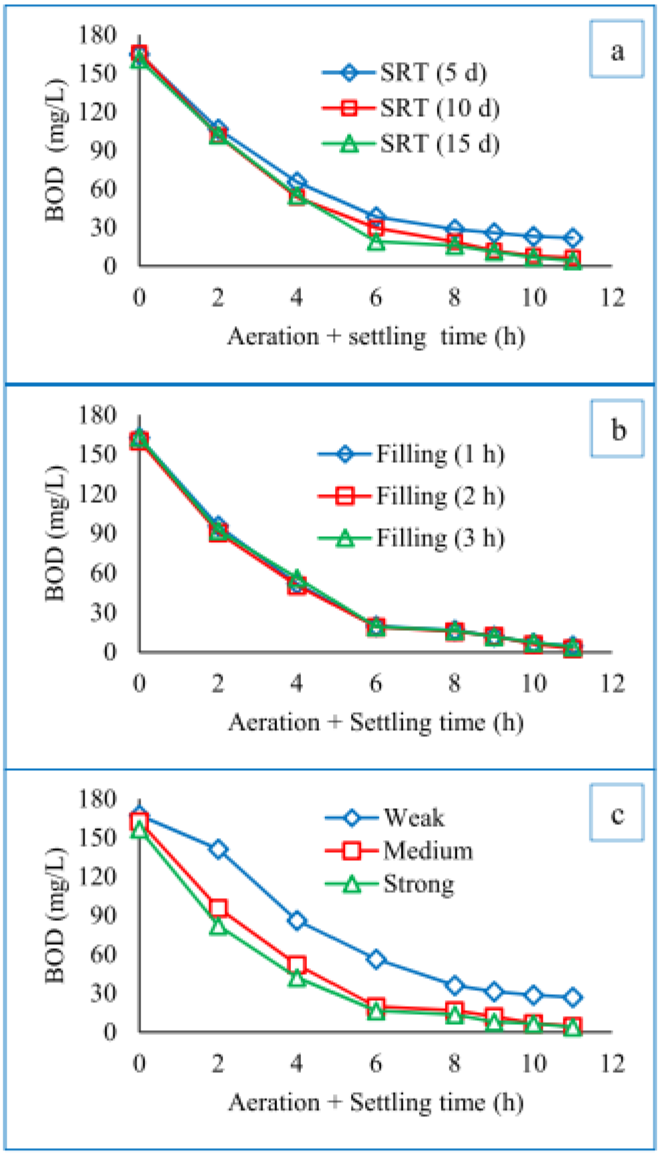

Fig. 3 Changes of BOD concentration for different (a) SRTs (b) Filling times (c) Aeration intensities.

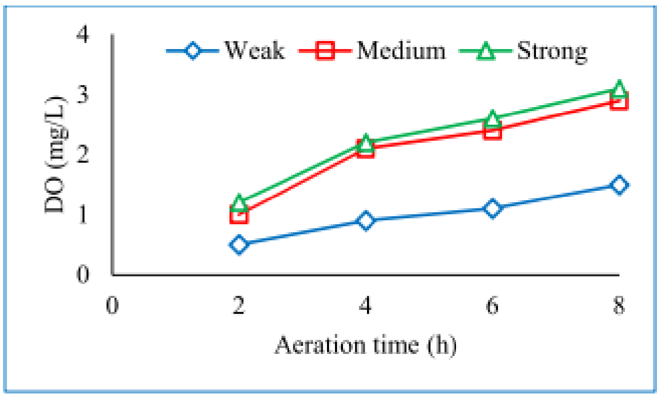

Fig. 4 Changes of DO concentration for three aeration intensities (weak, medium and strong).

COD removal efficiency

Results indicated that the COD removal efficiencies in all experiments were in a high correlation with results of BOD experiments. The variable parameters and operational conditions were the same as BOD experiments. The results indicated that the COD removal efficiencies are improved by increasing cell retention time. At the three cell retention times of 5, 10 and 15 d, the COD removal efficiencies were 86.12%, 92.81% and 95.28% respectively (**Fig. 5**). At the cell retention time of 15 d and filling time of 1 h the optimum result obtained with the COD removal efficiency of 94.58% which influent COD concentration decreased from 252.3 mg/L to 13.7 mg/L. And also, at the filling time of 2 and 3 h the COD removal efficiencies were 96.27% and 95.33% (**Fig. 5**). The filling time of 1 h was considered as the optimal result with regard to the experiments of COD. The COD removal efficiencies for the aeration intensities of weak, medium and strong were 83.8%, 97.13% and 97.44% with cell retention time of 15 d and filling time of 1 h (**Fig. 5**). The results of strong and medium aeration in the COD experiments were similar to BOD. In conclusion, the optimal results were obtained by cell retention time of 15 d, filling time of 1 h and medium aeration intensity.

