International Journal of Civil Engineering and Technology (IJCIET)
Volume 9, Issue 6, June 2018, pp. 1021–1028, Article ID: IJCIET_09_06_116
Available online at http://www.iaeme.com/ijciet/issues.asp?JType=IJCIET&VType=9&IType=6
ISSN Print: 0976-6308 and ISSN Online: 0976-6316

PERFORMANCE ASSESSMENT OF BIOLOGICAL TREATMENT OF SEQUENCING BATCH REACTOR USING ARTIFICIAL NEURAL NETWORK TECHNIQUE

Dr. Basim Hussein Khudair
Assistant professor, University of Baghdad/ Engineering College

Shatha Abdulrazzak Jasim
M.Sc. Student, University of Baghdad/ Engineering College

ABSTRACT

Artificial Neural Network (ANN) model's application is widely increased for wastewater treatment plant (WWTP) variables prediction and forecasting which can enable the operators to take appropriate action and maintaining the norms. It is much easier modeling tool for dealing with complex nature WWTP modeling comparing with other traditional mathematical models. ANN technique significance has been considered at present study for the prediction of sequencing batch reactor (SBR) performance based on effluent's (BOD_5/COD) ratio after collecting the required historical daily SBR data for two years operation (2015-2016) from Baghdad Mayoralty and Al-Rustamiya WWTP office, Iraq. The prediction was gotten by the application of a feed-forward ANN, based on influent BOD_5, COD and TSS concentrations. ANN ideal performance was measured based on the MSE and R^2 values. Higher R^2 value up to 94.1% with lowest MSE value were achieved suggesting good performance prediction by the model and its successful employment for the estimation of daily BOD_5/COD ratio of SBR biological wastewater treatment effluent.

Keywords: Artificial Neural Network, Performance assessment, Modeling, SBR, Al-Rustamiya WWTP.

Cite this Article: Dr. Basim Hussein Khudair and Shatha Abdulrazzak Jasim, Performance Assessment of Biological Treatment of Sequencing Batch Reactor Using Artificial Neural Network Technique, International Journal of Civil Engineering and Technology, 9(6), 2018, pp. 1021–1028
http://www.iaeme.com/IJCIET/issues.asp?JType=IJCIET&VType=9&IType=6

1. INTRODUCTION

Increased concern had been attentive on wastewater treatment plants (WWTPs) for the achievement of proper operation and control that could contribute in maintaining healthy environment [20]. Varying raw wastewater flow rates, characteristics, and strengths with related changing treatment conditions and complexity adopted at WWTP, would make plant's operation control faces complications [9]. Development of a durable mathematical path for assessment of plant's performance prediction depending on specified parameters' past observations can provide a robust control of a WWTP. As the biological reactions with interacting environmental conditions are often of nonlinear behavior, treatment processes would have a complex nature to be described by traditional linear models [24]. Better, representation of complex and non-linear relationships between system's input and output variables can be achieved by the application of artificial neural network (ANN) technique with higher level of accuracy, significance and commonly applied for water and wastewater treatment processes' control and forecasting [17]. The typical key parameters used for the plant's performance prediction are including chemical oxygen demand (COD), biological oxygen demand (BOD5) and total suspended solids (TSS). Till now, most of WWTPs modelling studies implemented these parameters and found out reasonable results. Where, ANN model was successfully employed to predict WWTP performance by prediction of effluent's BOD5 concentrations [18]. ANN model was also found to be a robust technique for effluent's BOD5, COD and total suspended solids (TSS) forecast to assess WWTP performance [13]. The same promising finding was achieved by the use of a simple neural network model for TSS removal, COD removal and sludge volume index (SVI) as an indication of plant's performance was demonstrated in [2]. In addition to various other ANN techniques for wastewater treatment modeling have been suggested earlier and more recently [21]. As the wastewater biodegradability represents the organic matters' portion that could be biologically reduced by bacteria which may eventually initiate the receiving water environment decline [19]. Accordingly, treated wastewater effluent biodegradability monitoring could offer ability for treatment processes evaluation and their subsequent possible pollution impact on the environment [7]. Some of strategies have been applied for estimating wastewater biodegradability as BOD5/COD ratio that represents a well-employed one for biodegradability estimation [1]. Since typical raw municipal wastewater BOD5/COD ratio levels are in (0.3-0.8) range then, the wastewater could be treated efficiently by biological processes if the ratio is ≥ 0.5. But a ratio < 0.3, would give an indication for reasonable toxicity presence or requirements for seeding or advanced oxidation techniques for biodegradability enhancement [16]. In correspondence, treated wastewater effluent's BOD5/COD ratio are in (0.1-0.3) range, definitely treated effluent would have lass biodegradability than influent's, if it had efficient treatment. At present study BOD5/COD ratio data for influent wastewater was in the range (0.31-2.48) such diverse range may be resulted from many contributions to the collection system of domestic sewage including industrial discharges, corresponding to effluent ratio in the range of (0.25-1.67), such high effluent ratio value provides an indication that effluent is still loading with considerable amount of organic matter with their adverse effects on the receiving body of water. Accordingly, at present study, it has been tried to develop relatively accurate estimation models using the biological wastewater treatment data for the prediction of sequencing batch reactor (SBR) performance at Al-Rustamiya WWTP. Thus, a decision could be made as soon as unexpected changes took place in influent's quality to maintain proper plant's operation by the application of artificial neural networks techniques based on past key parameters observations including BOD5, COD and TSS as input layer variables and BOD5/COD ratio as output layer variable [6].

