

Predicting the Performance of Gorgan Wastewater Treatment Plant Using ANN-GA, CANFIS, and ANN Models



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Published online December
31, 2019



Abstract

A reliable model for any wastewater treatment plant (WWTP) is essential to predict its performance and form a basis for controlling the operation of the process. This would minimize the operation costs and assess the stability of environmental balance. This study applied artificial neural network-genetic algorithm (ANN-GA) and co-active neuro-fuzzy logic inference system (CANFIS) in comparison with ANN for predicting the performance of WWTP. The result indicated that the GA produces more accurate results than fuzzy logic technique. It was found that GA components increased the ANN ability in predicting WWTP performance. The normalized root mean square error (NRMSE) for ANN-GA in predicting chemical oxygen demand (COD), total suspended solids (TSS) and biochemical oxygen demand (BOD) were 0.15, 0.19 and 0.15, respectively. The corresponding correlation coefficients were 0.891, 0.930 and 0.890, respectively. Comparing these results with other studies showed that despite the slightly lower performance of the current model, its requirement for a lower number of input parameters can save the extra cost of sampling.

Keywords: Artificial neural network, Wastewater, Fuzzy logic, Genetic algorithm

Received November 9, 2019; Revised December 9, 2019; Accepted December 18, 2019

1. Introduction

Minimizing the adverse impacts of wastewater discharged into the surface water bodies on the environment has always been a challenge. Wastewater treatment plants (WWTPs) are designed to convert the wastewater into more environmentally friendly water and return it to the environment. Therefore, it is important for the managers and plant operators to know how the performances of the plants are and how efficiently they work.

At any WWTP, there is an incoming wastewater flow; this flow is treated before it is allowed to be returned to the environment, lakes, or streams (1). A standard wastewater treatment process consists of a primary treatment including physical removal of floatable and settleable solids and secondary treatment which is mainly the biological removal of dissolved solids. Some other treatment plants have a tertiary treatment option. These stages create a complex system in which it is hard to predict the output quality of the effluent. Physical,

chemical, and biological processes are involved which are highly nonlinear and dynamic (2).

Models are tools that can help managers and decision-makers to predict the effluent quality in advance and operate the plant more efficiently. The main challenge in a good modeling practice is firstly to find a suitable and practical model, secondly to measure the minimum number of input parameters for the model, and thirdly to predict with enough accuracy. Most of the plants are operated based on experience and some small scale experimental results (2). Most of the pollutants, such as total suspended solids (TSS) and biochemical oxygen demand (BOD) are correlated to the inflow (3). An online system for generating short-term sewer flow forecasts was developed by Hernebring et al (4). Gernaey et al presented a more complex approach for phenomenological modeling of WWTP influent disturbance scenarios (5). Physically-based deterministic models are the industry standards for wastewater processing modeling. Some researchers used simpler models such as regression models (6–8) to

reduce the complexity of the modeling process. In recent years, using intelligent models such as artificial neural network (ANN), machine learning, and fuzzy logic are more popular due to their simplicity in modeling process. They are data-driven model types; therefore, they need historical data to accurately predict the output. Selecting the right topology and model construction are the main challenges for these models especially when the short historical data are available.

Dogan et al studied the abilities of ANN model to improve the accuracy of BOD estimation. In this study, the potential of an ANN technique in BOD estimation in Melen River was examined by comparing the results with observed BOD. From the obtained results, an ANN model appears to be a useful tool for prediction of the BOD in Melen River (9). In the study by Güçlü and Dursun, three independent ANN models trained with backpropagation algorithm were developed to predict effluent chemical oxygen demand (COD), suspended solids (SS) and aeration tank mixed liquor SS concentrations of Ankara central WWTP (10). Elmolla et al examined the implementation of ANN for the prediction and simulation of COD removal from antibiotic aqueous solution by the Fenton process and is very close to the experimental results with correlation coefficient (R^2) of 0.997 and mean square error (MSE) of 0.000376 (11). Estimation of oxygen demand levels using ultraviolet-visible (UV-Vis) spectroscopy and results showed that in most cases, the proposed technique (UV-ANN) has the best performance. The predicted values of BOD and COD using UV-ANN model were very close to values obtained using the standard models (12).

