Journal of Applied Research in Water and Wastewater 9(2018) 399-406

Journal of
Applied Research in Water and Wastewater

Journal homepage: www.arww.razi.ac.ir

Original paper

Application of artificial neural networks for the prediction of Gaza wastewater treatment plant performance-Gaza strip

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ARTICLE INFO

Article history:
Received 27 May 2018
Received in revised form 27 June 2018
Accepted 30 June 2018

Keywords:
Artificial neural network
BOD
COD
Gaza wastewater treatment plant
Prediction
TSS

ABSTRACT

This paper is concerned with the use of artificial neural network and multiple linear regression (MLR) models for the prediction of three major water quality parameters in the Gaza wastewater treatment plant. The data sets used in this study consist of nine years and collected from Gaza wastewater treatment plant during monthly records. Treatment efficiency of the plant was determined by taking into account of influent input values of pH, temperature (T), biological oxygen demand (BOD), chemical oxygen demand (COD) and total dissolved solids (TSS) with effluent output values of BOD, COD and TSS. Performance of the model was compared via the parameters of root mean squared error (RMSE), mean absolute percentage error (MAPE) and correlation coefficient (r). The suitable architecture of the neural network model is determined after several trial and error steps. Results showed that the artificial neural network (ANN) performance model was better than the MLR model. It was found that the ANN model could be employed successfully in estimating the BOD, COD and TSS in the outlet of Gaza wastewater treatment plant. Moreover, sensitive examination results showed that influent TSS and T parameters have more effect on BOD, COD and TSS predicting to other parameters.

1. Introduction

The wastewater usually is exposed to many changed processes that can remove maximum of the pollutants such as organic substances, ammonium, phosphorus, nitrogen and other residuals from industrial surroundings and urban or rural areas community. Wastewater treatment processes are very complex, intensely nonlinear and considered by uncertainties concerning to its parameters (Henze et al. 1996). Boogaard and Eslamian. (2015); Hamdy and Eslamian. (2015) were focused on wastewater monitoring, wastewater treatment, sustainable reuse and recycling for treated urban wastewater to conserve the water resources for management purpose. Sewage management–including the collection, treatment and disposal of sewage has been a major environmental challenge in the Gaza Strip for several decades. Recent reports showed that about 60% of the population lives in areas with sewage networks, while the rest uses septic tanks and cesspits (Ashour et al. 2009). Due to low per capita water consumption, the sewage in the Gaza Strip is highly concentrated, with characteristic influent levels of biological oxygen demand (BOD) of up to 600 mg/l as compared to 250 mg/l, which is the standard for urban sewage. Given that the Gaza wastewater treatment plant function only irregularly, little sewage is treated and most returned to lagoons, wadis and the sea. Sewage systems were effected in several ways during the aggressions. First, as the electricity supply collapsed, transfer pumps ceased to function, resulting in sewage being diverted to the nearest available lagoons, including infiltration lagoons. Second, the limited treatment that had been taking place in sewage treatment plants also ceased due to electricity shortages. The effluent leaving sewage treatment plants to be disposed of in the sea or by infiltration in the groundwater was therefore entirely untreated. Recent data (CMWU. 20093) on Gaza wastewater treatment plant shows an inflow BOD of 415 mg/l and effluent BOD of 172 mg/l, with 58% efficiency. Evaluation of water quality parameters is necessary to enhance the performance of an assessment operation and develop better management and planning for water resources (Abyaneh 2014). The traditional modelling techniques may possibly present relatively good predictions for water quality variables; yet such models need large data and group of input data sets that are often unknown. The wastewater treatment method is quite complex. However, the advances in intelligent methods make them conceivable to use in complex systems modeling (Hanbay 2008). Artificial neural network (ANN) can be used for better prediction of the process performance owing to their high accuracy, adequacy and quite promising applications in engineering, water sciences and environmental fields (Govindaraju 2002; Maier & Dandy. 2000; Maier and Dandy. 2000; Neelakantan et al. 2001). There are definite key descriptions of parameters, which can be used to evaluate the wastewater treatment plant performance. These parameters include chemical oxygen demand (COD), BOD and total suspended solids (TSS). Until now, most of the current studies for modeling wastewater treatment plants (WWTPs) used these parameters. The ANN established models find out acceptable results. ANN model was developed for BOD removal process in horizontal subsurface flow constructed wetlands by Akratos et al. (2008). Mjalli et al. (2007) used neural network with single input and multi-input layers and gave comparable predictions of the plant performance criteria. Prediction of BOD and suspended solid (SS) concentrations based on ANN were presented by Hamed et al. (2004). TSS is an indication of plant performance. A simple prediction models based on neural network for TSS was demonstrated by (Belanche 2000). Many other ANN models for wastewater treatment performance prediction have been

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proposed either in the past (Zhua et al. 1998; Choi and Park 2000; Choi and Park 2000; Oliveira-Esquerre et al. 2001; El-Din and Smith 2002; Geissler et al. 2005; El-Din et al. 2004; Pai et al. 2012) or more recently (Zhang and Hu. 2012; Vyas et al. 2011; Nasr et al. 2012; Djeddou 2014; Yordanova e t al. 2014; Guo et al. 2014; Bagheri et al. 2015; Kundu et al. 2014; Gholikandi et al. 2014; Pakrou et al. 2015; Guo et al. 2015; Djeddou and Achour 2015; Djeddou and Achour 2015). Due to numerous problems in the recording and measurement of wastewater quality such as BOD and COD, the main objective of the present paper is to find the optimized topology of the ANN and compare the obtained prediction results with multiple linear regression (MLR) model for prediction of complex wastewater quality data; to select the best method in prediction of the wastewater quality data, and to evaluates the results of the multilayer perceptron and radial basis function type of ANN in prediction of BOD, COD and TSS and selecting the optimized topology. As a first case study for predicting the performance of Gaza wastewater treatment plant it is hoped that, the results of this study would contribute in assisting the local authorities in developing plans and policies to reduce the pollution generated from the wastewater treatment plant and improve its performance.