2. MATERIALS AND METHODS

2.1. Description of SBR

Recently, in 2014 five units of SBR system, as shown in Plate (1), were added to Al-Rustamiya WWTP project in order to handle increasing amounts of wastewater received by the use of such new and promising technology. The influent wastewater is screened first, then, in the intermediate pits, a first separation is made between heavy and light material that is partially captured in the intermediate pits and the wastewater. Next, the collected wastewater is transferred from the influent pump pit to the compact aerated pre-treatment unit at which fine particles and sand would be removed by grit press and sand removals. After that, the pre-treated wastewater will then flow to SBR system which consists of five SBR units and each SBR unit consist of three sub-tanks. Each SBR unit has useful volume of 1246.4 m^3, 34.5 diameter and water height of 4 m. One of the typical properties of the SBR-system is that every compartment goes through a certain cycle including organic matter accumulation in continuous aeration and sludge sedimentation. This cycle is controlled by a matrix, which gives a lot of flexibility [22].

Plate 1 SBR units at Al-Rustamiya WWTP

2.2. Data Preprocessing

In the analysis of data in ANN and other approaches need to perform data normalization in order to get relatively same range for each input values had been presented to the ANN model in an effort to get stable weight and biases concurrence [11]. The input parameters were scaled up in the range 0 to 1. Data normalization could be processed by the mathematical equation as given in Eq.1 [10]:

$$z_i = \frac{x_i - \min(x)}{\max(x) - \min(x)} \tag{1}$$

Where: $x_i = (x_1, ..., x_n)$ and z_i is the corresponding normalized data.

After the data sets preprocessing, the new input normalized data sets are presented into the networks. Finally, for comparison accomplishment between the ANN results and the actual ones, the rescaled ANN results have to be transformed back for the same original targets ranges by the following mathematical equation Eq.2 [14].

$$(rescaled)z_i = z_i \times (max(x) - min(x)) + min(x) \tag{2}$$

3. ARTIFICIAL NEURAL NETWORK MODELING

ANNs architecture contains input layer, one or more hidden layer, and output layer interconnected with each other with sum of processing elements defined as neurons that also interacting with each other by specified weight and linked to all next layer's neurons. The feed-forward back-propagation training algorithm is the common model being used for various engineering's problems [3].

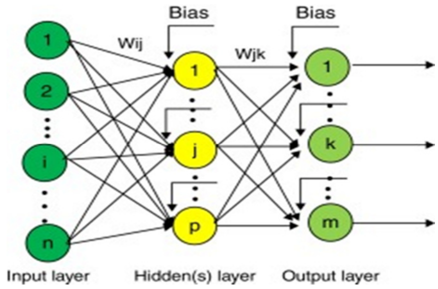

Figure 1 General feed-forward back-propagation ANN structure.

As exhibited in Fig. 1. The input layer at which the data is presented. Whereas, complex relationships are enabled to be computed at the hidden layers between inputs and outputs which eventually being figured out at the output layer. Frequently, the hidden layers number is identified according to the problem's complexity. However, most of cases modeling investigations are accomplished with one hidden layer. On the other hand, the number of the hidden layer's neurons is usually identified by trial and error strategy with minimum value start and subsequent increase depending on the case's nature [8, 16]. For ANN training achievement, the output and their effecting input data series are introduced to the network. The input would be processed in the back-propagation training algorithm with the help of the hidden layer neurons and that of the output layer process by multiplying each input by its weight. Then, the result is summed and processed by means of a nonlinear transfer function, also defined as activation function, to eventually figure out results. The most widely used activation functions are the sigmoid and hyperbolic tangent functions. The back-propagation training is basically a descendant gradient technique to lessen the network's error function [4].