WWTP of Gorgan, with the capacity of 686 L/s to service more than 500 000 people per day, is of great importance.

Considering numerous problems in the registration and measurement of wastewater quality such as BOD, COD and TSS, the main aim of the present study was: 1) to find the optimized topology of the ANN and new regression models for prediction of complex wastewater quality data, 2) to select the best model in prediction of the wastewater quality data, and 3) to evaluate the results of the ANN, artificial neural network-genetic algorithm (ANN-GA), and co-active neuro-fuzzy logic inference system (CANFIS) in the prediction of BOD, COD and TSS removals and selection of the optimized topology. Using this model can reduce the cost of the experiment. It was also more efficient in wastewater treatment by predicting the parameters output based on wastewater input parameters.

2. Materials and Methods

2.1. Study Area

The data set used in this study was gathered through continuous monitoring of samples from Gorgan WWTP, Golestan, Iran ($36^{\circ}52'40''N$ $54^{\circ}26'12''E$). This WWTP was constructed and came into operation in 2014. Fig. 1 shows the location of the WWTP. The wastewater quality parameters were measured in Gorgan Wastewater Treatment Laboratory from April 2014 to October 2015. Based on measured values of different variables, input factors (variables) of the treatment including pH, TSS, charge (Q), BOD, and COD were selected for the model development. The output parameters of treatment were BOD, COD, and TSS. The weekly measuring of seven wastewater quality parameters was conducted during 2 years (2014–2015).

Statistical values of the wastewater quality parameters are presented in Table 1. In this table, X_{mean} , X_{max} , X_{min} ,

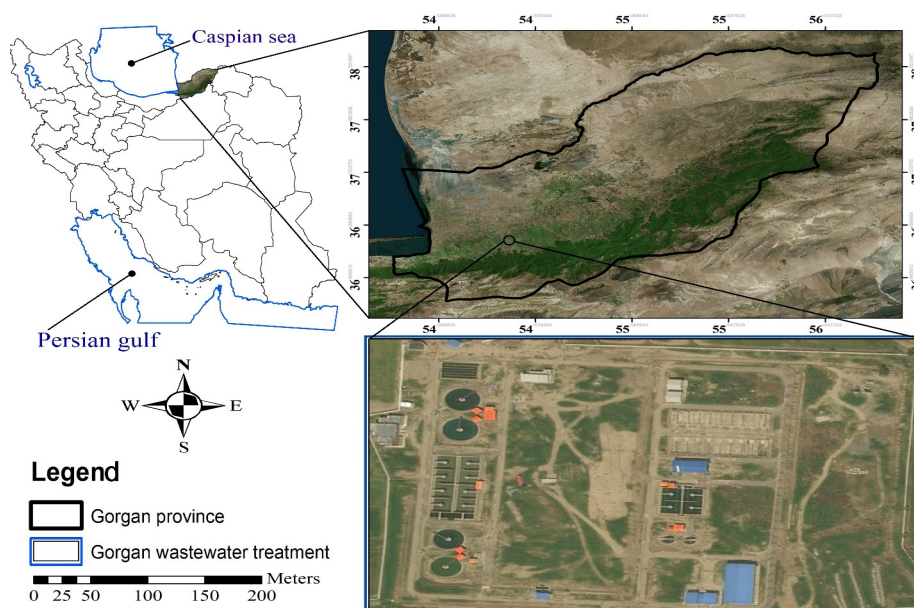


Fig. 1. Location of Gorgan WWTP.

Table 1. Wastewater Quality Parameters Measured During 2014-2015 in Gorgan WWTP

CV	SD _x	X _{min}	X _{max}	X _{mean}	Unit	Data Set
0.41	48.63	83	320	117.38	mgL ⁻¹	BOD
0.28	50.83	101	343	179.57	mgL ⁻¹	TSS
0.17	1269.56	5284	11519	7631.62	m ³ h ⁻¹	Q
0.03	0.24	7.04	7.94	7.46	--	pH
0.017	93.16	171	628	555.193	mgL ⁻¹	COD

Abbreviations: COD, chemical oxygen demand; TSS, total suspended solids; BOD, biochemical oxygen demand. CV: coefficient of variation SD: standard deviation Q: charge

SD_x and CV indicate the mean, maximum, minimum, standard deviation, and coefficient of variation of the data set, respectively.