2. Materials and methods
2.1. Study area

The study area is the Gaza wastewater treatment plant, which lies to the southwest of Gaza city. The exact location inside the plant is the drying lagoons, which are being used as filtration basins. Treated wastewater and produced sludge are disposed to open areas a few meters beside the plant itself. The plant is close to less urbanized and agricultural areas. Fig. 1 shows the location of the Gaza wastewater treatment plant. The area has a long history of exposure to wastewater and sludge. Large areas have been used for the disposal of raw sewage effluents and untreated sludge from 1977 up to date. The plant was designed to treat about 42,000 m^3 per day but now facing a daily inflow of more than 90,000 m^3. This has overcome the biological stage of the treatment process. As an emergency measure to stop sewage from overflowing, scarcely treated wastewater is currently piped to the coast, where the dark grey liquid can be seen, and smelled, flowing along the beach of Gaza (Shomar 2011). The GWWTP comprises two sections including: operation and laboratory. The operation section is responsible for the daily operations of the plant and to monitor the performance of the different mechanical facilities in the plant and to record the daily activities while the laboratory is responsible for monitoring the quality of influent and effluent coming to the plant or discharging to the sea or infiltration ponds.

2.2. Data collection

Historical monthly database describing the operation of the wastewater treatment plant in Gaza city for a period of approximately 9 years (2007-2015) with a total of 108 data vectors were obtained from (Gaza wastewater treatment plant operators). These variables include influent and effluent temperature (T), pH, BOD, COD and TSS variables. ANN input and output variables of GWWTP has to be chosen based on engineering judgment on which input and output may have a significant effect in predicting effluent BOD, COD and TSS. Using MATLAB software proper training validating and testing is done and branded constructive algorithm is applied to the network.

2.3. Artificial Neural Networks (ANNs)

ANNs are sensitive to the composition of the training data set and to the initial network parameters (Talib et al. 2009), it comprised of three independent layers, the input layers, where the data introduce to the ANN, the hidden layers, where data are processed that can be either multiple layers or a single layer, and output layers, where the result of ANN are produced (Diamantopoulou et al. 2005). Each layer consists of several processing neurons. Each neuron in a layer operates in logical similarity. Information is transmitted from one layer to others in serial operations. The most widely used training algorithm for neural networks is the back propagation algorithm (Civelekoglu et al. 2007). The multilayer perceptron (MLP) is an example of an artificial neural network that is used extensively to solve a number of different problems, including pattern recognition and interpolation (Haykin 2005), (Musavi and Golabi. 2008) that feed the input data to the neural layer to produce desire output (Talib and Amat. 2012). Each layer is composed of neurons. In each neuron, a specific mathematical function called the activation function accepts input from previous layers and generates output for the next layer. Each layer is interconnected with each other by weights. In the experiment, the activation function used is the hyperbolic tangent sigmoid transfer function (Fausett 1994). This paper demonstrating the application of artificial neural networks to predict the performance of the Gaza wastewater treatment plant through predicting the major indicators of the wastewater quality. Two types of feedforward networks are used to construct the ANN predictive model. They are MLP and RBF neural networks; both are trained on the collected data for building predictive models for the wastewater quality parameters prediction. The chosen MLP one hidden layer was trained using the backpropagation incorporated with LM algorithm. The RBF network was trained using Orthogonal Least Squares (OLS) algorithm. Before running all models data sets were normalized to be included within the interval {0, 1} (Saen 2009). The methodology used to train, validate and test ANNs models is described below. Five models are developed (MLP networks) to choose the best model for predicting wastewater quality parameters including: BOD, COD and TSS and then to compare results with RBF and MLR statistical model.

