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Estimation of BOD in wastewater treatment plant by using different ANN algorithms

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Abstract. The measurement and monitoring of the biochemical oxygen demand (BOD) play an important role in the planning and operation of wastewater treatment plants. The most basic method for determining biochemical oxygen demand is direct measurement. However, this method is both expensive and takes a long time. A five-day period is required to determine the biochemical oxygen demand. This study has been carried out in a wastewater treatment plant in Turkey (Hurma WWTP) in order to estimate the biochemical oxygen demand a shorter time and with a lower cost. Estimation was performed using artificial neural network (ANN) method. There are three different methods in the training of artificial neural networks, respectively, multi-layered (ML-ANN), teaching learning based algorithm (TLBO-ANN) and artificial bee colony algorithm (ABC-ANN). The input flow (Q), wastewater temperature (t), pH, chemical oxygen demand (COD), suspended sediment (SS), total phosphorus (tP), total nitrogen (tN), and electrical conductivity of wastewater (EC) are used as the input parameters to estimate the BOD. The root mean squared error (RMSE) and the mean absolute error (MAE) values were used in evaluating performance criteria for each model. As a result of the general evaluation, the ML-ANN method provided the best estimation results both training and test series with 0.8924 and 0.8442 determination coefficient, respectively.

Keywords: artificial bee colony; artificial neural networks; biochemical oxygen demand; teaching-learning base algorithm; wastewater treatment plant

1. Introduction

Turkey is among the richest countries in terms of streams (State Planning Organization 2001). However, on the one hand increasing population and rapid urbanization on the other hand the pollution of rivers, lakes, seas and other water resources it is becoming a challenge to supply enough water for drinking and industrial use. Therefore, the effective control and operation of the wastewater treatment plants are more important than ever before.

Water quality management of the wastewater treatment plants is carried out to determine the reasonable value of the pollution load, to ensure environmental quality and to control the deteriorated environmental interaction. After pollutant parameters and pollution loads are determined, in order to improve pollution control and water quality, the reason of these loads must be monitored and examined. For that reason, a mathematical model should be established in the wastewater treatment plant and the parameters should be simulated in the computer environment.

BOD is one of the most basic parameters used in the management and planning of wastewater treatment plants. It can be defined as the amount of oxygen needed for the aerobic microorganisms present in the sample to oxidize the organic substance to a stable organic form. Testing for BOD requires considerable time and responsibility for preparation and analysis. These experiments take five days. Data collection and evaluation takes place on the 5th day (Chapman 1992).

Various water quality models have been developed, such as traditional mechanical approaches, to manage best practices to maintain water quality. Many of these models require several different input data sets that are not readily available, high priced and time-consuming process. (Dogan *et al*. 2008). Determination of the parameters that are difficult to measure using variables that can be easily measured is widely performed in complex system models. (Huang *et al*. 2015).

The cost of analysis is high because the measurement is difficult and time consuming. If the BOD can be associated with other parameters, shorter measurement time and low measuring cost, will be possible to facilitate operation and control in a treatment plant. Therefore, it is essential to find a way to increase accuracy and to decrease costs of BOD measurements. Several modeling studies have been carried out in order to obtain the rapid biochemical oxygen demand and to avoid the negative conditions that may occur during the analysis (Nas 2001).

It is necessary to establish a reliable model for the wastewater treatment plant and to control its performance and its operation. This process is both complex and has a nonlinear effect due to difficulty of modelling using mechanical approaches. Estimating plant operating parameters using conventional experimental techniques is a

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time-consuming procedure and makes process control difficult. (Dogan *et al*. 2008).

Nowadays, the new computing and estimation methods take place in the traditional methods. In fact, it has been proved that such artificial intelligence techniques are a powerful alternative to conventional hydrological prediction models (Yilmaz *et al*. 2018).

In recent years, mathematical models have been widely used to explain the relationship between water quality parameters. Non-linear problems do not allow modeling with classical methods. Therefore, better methods are inevitable, these are called soft computing in the literature such as artificial neural networks (ANN), fuzzy logic (FL), adaptive neural fuzzy systems (ANFIS). Regression models are also applied in the recent studies (Karakaya 2012, Civelekoglu 2006). In recent years, the "black box" modeling approaches based on the database have been successfully applied to various WWTPs (Cote *et al*. 1995, Van Dongen and Geuens 1998, Lee *et al*. 2002, Ragot *et al*. 2001, Yoo *et al*. 2002, Mjalli *et al*. 2006). Fuzzy modeling has become an efficient alternative to define this nonlinear biological process. (Fu and Poch 1998, Huang and Wang 1999, Tay and Zhang 1999, 2000, Ragot *et al*. 2001, Yoo and Lee 2001, Civelekoglu 2006, Kermani and Scholz 2013, Nadiri *et al*. 2018).

Biochemical oxygen demand estimation and process monitoring studies are carried out by using artificial neural networks in the wastewater treatment plants (Verma and Singh 2013, Yilmaz and Dogan 2008, Dogan *et al*. 2007, Sezer 2007, Hamed *et al*. 2004).