Fig. 2 shows simple structure of the used ANN in this study with 5 neurons in the input layer and 3 neurons in the output layer.

Tangent hyperbolic (Tan.) activation function and learning rules of Levenberg Marquardt (LM) algorithm were used in this study. The LM algorithm is one of the most appropriate higher-order adaptive algorithms known for minimizing the error of a neural network. It is a member of a class of learning algorithms called “pseudo-second-order methods” (13). Finally, the best structure with different number of neurons in hidden layers was determined using trial and error procedure.

2.1.1. Adaptive GA-ANN

Principles of GA were presented by Holland (14) at the University of Michigan, USA. GA, as a particular class of evolutionary methods that use techniques inspired by Darwin’s theory of evolution and evolutionary biology, is a search technique used to find exact or approximate solutions to optimization and search problems (15). Techniques inspired by evolutionary biology used in GA are inheritance, mutation, selection, and crossover. GA is implemented in a computer simulation in which a population of abstract representations (chromosomes

or the genotype of the genome) of candidate solutions (individuals, creatures, or phenotypes) to an optimization problem evolves toward better solutions. GA can be a learning algorithm for training ANNs to adjust the weights of the connections. In this study, the learning rate, momentum rate, and the number of neurons in the hidden layer were considered as genes in the chromosome (16). The goodness or fitness which is inversely related to the mean square error of the ANNs outputs was used to test the selected topologies in each trial.

The training performance of ANNs using GA starts by initializing the connection weights and the input layer nodes. After estimating the output values at the output layer, the global error is then calculated as the fitness value of the objective function. The procedure is repeated and when the global optimal solution is reached after a sufficient number of generations, the procedure stops. It is notable that a generation in GA is highly analogous to iteration in the backpropagation algorithm, and the goal in both algorithms is to update the connection weights. Once the connection weights are updated at the end of a generation, the fitness value of the objective function can be calculated. In this way, a fitter population of chromosomes is created. This procedure is repeated to reach a population of chromosomes with an acceptable fitness 17).

The training performance of the ANN using the GA

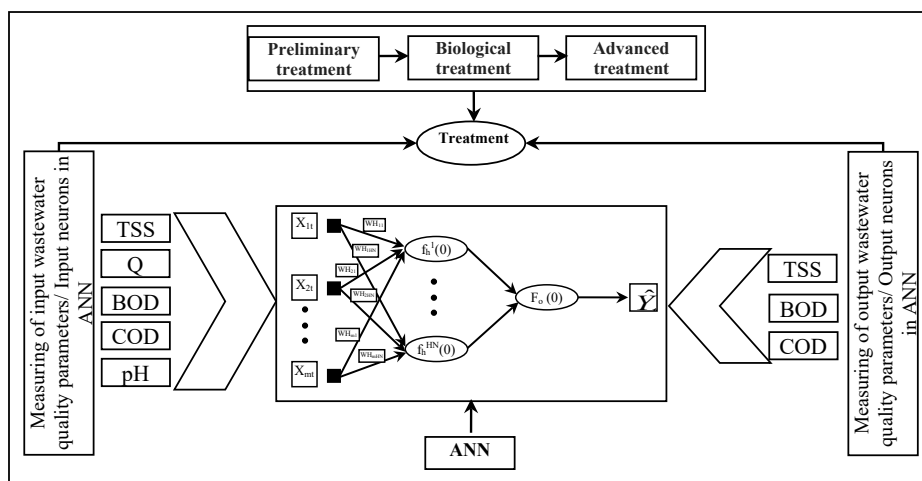


Fig. 2. Developed ANN Structure in WWTP.

has two parts. The first part uses training data to train the ANN. The second part uses the developed ANN in the first part to test the entire range of the smoothing factor for the optimal operation over the testing data. The GA can produce the ANN which can be operated best over the testing data. However, when the ANN is trained using the GA, it requires much more time than when the backpropagation algorithm is used as a search technique (17).