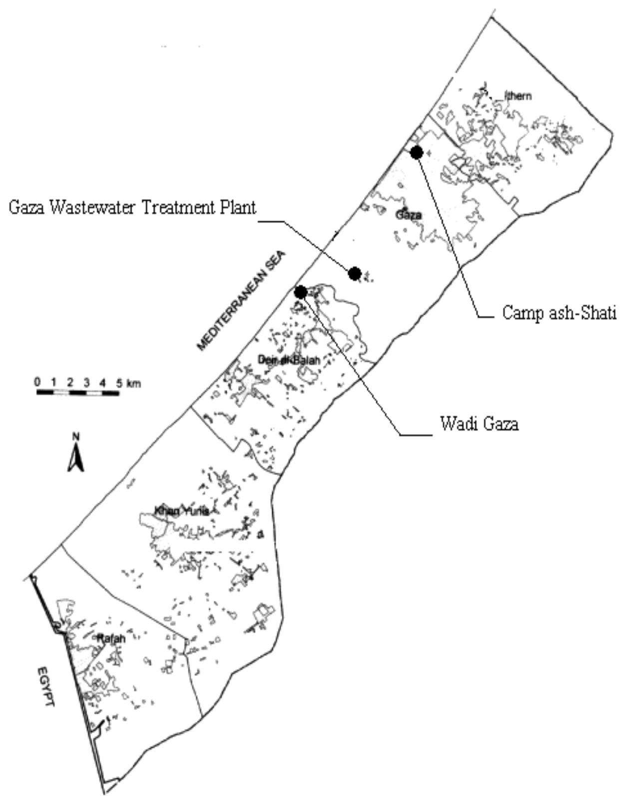

Fig. 1. Map shows the location of Gaza wastewater treatment plant

2.4. Data statistical and multiple linear regression

The collected data were entered as Microsoft Excel sheets, uploaded to Statistical Package for Social Sciences (SPSS) and analyzed using min, max, average, standard deviation tools. In addition, the Pearson correlation coefficient (a measure of linear association) is used to measure the linear association among the selected parameters. The training, validation and testing of the developed ANN models were carried out using neural network toolbox in the MATLAB. Two types of feedforward networks are used. They are multilayer perceptron and radial basis function neural networks. Root mean squared error, mean absolute percentage error and correlation statistics were calculated using MATLAB software. Statistical methods, such as MLR models, are good tools used to investigate any relationship between dependent and independent parameters of small sample numbers (Razi and Athappilly 2005). In this study the MLR is a method used to model the linear relationship between a dependent parameter and one or more independent parameters. MLR is based on least squares. In the best model, sum of square error between observed and predicted parameters should be minimum value. However, in this paper MLR statistical model is used for comparison purpose with the predictions of ANN developed model.

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2.5. Data processing and training

Computationally competent deterministic approach, first-order gradient method (back propagation) because of its increased ability to find global optima in the error surface, was used to conduct the ANN training. The aim of model (ANN training) is to find a set of model parameters that enables a model with a given functional form to best represent the desired input/output relationship (Glorot and Bengio 2010). At early stage of the Gaza wastewater treatment plant performance prediction, inlet and outlet wastewater quality data, over a period of nine years beginning from 2007 to 2015 were collected. The all collected data (108 readings) in this study are combined in one set to examine the possibility for developing a neural network model for predicting the effluent wastewater quality parameters including: BOD, COD and TSS. The main obtainable selected influent wastewater quality parameters including: T, pH, BOD, COD and TSS. The MLP network had attained good results when trained using the backpropagation incorporated with Levenberg Marquardt algorithm. The tangent hyperbolic function is used as the activation function in the hidden layer neurons. The linear activation function is used in the output layer neurons (Haykin 2005). The RBF network is trained using the backpropagation incorporated with the orthogonal least squares algorithm and the Gaussian radial basis function is used as the activation function in the hidden layer. The linear activation function is used in the output layer (Chen et al. 1991). Before running ANN networks, the data set was divided into three data sets 60% of the data used for training purpose, 20% used for validation and 20% used for testing the networks performance and then data was normalized to be included within the interval {0,1} (Saen 2009). The MLP network training procedure started with utilizing 10 neurons in the hidden layer, then gradually the number of neurons increased till 18 neurons and at 14 neurons the performance of the developed network was good. The architecture of the developed MLP neural network for predicting BOD, COD and TSS contains three layers, 5 neurons in the input, 14 neurons in the hidden layer and 3 neurons in the output layer. The input neurons made from five influent important parameters including: T, pH, BOD, COD and TSS. For training RBF neural network same input neurons was used as utilized for MLP network. During training process, the RBF neural network performed good at 17 neurons in the hidden layer. Referring to Rounds (2002) study linear regression can be considered as a different instance of ANN model, which uses linear transfer functions and certainly not hidden layers. If the linear model attains as well as other complex ANN, then using the nonlinear neural networks may not be realistic and so the linear models are appropriate as a basis for comparison. However, in this study the linear regression is used to compare the prediction results attained from both developed MLP and RBF neural networks.

2.6. Evaluation criteria for ANN and MLR prediction

In order to determine which network structure is optimal, the performance of a calibrated model was evaluated against one or more criteria. In this paper, the ANN model performance was assessed using a quantitative error metric. The employed metrics belonging to this category include mean absolute percentage error, root mean square error and R correlation. Once a model structure has been chosen and the network trained, the selected model needs to be evaluated. In practice, the accuracy of a model is determined by the 'goodness of fit' between outputs of the model and the system given the same input. Hence, some validation tests need to be considered. Generally, the accuracy of a model must be evaluated for three sets of data samples. These data sets are: training data that express the effectiveness of learning, validation data set that used to save the model from overfitting problem, and the testing data set that measure the generalization capability of the network. There is a need to point out that the testing data set should ideally not have previously been presented to the network and it must represent the entire operation range (Cawley and Talbot 2010). In this study, the mean absolute percentage error (MAPE), root mean square error (RMSE) and correlation coefficient (r) have been considered as evaluation criteria.

$$MAPE = \frac{100}{N} \times \sum_{k=1}^{N} \left| \frac{X_k - Y_k}{X_k} \right| \tag{1}$$

$$RMSE = \frac{1}{N} \sum_{k=1}^{N} (X_k - Y_k)^2 \tag{2}$$

$$r = \frac{(X_k - \bar{X})(Y_k - \bar{Y})}{\sqrt{\sum_{k=1}^{N} (X_k - \bar{X})^2 \sum_{k=1}^{N} (Y_k - \bar{Y})^2}} \tag{3}$$

where X_k is the is the actual observation time series values; Y_k is the predicted time series values, N is the number of values in the data set; $\bar{X}$ is the mean of observed values and $\bar{Y}$ is the mean of predicted values.