At present study, IBM SPSS Statistics 23 software was used for neural network modeling application, the ANN model was validated using one-layered feed-forward neural network with back-propagation training algorithm with employment of hyperbolic tangent activation function to link between input and hidden layer. Whereas, sigmoid activation function was used to link between hidden and output layers, the formula for both of mentioned function are illustrated in Eq. (3) and Eq. (4) respectively [10]. The ANN training was achieved by introducing the input data series to the network and continuing training till minimum average mean square error (MSE) is achieved [23]:

$$\gamma(c) = tanh(c) = \frac{(e^{c}-e^{-c})}{(e^{c}+e^{-c})} \qquad 3$$

$$\gamma(c) = \frac{1}{(1+e^{-c})} \qquad 4$$

When training is done, trained neurons' weights are stored in the network memory and the network initiates the estimation of the target output values for corresponding training data. After that, the trained network estimated output would be compared with the set of actual data that was introduced to the network previously for testing the model performance [5]. At all these steps, a random selection strategy was used to assign 64% of all data as training data and 19% as testing one, while17% of the data were used for validation. The suggested ANN model performance could be evaluated based on many statistical parameters, like the coefficient of determination ($R2$), MSE, and others. A well data representing model should be of $R2$ value close to 1 with minimum error. In the present study, only one hidden layer was selected. The hidden layer neurons number was tested from 1 to 20. The neural network inputs include initial concentrations of (BOD5, COD and TSS) (mg/L) with BOD5/COD ratio as selected target.

4. RESULTS AND DISCUSSION

As the R^2 value and MSE provide an indication of how “close” the matching is between two data sets as actual target data set and the predicted target data set. It was observed from Fig. 2 varying MSE value were obtained with neuron numbers variation, but lower values of MSE for train and test data of 0.0007 and 0.0002 respectively, was observed at 11 neurons in one hidden layer. Hence, 11 hidden neurons were considered for optimization in the present study.

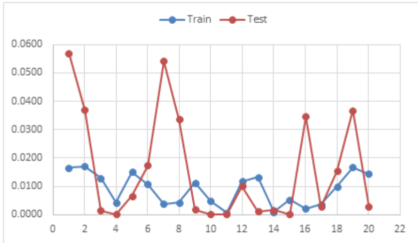

Figure 2 MSE of trained and tested data with No. of neurons in hidden layer

As shown in Fig. 3 the correlation factor, for two sets, a pretty high proof of the correctness of trained ANN model. Since the coefficient of determination $R2$ levels are ranged between (-1 to +1). Then, as higher absolute $R2$ level and closer to (+1) is gotten by the model, as higher correlation between the actual target and the forecasted target values. At present study, the gained model $R2$ level was close to 1 with 0.941 value, which indicate a reasonable fitting to experimental data that in turn suggest respectable model ability for accurate predictions. Such establishment is consistent with a related study mentioned that a value of $R2 \geq 0.8$ provides an indication of strong correlation existence between observed and predicted variables [12].

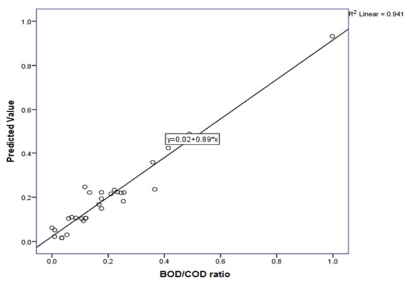

Figure 3 Regression plot for selected ANN model performance.

Thus, the proposed ANN model predicted the behavior of BOD_5/COD ratio values with respectable accuracy and excellent fit. Where, the gained predicted effluent BOD_5/COD ratios had a considerable match with the actual ratio levels based on the relatively lower MSE value and corresponding higher R^2 one, that suggest valuable model's performance.

Formulation of effluent BOD_5/COD ratio could be derived by implementation of the inputs, normalization and gained weights of the ANN model. In Tables 1 and 2, the weights and bias values in the derivations of ANN based formulations are given where each input is multiplied by a connection weight as mentioned that signifies the connections' strength between the input and output layers' neurons with the hidden layer's neurons.

In a simple manner, to get a result first of all weights are gathered, then using the adopted activation function that in our case is a logistic sigmoid one at which the weights and biases would be implemented to obtain outputs. Next, the gained result would be rescaled as inputs and outputs had prior normalization as mentioned.

When taking data range diversity with possible error measurements, wastewater nature and biological processes complexity into consideration with corresponding successful target prediction, it can be said that ANN method offers an economical and useful technique that can be used in prediction of effluent pollutants levels and efficiency where both of them are costly and time-consuming **[15]**.