Phosphorous and nitrogen removal efficiency

The experiments to determine nitrogen and phosphorous removal efficiencies were performed in accordance with optimal conditions had been achieved by former experiments for BOD, COD, MLSS and MLVSS. Therefore, the experiments were conducted at the cell retention time of 15 d, filling time of 1 h and medium aeration. Nitrogen is supposed to be removed by SND mechanism in the aerobic stage, the influent organic carbon and dissolved oxygen (DO) concentration are very important parameters (Guo *et al.*, 2011). The results indicated that TN concentration decreased from 25 mg/L to 20.3 mg/L at the end of filling stage which implied denitrification had taken place slightly. The settling stage improved the denitrification conditions and the TN removal efficiency was 89.7% (**Fig. 6**). The results showed that at the end of aeration phase the $NH_4^+ - N$ concentration decreases to 4.46 mg/L from its initial value of 18.4 mg/L (75.72% removal efficiency). By increasing hydraulic retention time the $NH_4^+ - N$ removal efficiency reached to 92.75% at the end of settling phase (**Fig. 6**).

The anaerobic phase is very important for traditional phosphorous removal, intracellular poly-P is hydrolyzed to phosphate and released to wastewater by PAOs. Meanwhile, carbon sources is converted to PHA as energy storage for the subsequent aerobic phase after influent for biological phosphorous removal (Chen *et al.*, 2005). Thus BPR could not be realized without PHA accumulation in an anaerobic zone during the process (Wang *et al.*, 2008). Phosphorous is removed by PAOs which release ortho-phosphate in anaerobic stage and take up ortho-phosphate in the subsequent aerobic stage (Guo *et al.*, 2011). To investigate phosphorous removal efficiency the experiments were performed in a trend the same as nitrogen (**Fig. 6**).