3. Results and discussion

3.1. Data set statistical analysis

The data of wastewater quality were made and used for training of artificial neural networks for predicting the BOD, COD and TSS of wastewater effluents in Gaza wastewater treatment plant. All collected data were entered as Microsoft Excel sheets, uploaded to SPSS software, and analyzed using min, max, average, standard deviation statistical and coefficient of variance (CV) tools. Additionally, the correlation coefficient (a measure of linear association) were used to measure the linear association among the wastewater quality parameters. Table.1 shows the statistical analysis summary of wastewater quality parameters in the Gaza wastewater treatment plant. The treatment process in Gaza wastewater treatment plant showed good performance when it is compared with the wastewater treatment plant in Yazd-Iran. The measured average of BOD, COD and TSS concentrations of raw wastewater in Yazd treatment plant, were around 272.08, 577.13, 258.66 mg/L, where the concentrations of treated wastewater were around 135.18, 307, and 139.75 respectively (Farzadkia et al. 2014).

Table 1. Statistical analysis summary of GWWTP wastewater quality parameters.

Parameters	Ranges	Data Statistics Average	S.D	CV
Input Layer				
T (ºC)	13.8-32	22.71	4.30	0.188
pH	6.75-8.56	7.81	0.24	0.031
BOD (mg/l)	380-840	495	79.46	0.160
COD (mg/l)	720-1520	991	163.42	0.164
TSS (mg/l)	363-80	501	88.40	0.176
Output layer				
BOD (mg/l)	40-230	103	34.75	0.339
COD (mg/l)	53-412	230	79.24	0.344
TSS (mg/l)	42-300	113	41.38	0.367

The study of correlation coefficient is mostly measures the association between two or more functionally independent variables. The values of correlation coefficient during this study are calculated using SPSS software. Pearson's correlation was used to detect linear associations between various variables. Influent BOD is inversely correlated with effluents of Temp, BOD, COD, TSS, T influent and positively with influent of COD, TSS and pH. Influent COD is inversely correlated with effluent of T, BOD, COD, TSS, T influent and positively with influent of pH, BOD, TSS and effluent of pH. Influent TSS is positively correlated with influent of pH, BOD, COD, pH effluent and inversely is correlated with effluent of T, BOD, COD, TSS and T influent. Effluent BOD is inversely correlated with influent T, pH, BOD, COD, TSS, effluent T, pH and positively correlated with effluent COD and TSS. Effluent COD is inversely correlated with influent T, pH, BOD, COD, TSS and effluent Temp and pH and positively correlated with effluent BOD and TSS. Effluent TSS is positively correlated with

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effluent BOD, COD and pH and inversely correlated with influent T, pH, BOD, COD, TSS and effluent T. Effluent BOD is found to be strongly correlated with effluent COD and TSS (r=0.89 and 0.77) and moderately to weakly correlated with influent T, pH, BOD, COD, TSS and effluent T and weakly with effluent pH. Effluent COD is correlated moderately to weakly with influent T, BOD, COD, TSS and effluent Temp and poorly with influent pH and effluent pH and correlated strongly with effluent BOD and TSS (r=0.89 and 0.72). Effluent TSS is found to be strongly correlated with effluent BOD and COD (r=0.77 and 0.72) is correlated moderately to weakly with influent Temp and effluent T and poorly with influent pH, BOD, COD, TSS and effluent pH.

Table 2. Variation in R value with change in number of neurons and hidden layers.

Models	Architecture	Train R	Valid R	Test R	All R	Remarks
M1-MLP	5-10-3	0.8858	0.6360	0.7837	0.8018	Architectures with 14 neurons in
M2-MLP	5-12-3	0.8713	0.7859	0.6831	0.8032	the hidden layer is selected the
M3-MLP	5-14-3	0.8220	0.7855	0.8181	0.8134	optimum model for prediction of
M4-MLP	5-16-3	0.8207	0.7183	0.7318	0.7725	BOD, COD and TSS. M3 is the
M5-MLP	5-18-3	0.8574	0.7107	0.6540	0.7811	best model.

3.2. Performance of the ANN

Because of the lack of theoretical foundations, training a neural network requires a long trial and error process, experimenting different combinations of learning rates, momentum terms, transfer functions, and network architectures. The determination of the learning rates and other network parameters is fundamental to train the network successfully. So as to overcome this difficulty, LM algorithm is used in this work to reduce the random nature of the determination of the training parameters, improving the training process and, therefore, the forecasting performance of the network. During training, the weights of the neural network was adjusted in order to minimize the error between the network output and the target value for all of the records in the training set. To ensure that the network does not over-fit the training data (by learning patterns specific only to the training set), the performance of the network on the validation set was periodically evaluated. When performance on the validation set begins to degrade, training was stopped. To predict the future concentrations effluent of BOD, COD, and TSS (one month a head) in the wastewater quality of GWWTP, feedforward MLP and RBF neural networks are employed. For this purpose, several algorithms are used during training process including: Backpropagation (BP), Levenberg Marquardt (LM), Conjugate gradients (CG), Resilient backpropagation (rprop) and Gradient descent (GD). During the MLP network training process five models were developed to choose the optimal model for predicting the GWWTP performance. ANN model architecture refers to the layout of neurons and the number of hidden layers. The feed forward backpropagation training algorithm is a supervised training mechanism and is normally adopted in most of science and the engineering applications. The primary goal of training is to minimize the error at the output layer by searching for a set of connection strengths that cause the ANNs to produce outputs that are equal to or closer to the targets (Tarke et al. 2016). Atypical ANN model with a backpropagation incorporated with LM algorithm is constructed to predict BOD, COD and TSS concentrations. From the candidate models described above; because of the reason that the R values are closer to each other for the train, validation and test sets, is minimal in comparison, the MLP one hidden layer based BOD, COD and TSS prediction model with 14 neurons in the hidden layer is selected as optimum model for predicting the performance of GWWTP. The analysis of the performance statistics is supported by plot of the measured values of BOD, COD and TSS against the predicted values for the five setting of MLP network are presented in Table 2. Figs. 2 and 3 show the performance of MLP and RBF neural networks.