2.1.2. Co-active Neuro-fuzzy Inference System

Among the new techniques of modeling, fuzzy systems have a special place. The fuzzy expert system consists of linguistic rules relating the membership functions of the input variables to the membership function of the output variable. A series of IF-THEN statements relate the input to the output variables. In this study, fuzzy logic was used as CANFIS model. The CANFIS model integrates adaptable fuzzy inputs with a modular neural network to rapidly and accurately approximate complex functions. Fuzzy inference systems (FISs) are also valuable, as they combine the explanatory nature of rules (membership functions) with the power of ANNs. These types of networks solve problems more efficiently than ANNs when the underlying function to model is highly variable or locally extreme (18). The characteristics of CANFIS were emphasized by the advantages of integrating ANNs with FIS in the same topology (19). Takagi–Sugeno fuzzy structure (20) was preferred in this article. In addition, the membership function used in this study was the Gaussian fuzzy axon type which uses a Gaussian-shaped curve as its membership function to each input neuron.

For modeling, the experimental data sets were divided into a training set (80% of the data) and validation set (20% of the data set). NeuroSolutions version 5 was used for training and testing of the network. In NeuroSolutions, the criteria used to evaluate the fitness of each potential solution are the lowest cost achieved during the training run (13). To avoid overtraining, the early stopping technique was used in training (21).

2.2. Evaluation Criteria for ANN, CANFIS and ANN-GA Predictions

Various structures were tried to find the optimal ANN models. The normalized root mean square error (NRMSE), mean absolute error (MAE) and average absolute error (AAE) were used for evaluating the models. NRMSE, MAE and AAE values close to 0 indicate an optimal model. The NRMSE, MAE, and AAE are defined as:

$$NRMSE = \frac{\sqrt{\frac{1}{n} \sum_{i=1}^n (X_i - Y_i)^2}}{\bar{X}} \tag{1}$$

$$MAE = \frac{1}{n} \sum_{i=1}^n |X_i - Y_i| \tag{2}$$

$$AAE = \frac{1}{n} \sum_{i=1}^n \left| \frac{X_i - Y_i}{\bar{X}_i} \right| \tag{3}$$

Correlation coefficient (r) is a common criterion for goodness of fit for regression models (22). It is calculated as follow:

$$r = \frac{\sum (X_i - \bar{X})(Y_i - \bar{Y})}{\sqrt{\sum (X_i - \bar{X})^2 \sum (Y_i - \bar{Y})^2}} \tag{4}$$

Where X_i and Y_i are the observed and estimated values of i th, respectively, \bar{X} and \bar{Y} are the average of X_i and Y_i , and n is the total numbers of data.

3. Results and Discussion

For evaluation of WWTP performance, the values of BOD, COD, and TSS in input and output of treatment were compared. Fig. 3 shows wastewater treatment performance.

As Fig. 3 shows, the values of BOD, COD and TSS in output treatment have decreased greatly. The performance evaluation indicated that 95.3% COD removal, 90.0% TSS removal and 97.3% BOD removal efficiencies were achieved. These values are in line with other studies (23).

To find the interactions between different variables, correlation coefficient values were estimated as shown in Fig. 4. shows that the maximum correlation exists between input TSS and output TSS (0.476).

The statistical criteria of NRMSE, MAE, and AAE for optimized structure of ANN, ANN-GA, and CANFIS in prediction of each parameter are given in Table 2.

Table 2 indicates that the structure of Tanh transfer

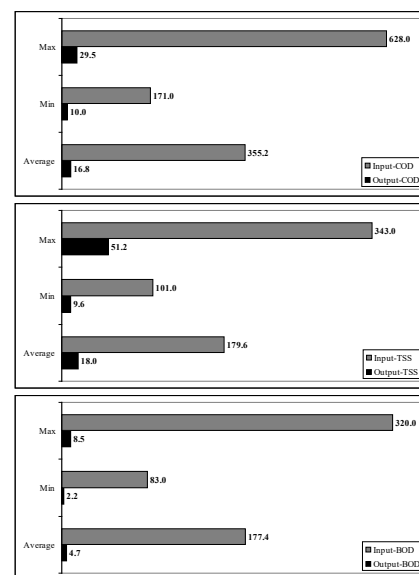


Fig. 3. Evaluation of WWTP Performance.