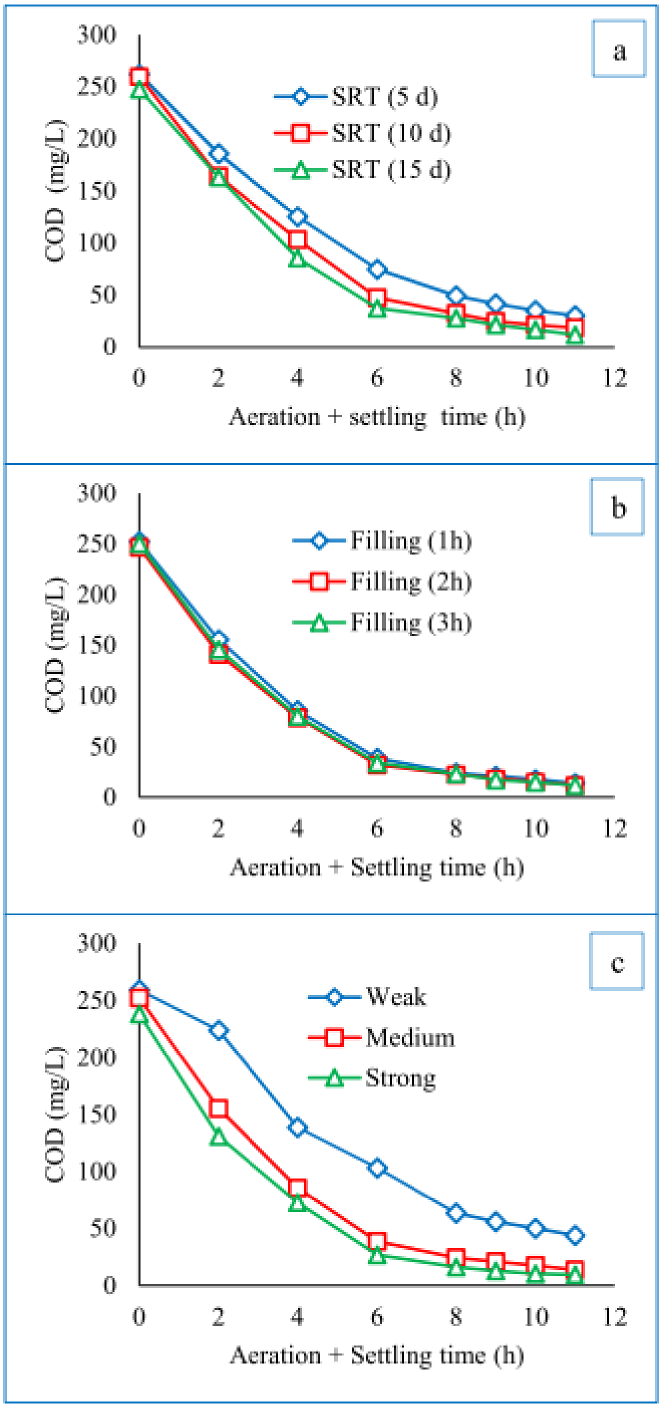

Fig. 5 Changes of COD concentration for different (a) SRTs (b) Filling times (c) Aeration intensities.

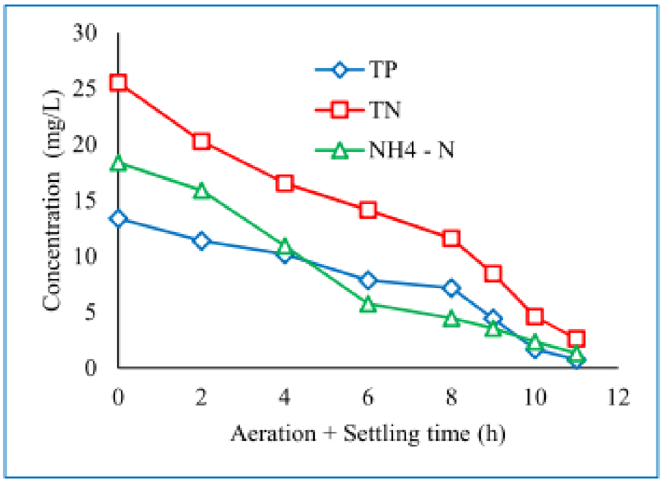

Fig. 6 TP, NH4-N and TN removal efficiency at the hydraulic retention time of 10 h.

The initial TP concentration at the beginning of experiment was as high as 13.4 mg/L. Then by initiating settling stage the anaerobic condition improved TP removal efficiency so that the TP removal efficiency was 94.27% at the end of settling phase. According to the results for nitrogen and phosphorous removal the optimal time for settling stage is 3 h. Thus, by considering the filling time of 1 h and aeration time of 6 h the optimal hydraulic retention time is 10 h.

Evaluation and modeling of MLVSS

MLSS and MLVSS are both used as measures of the microorganism concentration in the activated sludge system. MLSS includes both the volatile and inert solids in the mixed liquor. MLVSS more closely approximates the biologically active portion of the solids in the mixed liquor, as microbial cellular material is organic and volatilizes or burns at 550 °C (Metcalf *et al.*, 2010).

Biological treatment of wastewater basically depends on the activity of degraded microorganisms in the sludge. In other words, MLSS can directly affect removal of organic pollutants (Wu *et al.*, 2011). To examine the effects of changes in the MLSS and MLVSS concentrations in the removal efficiencies and hydraulic retention time experiments were executed at the cell retention times of 5 d, 10 d and 15 d. The results demonstrated that at the cell retention time of 15 d the MLSS and MLVSS reached to their maximum values.

The MLSS and MLVSS values were 1966 mg/L and 1636 mg/L respectively at the aeration time of 6 h. The results indicated that the filling time of 1 h and medium aeration can be considered as the optimal conditions. Too high or too low MLSS would limit the COD and $NH_4^+ - N$ removal. When MLSS was too low pollutants would not fully removed, when MLSS was too high degraded microorganisms received insufficient nutrition. Under such conditions, the self-degradation of microorganisms resulted in lower removal efficiencies of COD and $NH_4^+ - N$ (Wu *et al.*, 2011). According to our results after the aeration time of 6 h MLSS and MLVSS decreased because of self- degradation. After aeration time of 6 h the removal efficiencies are decreased with regard to the results of other researches which mentioned before. On the other hand, the BOD and COD changes indicated that the most removal efficiencies are obtained between the aeration times of 2 and 6 h. This can be understood by the steep slopes of changes before aeration time of 6 h in comparison to changes after aeration time of 6 h.