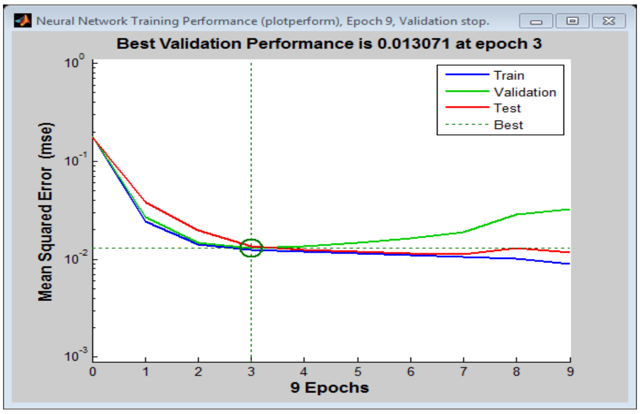

Fig. 2. MLP network training performance.

Table 2 shows the variation of R value with varying hidden layer neurons number. Hyperbolic tangent transfer function with 14 numbers of neurons in one hidden layer showed the best model performance. In this study the best network training results was achieved at 9 epochs using LM learning algorithm. Hence, the suitable optimum architecture for prediction was determined to consist of an input layer with five neurons, a hidden layer with 14 neurons and an output layer with three neurons.

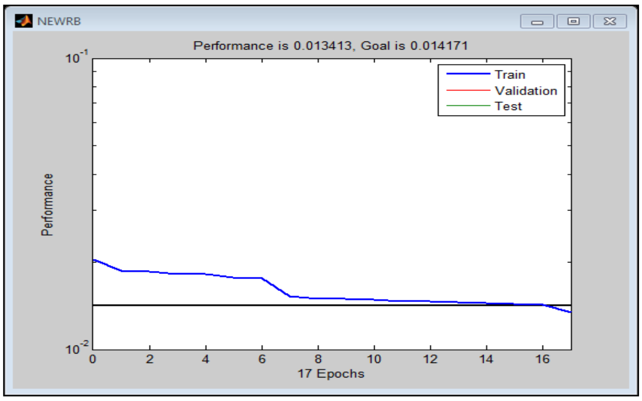

Fig. 3. RBF network training performance.

3.3. Prediction of ANN

In a WWTP, there are certain key descriptive variables which can be used to assess the plant performance. These variables include biological oxygen demand, chemical oxygen demand, and total suspended solids. Most of the available literature on the application of ANNs for modelling WWTPs utilized these variables and found that the ANN-based models provide an efficient and robust tool in predicting WWTP performance. For modelling WWTPs using ANN, Hamoda et al. (1999) found a correlation index of 0.74 for BOD prediction; Belanche et al. (1999) found 0.504 for COD prediction; Häck and Köhne (1996) found 0.92 and 0.82 for COD and nitrate prediction, Abyaneh (2014) found RMSE = 25.1 mg/L, r = 0.83 for the prediction of BOD and for the prediction of COD found RMSE = 49.4 mg/L, r = 0.81, and Nasr et al. (2012) found that the ANN can predict the plant performance with a correlation coefficient between the observed and predicted output variables reached up to 0.90, respectively. This paper addresses the problem of how to capture the complex relationships that exist between process variables and to diagnose the dynamic behavior of Gaza WWTP by applying an ANN model. Nonthreatening operation and control of the plant can be achieved by developing an ANN model for predicting the plant performance based on past observations of certain key product quality parameters. The regression button in the training window of network in MATLAB performs a linear regression between the network outputs and the corresponding targets. Fig.4 shows the best model regression results. It is observed that the output tracks the targets very well using MLP for training (R-value= 0.82202), validation (R-value= 0.78551) and testing (R-value= 0.8181). These values can be equivalent to a total response of R-value= 0.81343. It is observed that the output tracks the targets very well using RBF for training (R-value= 0.81559), validation (R-value= 0.76837) and testing (R-value= 0.70076). These values can be equivalent to a total response of R-value= 0.79024. The prediction results of MLP model found to be slightly better than RBF in training, validation and testing data set.

There are many statistical tools for model validation, but the primary tools for most process modeling applications include correlation coefficient (r), root mean squared error (RMSE) and mean absolute percentage error (MAPE). Summary of these statistical tools used in the evaluation of developed models prediction results as well as multiple regression model are given in Table 3. It can be understood from the results presented in Table 3 which shows the coefficient correlations between the observed and predicted values of BOD, COD and TSS using MLP, RBF and MLR for training, validating and testing the developed models. The correlations between the predicted and actual values of BOD, COD and TSS for MLP, RBF model are found to be near strong and better than MLR model whereas coefficient correlation values are [0.7846, 0.7594, 0.7655], [0.7162, 0.7062, 0.7183] and [0.5425, 0.5263, 0.5372] respectively. It also understood that in all developed models predictions of the BOD with ANN and MLR models were found to be better than TSS and COD. In this case the achieved results reveal that the developed MLP and RBF (neural network models) have satisfactory competence and accuracy in predicting BOD, COD and TSS concentrations in the water quality of Gaza wastewater treatment plant as shown in Table 3.