5. CONCLUSION

In WWTPs, indicator as BOD_5/COD ratio monitoring have a lot of advantages as such correct and quick result can be minimize the need for experimental practice and thus reduction of operation costs. In addition to that, ANNs with their fast-learning property can provide the ability to reveal a solution to a case that never considered before. This study confirms the ability of the proposed artificial neural network model to forecast the performance of SBR at Al-Rustamiya WWTP with very satisfactory results that would help the operators to make quick response for possible wastewater fluctuations through the knowledge of the parameters affecting the efficiency of the treatment, new output and efficiency values can be produced by means of using ANN analysis without doing further experimental studies.

Table 1 Weight and bias values between input and hidden layer

Input Layer weights	Predicted										
	No. of hidden layer neurons										
	1	2	3	4	5	6	7	8	9	10	11
Bias	-1.404	-0.407	0.944	-0.509	0.711	-0.557	2.545	-0.208	-0.191	-1.09	-0.977
BOD_5	-0.914	0.132	0.328	-2.055	-1.146	0.867	2.173	0.349	-0.195	-0.456	-2.441
COD	3.484	0.089	-0.823	0.231	0.037	-0.084	-0.452	0.9	-0.149	0.767	-0.878
TSS	2.196	-0.367	-1.373	0.982	-0.689	0.583	-0.578	0.172	0.275	1.857	-1.224

Table 2 Weight and bias values between output and hidden layer

Output Layer weights	Predicted											
	Bias	No. of hidden layer neurons										
		1	2	3	4	5	6	7	8	9	10	11
$\frac{BOD_5}{COD}$	0.265	2.342	-.350	0.950	-.053	-.128	0.684	-.258	00.566	0.188	-.222	2.146

REFERENCES

[1] Amat, A.M.; Arques, A.; García-Ripoll, A.; Santos-Juanes, L.; Vicente, R.; Oller, I.; Maldonado, M.I.; Malato, S. A Reliable Monitoring of The Biocompatibility of An Effluent Along an Oxidative Pre-Treatment by Sequential Bioassays and Chemical Analyses. Water Res. 2009, 43, 784-792.

[2] Banaeia, K. F., Zinatizadeh, L. A. A., Mesgara, M. and Salarib, Z., 2013, Dynamic Performance Analysis and Simulation of a Full Scale Activated Sludge System Treating an Industrial Wastewater Using Artificial Neural Network, International Journal of Engineering, IJE TRANSACTIONS B: Applications, Vol. 26, No. 5, pp. 465-472.

[3] Chen, M., Challita, U., Saad, W., Yin, C. and Debbah, M., 2017, Machine Learning for Wireless Networks with Artificial Intelligence: A Tutorial on Neural Networks, A research supported by the U.S. National Science Foundation under Grants CNS-1460316 and IIS-1633363, arXiv:1710.02913v1 [cs.IT].

[4] Cheng, C., Niu, W., Feng, Z., Shen, J. and Chau, K., 2015, Daily Reservoir Runoff Forecasting Method Using Artificial Neural Network Based on Quantum-behaved Particle Swarm Optimization, Water 2015, 7, 4232-4246; doi:10.3390/w7084232.

[5] Chlyah, Y., 2016, Method for Optimal Arrangement of Clay Properties Based on Artificial Neural Networks Capstone Design, School of Science and Engineering.

[6] El Monayeri, D. O., 2016, Comparative Study to Assess the Performance of an Integrated Treatment System Using ANN vs. GPS_X, International Journal of Applied Engineering Research, Vol. 11, No. 8, pp. 5604-5609.

[7] Escobar, I.C.; Randall, A.A.; Taylor, J.S., 2001, Bacterial Growth in Distribution Systems, Effect of assimilable organic carbon and biodegradable dissolved organic carbon. Environ. Sci. Technol. 35, 3442-3447.

[8] Esmi, S., 2016, Sensor Modeling with a focus on noise modeling in the context of Self-Driving Vehicles using Neural Network, Master's thesis in Complex Adaptive Systems, Department of Physics, Chalmers University of Technology, Gothenburg, Sweden.

[9] Hasanlou, H., Mehrdadi, N., Jafarzadeh, T. M. and Hasanlou, H., 2012, Performance Simulation of H-TDS Unit of Fajr Industrial Wastewater Treatment Plant Using a Combination of Neural Network and Principal Component Analysis, Journal of Water Resource and Protection, Vol. 4, No. 5, Article ID:19471, pp. 311-3-17.

[10] IBM Corporation 1989, 2011, IBM SPSS Neural Networks 20, User's Guide.