The RBFANN used 70% of normalized data to train and 30% to test models with network function of NEWRBE (Çinar *et al.*, 2006). The RBFANN applied NEWRBE to the data for more than 50 times in order to minimize error. The optimal network was chosen on the basis of the minimum average error as well as suitable match. The MLPANN used function of newff and as a result, it created a feed-forward back propagation network. The MLPANN with network function of newff chose 70% of normalized data to train, 15% to test and 15% to validate the MLPANN models (Çinar *et al.*, 2006). The MLPANN was trained by different learning algorithms for maximum 1000 epochs. However, the Levenberg–Marquardt algorithm resulted in the most suitable models to train and test data after less than 70 iterations. Based on this study, best resulted models were obtained with the hidden layer consisting of 10 neurons. The optimal transfer function for the hidden layer was found to be hyperbolic tangent sigmoid (tansig) function while the optimal transfer function for the output layer was a linear one (purelin). **Fig. 7** shows the results of the MLVSS modeling by RBFANN and MLPANN for train and test data.

The training procedures for simulation of MLVSS were highly collaborated for both RBFANN and MLPANN. The train and test models for both MLPANN and RBFANN demonstrated perfectly matched results between the experimental and the simulated values of MLVSS. The values of RMSE for train and test (verification) models obtained by MLPANN were 31.82 mg/l and 40.25 mg/l respectively, and the value of R^2 was 0.99 for both models. The values of RMSE for train and test models obtained by RBFANN were 69.04 mg/l and 43.87 mg/l respectively, and the value of R^2 was 0.99 for both models. It was observed that the MLPANN has stronger approximation and generalization ability than the RBFANN with regard to our experimental data for MLVSS. Simulation of MLVSS by MLPANN and RBFANN according to all experimental data for 90 d have been shown in (**Fig. 8**).

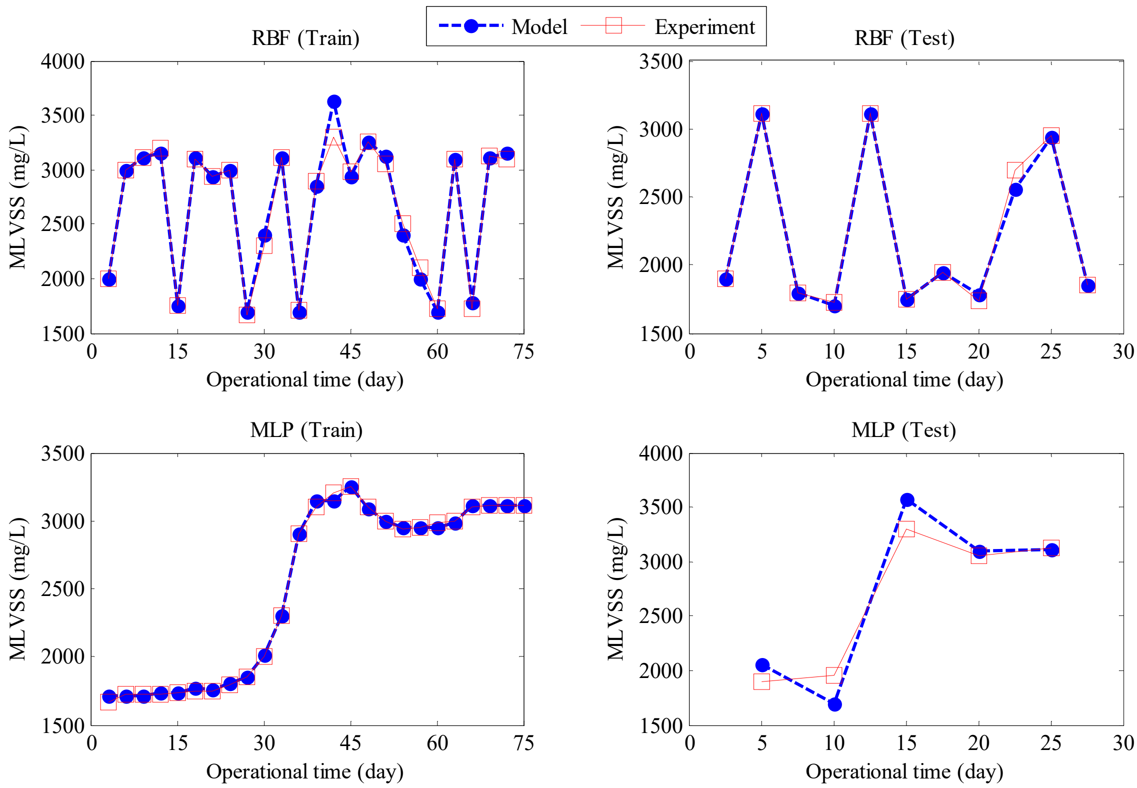

Fig. 7 MLVSS models by RBFANN and MLPANN for train and test (verification) data.