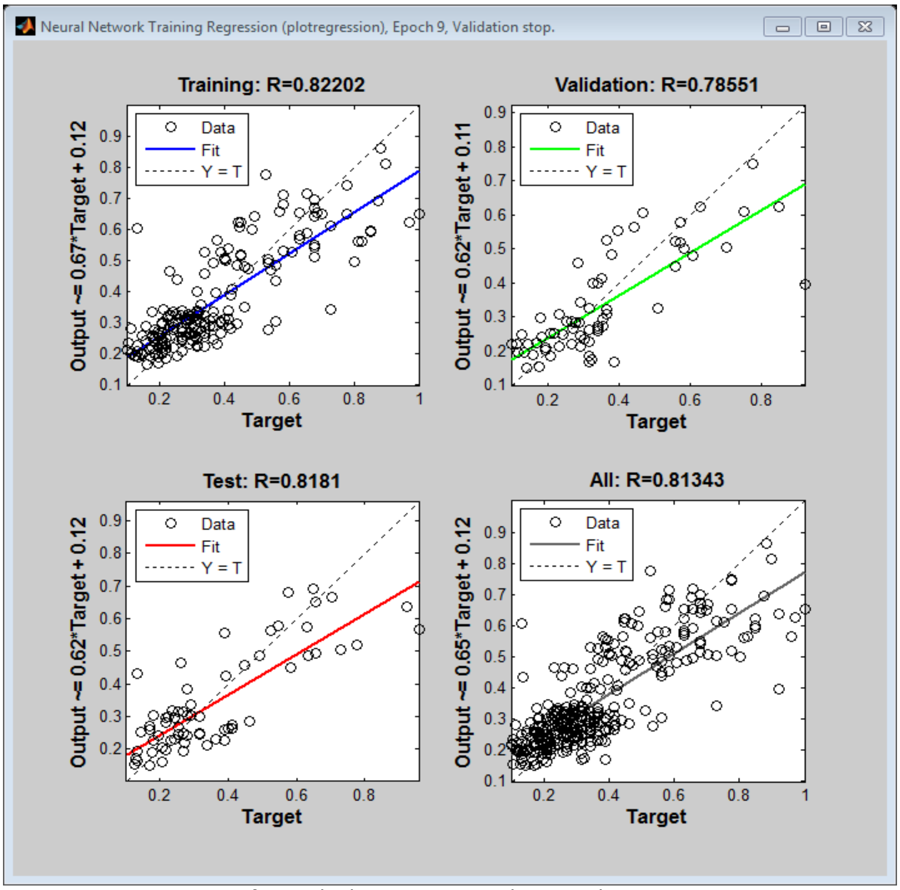

Fig. 4. The best ANN network regression.

Table 3. Analytical comparison between MLP, RBF and MLR prediction results.

Parameters	Models	Performance		
BOD		R	RMSE	MAPE (%)
	MLP	0.7846	29.69	25.45
	RBF	0.7162	31.46	27.85
	MLR	0.5425	32.61	30.53
COD				
	MLP	0.7594	59.48	26.29
	RBF	0.7062	63.39	28.77
	MLR	0.5263	68.92	32.66
TSS				
	MLP	0.7655	37.38	26.33
	RBF	0.7183	38.13	28.15
	MLR	0.5372	38.28	29.48

3.4. Comparison between ANNs and MLR predictions

Figs. 5, 6 and 7 show comparisons of MLP and RBF neural networks prediction results of effluent BOD, COD and TSS with the conventional method (MLR model) predictions. From the figures it can be seen that the performance of MLP is slightly better than RBF and both are better than MLR.

This good predictions result obtained from the ANN models is due to the good correlation between the selected input and output data. From the above shown figures it can be understood that ANN predictions are better than conventional methods. The good prediction results prove that the chosen approach is adept and appropriate for modeling the performance of Gaza wastewater treatment plant.

3.5. Sensitivity of input parameters

Additional analysis about the sensitivity of the prediction results against the input factors are done on the results of ANN approximation for the optimal network. Thus, to determine the sensitivity and impact of different input factors, MLP network with 1 hidden layer and trained with backpropagation incorporated with LM algorithm was used. First, 5 parameters of wastewater quality were used as a primary input of ANN developed model. For the selection of the most important ANNs input parameters the periodic remove method was used. Then, by eliminating any input parameter, the structure of enhanced artificial neural network was run. With comparing neural network output by eliminating any input parameter, the network sensitivity to any input parameter was calculated. Sensitivity grade or impact of each of the input factors on the prediction results of the training, validation and testing data for the developed model results are presented in Fig. 8

It can be seen that TSS > Temp > BOD5 > COD > pH. It means that the TSS concentration is the most influential factor and Temp, BOD, COD, and pH are in the next levels. It can be concluded that ANN structure with 5 parameters in some places had a greater error than those of other structures, which means that increasing the number of input parameters is not always effective (Zare et al. 2011).