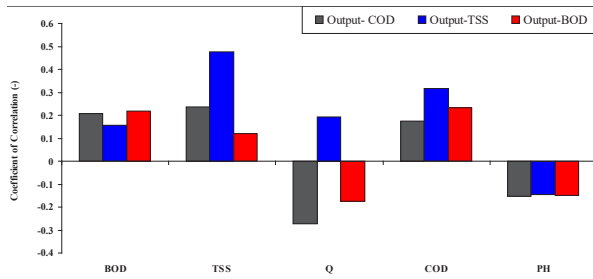


Fig. 4. Correlation Coefficient Between Input and Output Data of Treatment.

function with LM learning algorithm and 10 neurons in hidden layer is the best ANN structure and it has the lowest errors.

The best ANN results in the prediction of COD were as follows: NRMSE=0.16, MAE=2.04 mg/L, and AAE=0.120. Optimizing the ANN results using ANN-GA improved the results and reduced the error values. As can be seen in Table 2, the NRMSE, MAE and AAE values of COD parameter are 0.15, 1.46, and 0.072, respectively. The same results were obtained for the prediction of TSS and BOD. The NRMSE, MAE and AAE values of ANN in the prediction of TSS were 0.25, 5.41, and 0.234, respectively. However, the use of ANN-GA model decreased NRMSE, MAE and AAE values to 0.19, 1.82, and 0.106. Regarding BOD, ANN-GA results were better than ANN. The values of NRMSE, MAE, and AAE were

0.19, 0.69, and 0.140, respectively. In contrast, ANN-GA results were 0.15, 0.49, and 0.088. However, the use of fuzzy logic did not cause any improvement in any of the parameters. The error values in the prediction of all three parameters by CANFIS model were higher compared to ANN results. These results are consistent with the results of a previous study (17) in which better performance was observed using ANN-GA compared to CANFIS to improve the prediction of evapotranspiration. Moreover, another study showed that using GA-ANN model is better than ANN model for runoff prediction (24).

Moreover, the statistical criteria presented in Table 2 showed that the developed model was more accurate in predicting COD compared to BOD and TSS. The average value of NRMSE for COD was 0.18, while the average NRMSE values for TSS and BOD were 0.26 and 0.20, respectively.

With regard to the optimized ANN, ANN-GA, and CANFIS structures, estimated and observed values of COD, TSS, and BOD as well as time series and linear model fitted the data were presented in Figs. 5, 6, and 7, respectively.

A comparison of the observed and estimated COD concentrations is shown in Fig. 5 in time series and scatter plot with regression line. It can be seen from the graphs that the ANN-GA model for COD closely follow the observed values. The scatter plot also confirms this (Fig. 5). It can be clearly seen from the scatter plots that the ANN-GA COD has a higher r value (0.891) compared