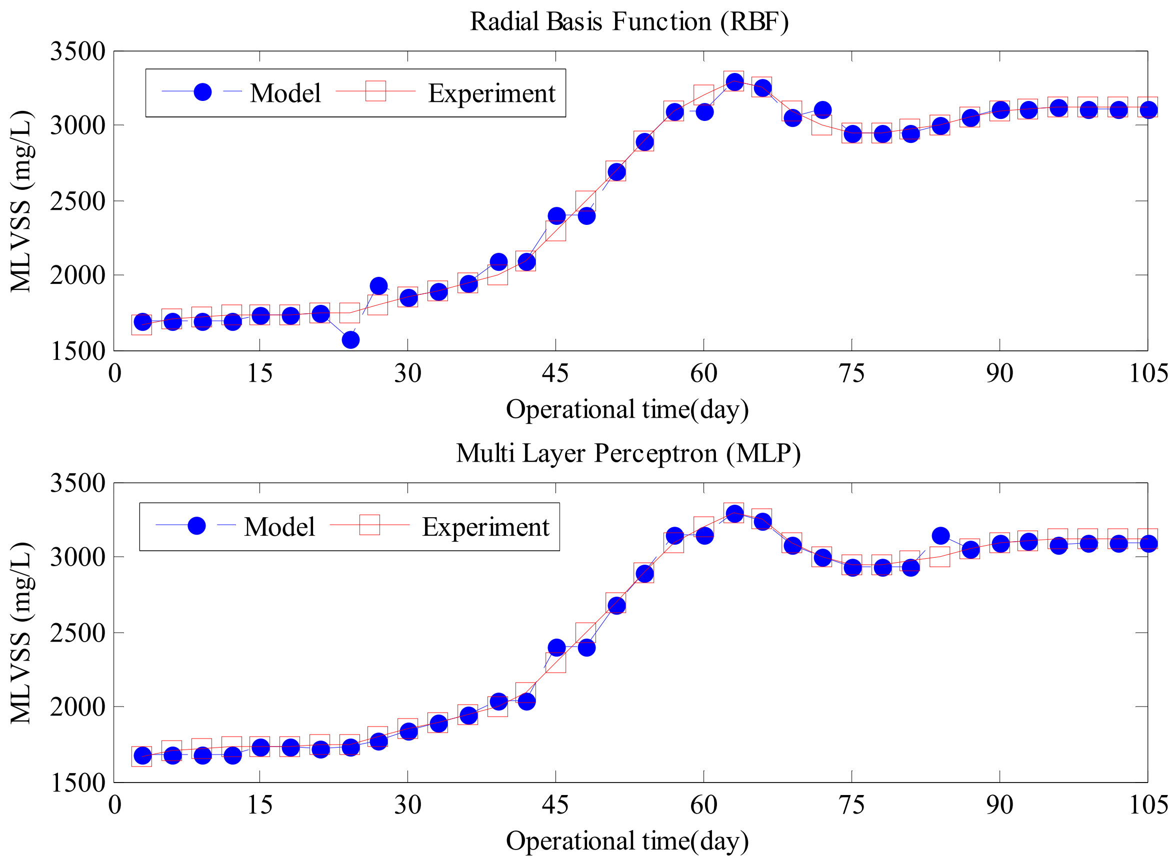

Fig. 8 MLVSS models by RBFANN and MLPANN for all experimental data.

The MLVSS was modeled by considering different single variables as inputs of ANNs in order to investigate the effects of each variable on the simulation of MLVSS. Furthermore, separate models were introduced in order to show the effects of joint input variables on the MLVSS. These inputs to train the networks were groups of two, three parameters. **Table 3** shows (HRT) among single input variables, (HRT and TSS) among groups of two variables and (HRT, TSS and SRT) between groups of three variables had the most considerable effects on the MLVSS models. Furthermore, the influence of each variable on the both RBFANN and MLPANN models in comparison to the other variables was examined by performing sensitivity analyses (Saltelli *et al.*, 2008). The sensitivity analyses determined the importance order of each input variable. The variable with higher rank of importance showed not only higher match between experimental and ANN models but also low RMSE and high R^2 values. **Table 3** shows the importance order of each input variable and the joint variables for MLVSS.