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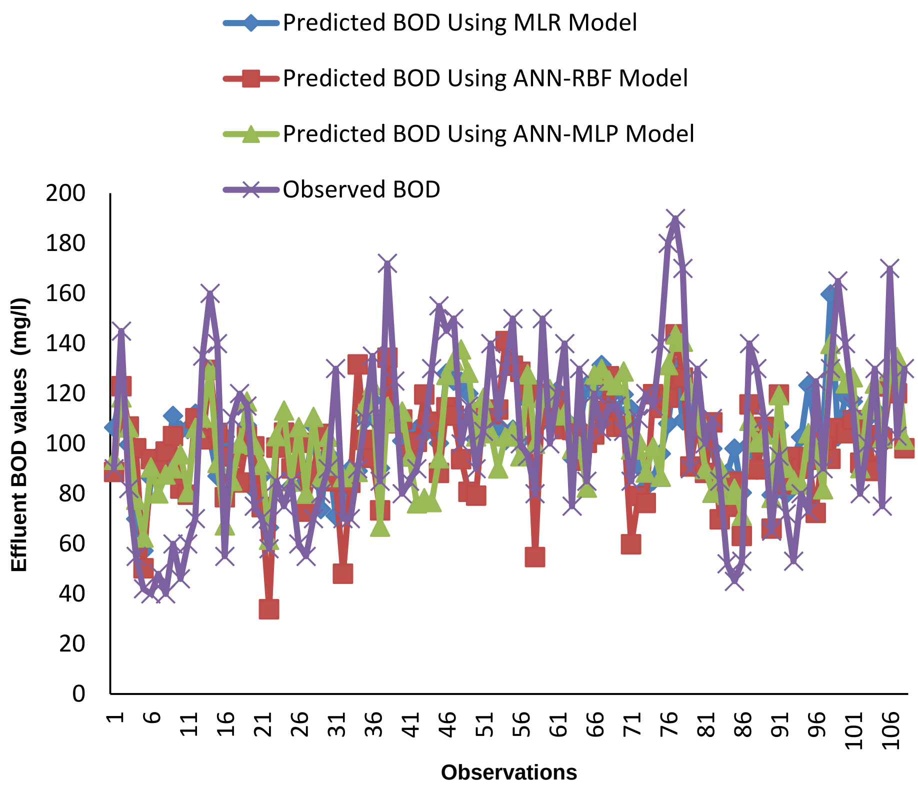

Fig. 5. Comparisons between MLP, RBF and MLR for predicting BOD.

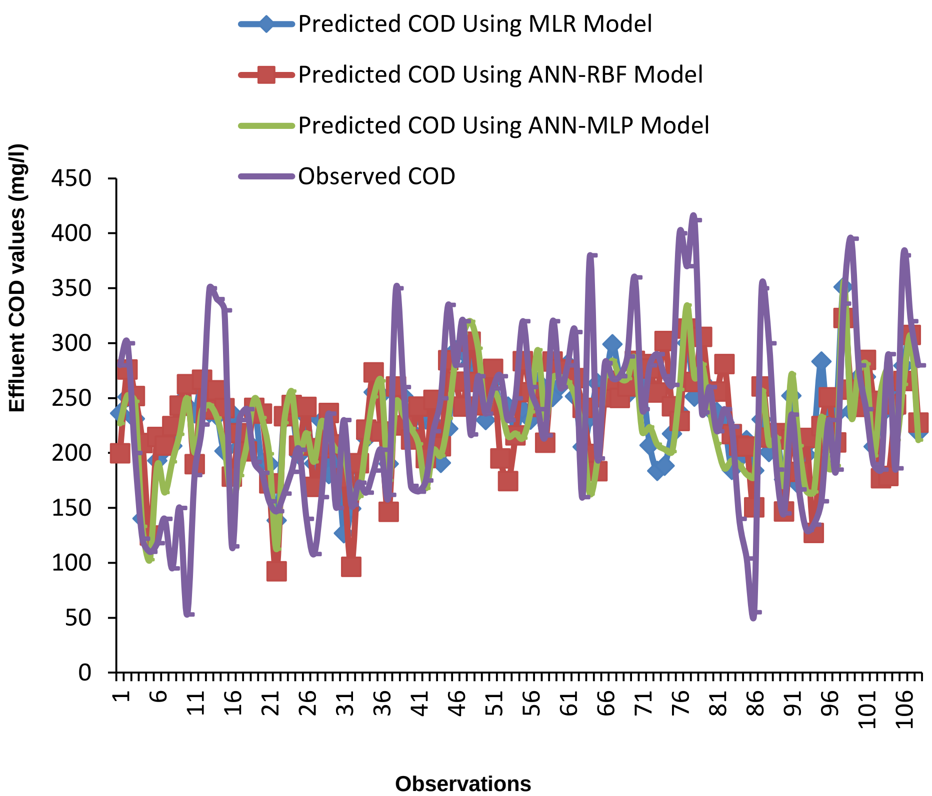

Fig. 6. Comparisons between MLP, RBF and MLR for predicting COD.