[11] Jin, J., Li, M. and Long Jin, L., 2015, Data Normalization to Accelerate Training for Linear Neural Net to Predict Tropical Cyclone Tracks, Mathematical Problems in Engineering, vol. 2015, Article ID 931629, 8 pages.

[12] Kundu, P., Debsarkar, A. and Mukherjee, S., 2013, Artificial Neural Network Modeling for Biological Removal of Organic Carbon and Nitrogen from Slaughterhouse Wastewater in a Sequencing Batch Reactor, Hindawi Publishing Corporation, Advances in Artificial Neural Systems, Vol. 2013, Article ID 268064, 15 pages

[13] Nasr, S. M., Moustafa, A. E. M. and El Kobrosy, G. S., 2012, Application of Artificial Neural Network (ANN) for the prediction of EL-AGAMY wastewater treatment plant performance-EGYPT, Alexandria Engineering Journal, Vol. 51, pp. 37–43.

[14] Pakrou, S., Mehrdadi, N. and Baghvand, A., 2014, Artificial Neural Networks Modeling for Predicting Treatment Efficiency and Considering Effects of Input Parameters in Prediction Accuracy: A Case Study in Tabriz Treatment Plant, Indian Journal of Fundamental and Applied Life Sciences Vol. 4 (S4), pp. 3732-3745.

[15] Qiao, J., Hu, Z. and Li, W., 2016, Soft Measurement Modeling Based on Chaos Theory for Biochemical Oxygen Demand (BOD), Water 2016, 8, 581; doi:10.3390/w8120581, 21 pages.

[16] Kadhim Naief Kadhim (Estimating of Consumptive Use of Water in Babylon Governorate-Iraq by Using Different Methods). (IJCIET), Volume 9, Issue 2, (Feb 2018).

[17] Tümer, E. A. and Edebali, S., 2015, An Artificial Neural Network Model for Wastewater Treatment Plant of Konya, International Journal of Intelligent Systems and Applications in Engineering, IJISAE, 3(4), pp. 131-135.

[18] Türkmenler, H. and Pala, M., 2017, Performance Assessment of Advanced Biological Wastewater Treatment Plants Using Artificial Neural Networks, International Journal of Engineering Technologies-IJET, Vol.3, No.3, pp.151-156.

[19] Tusseau-Vuillemin, M.H.; Dispan, J.; Mouchel, J.M.; Servais, P. Biodegradable fraction of organic carbon estimated under oxic and anoxic conditions. Water Res. 2003, 37, 2242-2247.

[20] Vijayan, A. and Mohan, S. G., 2016, Prediction of Effluent Treatment Plant Performance in a Diary Industry Using Artificial Neural Network Technique, Journal of Civil & Environmental Engineering, Vol. 6, Issue 6, pp. 1-4.

[21] Vyas, M., Modhera, B. and Sharma, K. A., 2011, Artificial neural network-based model in effluent treatment process, International Journal of Advanced Engineering Technology, IJAET, Vol.II, Issue II, pp. 271-275.

[22] Waterleau, Global Water Technology, 2009. WWTP of Mayoralty Baghdad, Baghdad, Iraq.

[23] Xi, C. and Erihe, 2013, Title: Artificial Neural Network and Fuzzy Logic in forecasting short-term Temperature, Case project report 2013, Telemark University College, Faculty of Technology.

[24] Zhang, R. and Hu, X., 2012, Effluent Quality Prediction of Wastewater Treatment System Based on Small-world ANN, JOURNAL OF COMPUTERS, VOL. 7, NO. 9, pp. 2136-2143.

[25] Benu Singh, Sunita Bansal and Puneet Mishra, Artificial Neural Network Modeling and Optimization In Honing Process, International Journal of Computer Engineering and Technology, 7(3), 2016, pp. 67–77.

[26] Henry Navarro and Leonardo Bennun, Descriptive Examples of The Limitations of Artificial Neural Networks Applied To The Analysis Of Independent Stochastic Data, International Journal of Computer Engineering and Technology (IJCET), Volume 5, Issue 5, May (2014), pp. 40-42.

[27] Sonal Bansal and Dr. Rinku Dixit, ECG Signal Analysis using Artificial Neural Networks - A Review. International Journal of Electronics and Communication Engineering and Technology, 9(2), 2018, pp.1–6.

[28] Sweety H Meshram, VinayKeswani, NileshBodne, Data Filtration And Simulation By Artificial Neural Network, International Journal of Electronics and Communication Engineering & Technology (IJECET), Volume 5, Issue 7, July (2014), pp. 46-55.