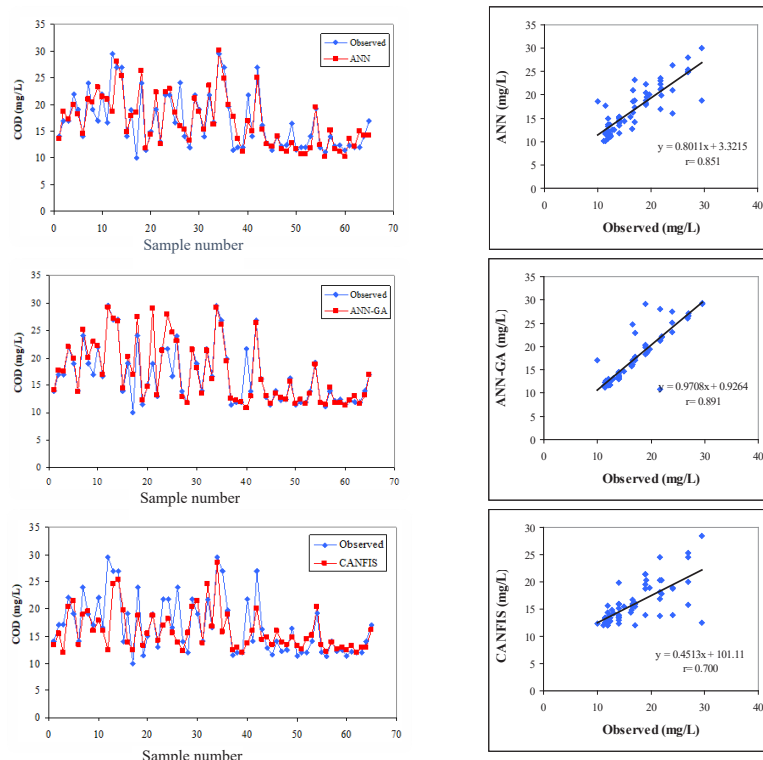


Fig. 5. COD Predictions of the ANN, ANN-GA, and CANFIS Models.

Table 2. Performance Results for COD, BOD and TSS Prediction by ANN, ANN-GA, and CANFIS Models

Model	MF	AF	LA	Structure	Parameter	NRMSE (-)	MAE (mg/L)	AAE (-)
ANN	--	Tan	LM	5,10,3	COD	0.16	2.04	0.120
	--	Tan	LM	5,10,3	TSS	0.25	5.41	0.234
	--	Tan	LM	5,10,3	BOD	0.19	0.69	0.140
ANN-GA	--	Tan	LM	5,10,3	COD	0.15	1.46	0.072
	--	Tan	LM	5,10,3	TSS	0.19	1.82	0.106
	--	Tan	LM	5,10,3	BOD	0.15	0.49	0.088
CANFIS	Bell	Tan	LM	2,2,2,2,2	COD	0.23	2.68	0.132
	Bell	Tan	LM	2,2,2,2,2	TSS	0.34	5.42	0.242
	Bell	Tan	LM	2,2,2,2,2	BOD	0.25	0.94	0.199

Abbreviations: ANN, artificial neural network; GA, genetic algorithm; COD, chemical oxygen demand; TSS, total suspended solids; BOD, biochemical oxygen demand; NRMSE, normalized root mean square error; MAE, mean absolute error; AAE, average absolute error; CANFIS, co-active neuro-fuzzy logic inference system; Tan, Tangent; LM, Levenberg Marquardt; MF, Membership Function; AF, Activation Function; LA, Learning Algorithm..

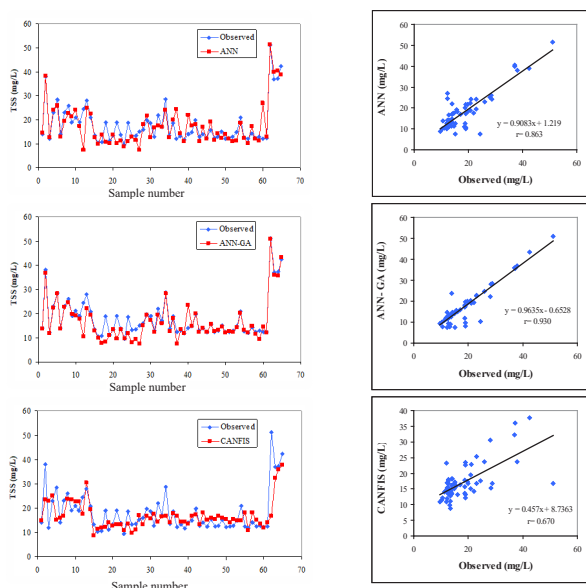


Fig. 6. TSS Predictions of the ANN, ANN-GA, CANFIS Models.

to ANN COD (0.851) and CANFIS COD (0.700). The difference between the measured and calculated values in some parts is due to the influence of factors other than 5 factors chosen as input parameters on the output of the models. Parameters such as climate, inflow rate, and temperature could also impact the results. Some of these parameters were not available for this research and could not be used in the models. On the other hand, using more input parameters would make the models more complex which is in contradiction with the ANN concept which uses simple structure. Therefore, although the use of more parameters can reduce the difference between the estimated values and observations, it would increase the cost of input data collection. In a study by Güçlü and Dursun in 2010 (10), the correlation coefficient was calculated as 0.85 for COD modeling. They used 8 input parameters which include flow rate, return activated sludge, waste activated sludge, DO, COD, SS, total Kjeldahl nitrogen, and COD load in modeling process