Evaluation and modeling of biokinetic coefficients

The biokinetic coefficients vary noticeably with operational conditions and other issues such as the type of wastewater and the system which is applied for wastewater treatment. The investigations showed that values of the biokinetic coefficients vary significantly with the change in MLSS concentration in each process for the activated sludge processes. However, this variability does not follow any definite pattern (Mardani *et al.*, 2011). In the current research, the biokinetic coefficients were computed for the BOD and COD experiments. The results indicated that the yield coefficient (Y), decay coefficient (K_d), maximum specific growth rate (K) and saturation constant (Ks) were 6.22 mgVSS/mgCOD, 0.002 1/d, 0.029 1/d and 20 mg COD/L (**Fig. 9**). The values of the biokinetic coefficients were found to be as follows: Y = 10.45 mgVSS/mgBOD, K_d = 0.01 1/d, 0.014 1/d and 3.38 mgBOD/L (**Fig. 10**). The results indicated that the biokinetic coefficients are quite different from the values which have been mentioned in current references for municipal wastewater. It is logical to compute these coefficients for each wastewater in each region and compare them with values in current references.

CONCLUSION

We concluded that the changes of cell retention time, filling time of the reactor and intensity of aeration can affect the removal efficiencies of BOD, COD, TN, $NH_4^- - N$ and TP. It was observed that removal efficiencies are increased with increase of cell retention time. Furthermore, the increase of filling time of the reactor did not significantly affect removal efficiencies.

Table 3. Effects of different single and joint variables on the MLVSS in the aeration reactor.

Input variable NO.	Radial basis function (RBF) models				Multilayer perceptron (MLP) models				Importance order
	R^2		RMSE (mg/l)		R^2		RMSE (mg/l)		
	Train	Test	Train	Test	Train	Test	Train	Test	
1	0.968	0.981	112.14	88.49	0.975	0.989	90.53	69.51	**1**
2	0.469	0.567	441.83	559.12	0.455	0.731	441.87	469.56	**4**
3	0.621	0.901	393.32	203.02	0.718	0.965	314.56	282.13	**2**
4	0.748	0.739	314.18	296.41	0.753	0.806	278.16	380.29	**3**
1–2	0.989	0.982	65.58	49.42	0.989	0.987	66.31	73.95	**2**
1–3	0.989	0.991	64.13	45.33	0.991	0.998	55.76	50.83	**1**
1–4	0.973	0.978	97.73	95.11	0.971	0.985	106.37	80.14	**3**
1–3–2	0.986	0.995	73.24	44.24	0.988	0.994	66.63	51.83	**2**
1–3–4	0.995	0.993	41.94	52.73	0.999	0.993	18.81	66.14	**1**
1–3–4–2	0.989	0.991	69.04	43.87	0.997	0.998	31.82	40.25	**1**

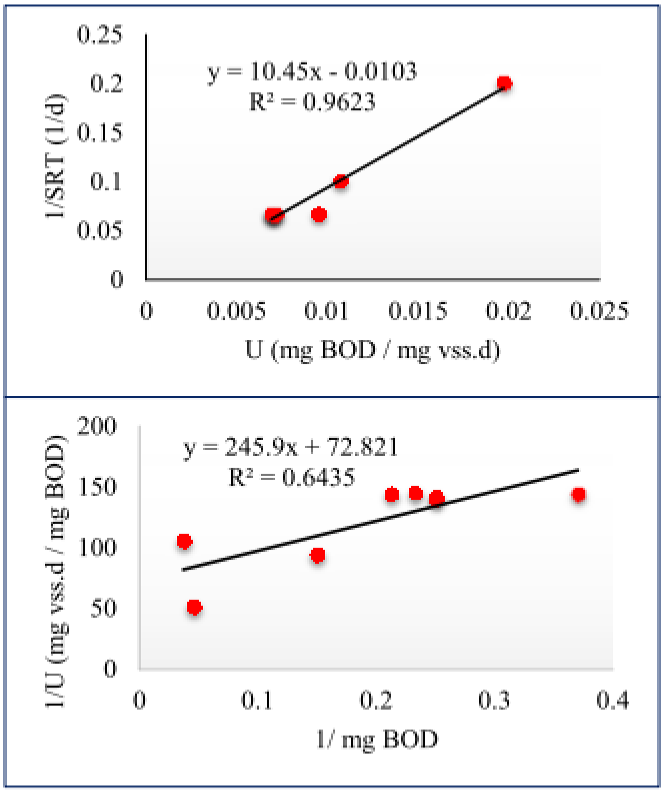

Fig. 9 Biokinetic coefficients according to BOD experimental results obtained in the study.