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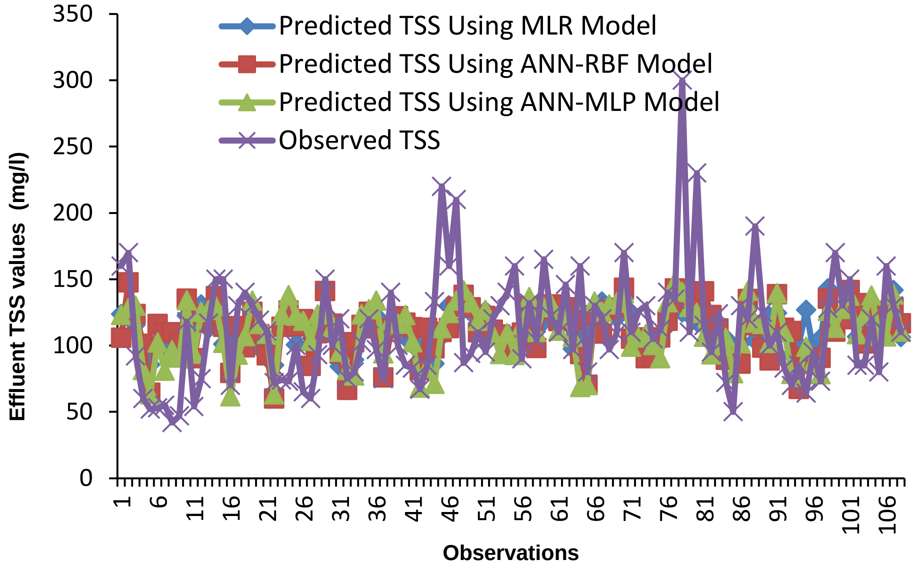

Fig. 7. Comparisons between MLP, RBF and MLR for predicting TSS.

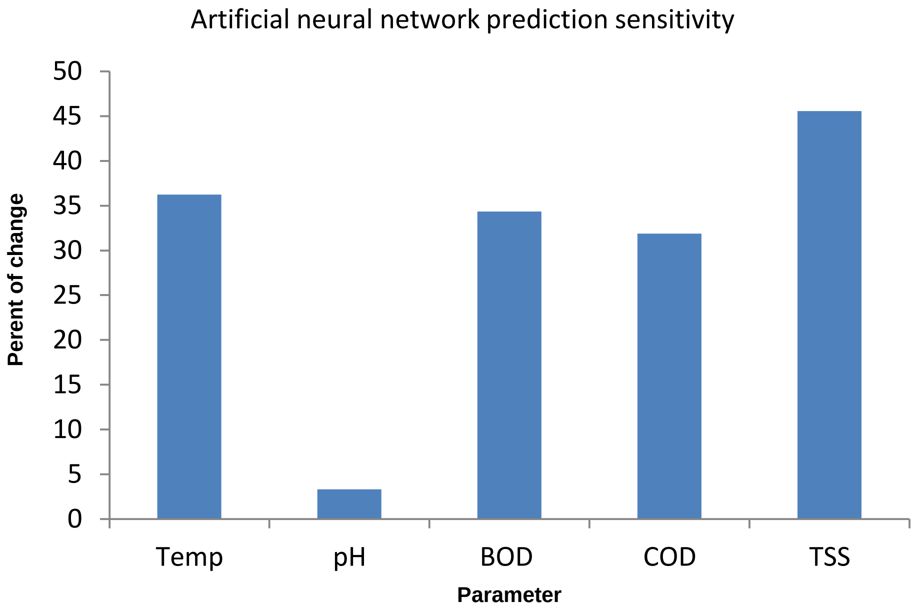

Fig. 8. Sensitivity of each input index for prediction of GWWTP water quality.

4. Conclusions

In the present study MLP and RBF neural networks were successfully developed to predict one month a head values of BOD, COD and TSS for modelling the Gaza wastewater treatment plant performance. Several scenarios were used to train MLP and RBF networks for choosing the best model for predicting the water quality of Gaza wastewater treatment plan. Performance of the models was evaluated using coefficient of correlation (r), RMSE, and MAPE. The results indicated that the ANN model with minimum input parameters, temperature (T), pH, BOD5, COD and TSS could be successfully used for predicting BOD5, COD and TSS effluent concentrations. It was found in the present study that ANN model trained with LM algorithm is an effective adsorbent for the prediction of BOD, COD and TSS concentrations. The choice structure had the highest correlation value (r = 0.81) and the least error (RMSE = 0.1374 mg/L for normal data). Comparison of the ANN and MLR models showed that the ANN model performed much better than the MLR. The results provided sufficient assessment of each model performance (for BOD predictions MLP model r= 0.78 and RMSE = 29.69 mg/L, RBF model r=0.71 and RMSE=31.46 and MLR model in contrast r= 0.54 and RMSE= 32.61 mg/L, for COD predictions MLP model r= 0.75 and RMSE= 59.48 mg/L, RBF model r=0.71 and RMSE=63.39 and MLR model in contrast r=0.52 and RMSE = 68.92 mg/L and TSS predictions MLP model r=0.76 and RMSE=37.38, RBF model r=0.718 and RMSE=38.13 and MLR in contrast r=0.537 and RMSE 38.28). In the three developed models, predictions of the BOD, COD and TSS concentrations with MLP found to be better than RBF and MLR models. In all developed models predictions of the BOD with ANN and MLR models were found to be better than TSS and COD. Further sensitivity analysis of the input factors effects on the developed ANN models were made for the best network. Sensitivity degree or impact of each of the input factors on the outcomes of the training, validation and testing data for predicting BOD, COD and TSS model result presented in the following order: TSS > Temp > BOD > COD > pH. It can be concluded that the concentration of TSS has the highest influence on the developed ANN model.

5. Future perspective

Further research efforts are to be suggested and directed towards an improved understanding of ANN performance in predicting other water quality parameters such as nitrate and heavy metals. It is also

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suggested to investigate the possibility of using support vector machine (SVM) for the prediction of Gaza wastewater treatment plant performance and then to compare the obtained results with the ANN technology.

Acknowledgement

The authors would like to thank the Middle East Desalination Research Centre (MEDRC) and Palestinian Water Authority (PWA) Project No: 15-DC-014 for their support and funding of the study.

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