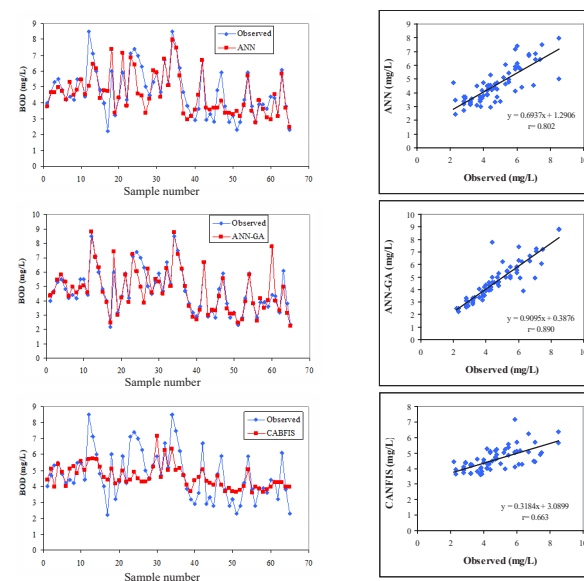


Fig. 7. BOD Predictions of the ANN, ANN-GA, and CANFIS Models

but in the present study, five parameters were used. There is no significant improvement in their model using extra input parameters. In a study, Pai et al found a prediction accuracy of 48.22 % for COD (25).

The scatter plots of observed and simulated TSS using ANN, ANN-GA, and CANFIS are presented in Fig. 6. The results indicate that ANN, ANN-GA, and CANFIS models could produce satisfactory results. The best results for the ANN, ANN-GA, and CANFIS models were $r = 0.863$, $r = 0.93$, and $r = 0.670$ for total data, respectively.

As Fig. 6 shows, approximately 93% of the data estimated with high accuracy and the low accuracy for the remaining 7% could be affected by unaccounted parameters. This low accuracy can be seen with higher degree in CANFIS model. The results of a study by Tümer and Edebali in 2015 (7) indicated that ANN model was more applicable for predicting TSS with $r=0.96$; however, they used more parameters as input for predicting TSS. These additional input parameters increased the accuracy.

On the other hand, they increased the cost of sampling and analysis. In addition, the developed model in this study can simultaneously predict 3 output parameters.

Fig. 7 illustrates the scatter plots for the ANN, ANN-GA, and CANFIS models for BOD. The proposed ANN and ANN-GA models have well learned the nonlinear relationship between the input and the output variables with r values of 0.802 and 0.890, respectively. Fig. 7 illustrates that the simulated and observed BOD values were closely clustered along the line for both models. Therefore, both ANN and ANN-GA models were capable of accurately predicting BOD using the minimum input parameters.

In this study, the correlation coefficient (r) values ranged from 0.663 to 0.890 for BOD. Another study showed that the correlation coefficient value of the selected ANN nodes in the input layer including water pH, total alkalinity, total hardness, total solids, COD, ammoniacal nitrogen, nitrate nitrogen, Cl, PO₄, K, and Na for predicting BOD was 0.87 (26). In the present study, only 5 input parameters which are easy to measure were successfully used for COD, TSS, and BOD estimation at the same time.

4. Conclusions

The results indicated that the use of GA technique can improve the ANN predicted results. However, the fuzzy logic technique showed the lowest performance. The study indicated that the ANN-GA can predict the plant performance with correlation coefficient (r) between the observed and predicted output variables reached up to 0.90. Moreover, ANN-GA provides an effective analyzing and diagnosing tool to understand and simulate the non-linear behavior of the plant, which can be used as a valuable performance assessment tool for plant operators and decision-makers. The selected model structure had the highest correlation value and the least error for prediction of COD, TSS, and BOD within one single model. Therefore, the model developed in this work has an acceptable generalization capability and accuracy. As a result, the neural network modeling could effectively simulate and predict the performance of WWTP.

Conflict of Interest Disclosures

The authors declared that they had no conflict of interest.

Acknowledgements

The authors are grateful to Malayer University for financial support.

Authors Contribution

MBV Investigation, Methodology, Software. KG: Methodology, Writing - review & editing. MP: Methodology, Supervision, Writing - review & editing. MV: Methodology, Writing - review & editing.

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