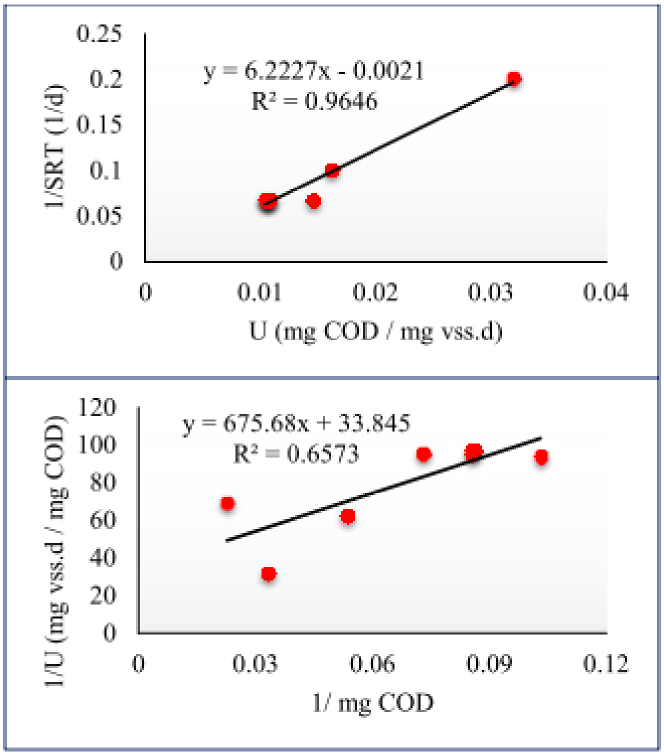

Fig. 10 Biokinetic coefficients according to COD experimental results obtained in the study.

The filling time of 1 h was considered as the optimal result. Furthermore, the removal efficiencies were increased with enhancements of aeration intensity, but the intensity of aeration did not improve removal efficiencies at the high intensities. The medium aeration was considered as the optimal result. The aeration time of 6 h was obtained as the optimal result according to the BOD, COD, MLSS and MLVSS experiments. Moreover, the settling time of 3 h gave the optimal result according to the nitrogen and phosphorous experiments. The optimal hydraulic retention time was 10 h including filling time of 1 h, aeration time of 6 h and settling time of 3 h. The biokinetic coefficients were quite different from the values which have been mentioned in the current references. The yield coefficient (Y), decay coefficient (K_d), maximum specific growth rate (K) and saturation constant (Ks) were 6.22 mgVSS/mgCOD, 0.002 1/d, 0.029 1/d and 20 mg COD/L according to COD experimental data. The values of the biokinetic coefficients were found to be as follows: Y = 10.45 mgVSS/mgBOD, K_d = 0.01 1/d, 0.014 1/d and 3.38 mgBOD/L according to BOD_5 experimental data.

Based on this study, the optimal models were obtained with the hidden layer consisting of 10 neurons. The optimal transfer function for the hidden layer was found to be hyperbolic tangent sigmoid (tansig) function while the optimal transfer function for the output layer was a linear one (purelin). The training procedures for simulation of MLVSS were highly collaborated for both RBFANN and MLPANN. The train and test models for both MLPANN and RBFANN indicated perfectly matched results between the experimental and the simulated values of MLVSS. The values of RMSE for train and test (verification) models obtained by MLPANN were 31.82 mg/l and 40.25 mg/l respectively, and the value of R^2 was 0.99 for both models. The values of RMSE for train and test models obtained by RBFANN were 69.04 mg/l and 43.87 mg/l respectively, and the value of R^2 was 0.99 for both models. It was observed that the MLPANN has stronger approximation and generalization ability than the RBFANN with regard to our experimental data for MLVSS.

ACKNOWLEDGMENT The authors are grateful to Ekbatan wastewater treatment plant for their technical and logistical assistance during this work which was supported by authors.

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