Moreno-Alfonso and Redondo (2001) introduced an intelligent wastewater treatment model using two groups of artificial neural networks to control the plant according to selected parameters. The output determines whether a serious decision, such as stopping the process, is warranted. They claim that a two-network system would be useful in managing WWTPs. By means of both the experimental notes and the feedback results, it is possible to make an estimate using the ANN without realizing the facts. (Krishna and Sree 2014). The ANN method has become one of the most effective and reliable techniques in many fields today. (Kankal *et al*. 2017).

2. Methods

2.1 Artificial bee colony (ABC)

The ABC algorithm is a new population-based metaheuristic approach that based on food search behaviour of honeybee swarms and proposed by Karaboga in 2005. The possible solution of each problem is represented by the location of the food source. The quantity of this source corresponds to the quality of the corresponding solution.

There are three groups of bees in the ABC algorithm. These are employed bees, onlookers, and scouts. The number of employed bees is equal to the number of food sources, because for every food source there is only one employed bee. The employed bees are responsible for bringing food to beehive from previously discovered food sources. Unemployed bees are scouts and onlookers. Onlookers are looking for random sources. The scouts are waiting for the beehive to wait for new resources using the information shared by the employed bees.

When each employed bee is working, it must comply with certain rules. So that the system can survive successfully with all its parts. The significance of this system is that the communication between each of these individuals, who work independently, can be achieved successfully (Uzlu 2014a,b,c). At the beginning stage, the scout selects a random series of food sources showing the population size following the equation:

$$x_{i,j} = x_j^{\min} + rand(0,1)(x_j^{\max} - x_j^{\min}) \tag{1}$$

where $x_j^{\min}$ and $x_j^{\max}$ are lower and upper bounds of the *j*th parameters of the solutions, respectively. Populations are evaluated by determining a cost function (f_i = f (x_i)) each solution (x_i) and solution are calculated according to their fitness values with following equation.

$$fit_i = \begin{cases} \dfrac{1}{1+f_i} & \text{if} f_i \geq 0 \\ 1+abs(f_i) & \text{if} f_i < 0 \end{cases} \tag{2}$$

In the employed bee phase; each employed bee searches for new neighbouring food sources and the neighbour solution related to the current solution in calculated by Eq. 3.

$$v_{ij} = x_{ij} + \varphi_{ij}(x_{kj} - x_{ij}) \tag{3}$$

where k {1,2 ..., SN}, is a randomly selected index that is not different to i,j ϵ {1,2 ..., D} defines a randomly selected parameter index and identifies the problem to be optimized. φ_{ij} is a random real number from the uniform distribution within the range [-1,1] (Kisi *et al*. 2012, Uzlu *et al*. 2014c).

Employed bees dance to try to persuade unemployed bees to come to their source of nutrition. When dancing bees are thought to follow the onlooker bees according to the quality of the nectars, it is considered that the number of onlooker bees who will visit abundant nectar source will be increased accordingly when choosing less or no nectar-free food source as less onlooker bees. This means that onlooker bees has chosen food source according to a probability proportional to the amount of nectar. The probability of choosing the *i*th food source as beings is calculated as:

$$p_i = \frac{fit_i}{\sum_{i=1}^{SN} fit_i} \tag{4}$$

2.2. Teaching Learning Based Optimization (TLBO)

TLBO is a social-based optimization algorithm that based on interaction between students and teachers in a class. The optimization simulates the teaching-learning process between a class teacher, the students and their interactions. In this method, the learning ability of the students is closely related to the teaching capacity of the teacher. Teacher trains students to get better grades. Successful students are selected at every stage of the algorithm to determine the best students.

Students can learn as much as the most experienced and most knowledgeable human teacher in the class. The algorithm aims to bring the level of any level to the level of the teacher, taking into account the current average. After the teacher phase, all the best function results are recorded for use at the student level. At the student level, students learn by discussing and interacting with each other. If one student is more knowledgeable, the other updates itself.

As mentioned before, the teacher's learning process is done to improve the average knowledge of the students. For this reason, the teaching process can be modeled as follows:

$$X_{new} = X_{old} + r(X_{teacher} - T_F \text{ x } X_{mean}) \tag{5}$$

where X_{old} and X_{new} represents student status before and after the teaching process. $X_{teacher}$ and X_{mean} are teacher status and mean status of the class, respectively. r is random coefficient between [0,1]. Also, T_F is a random coefficient with a value of [1,2] that indicates the learning rate of a student. This coefficient is calcutated by following equation:

$$T_F = \text{round}[1 + \text{rand}(0, 1)]. \tag{6}$$

In the student phase, each student shares knowledge with a random student and teaches a student with higher knowledge. This process is modeled as follows:

$$\begin{aligned} X_{jnew} &= X_{jold} + r(X_i - X_j) \text{ if } f_i > f_j \\ X_{inew} &= X_{iold} + r(X_j - X_i) \text{ if } f_i < f_j \end{aligned} \tag{7}$$

where, i and j are indices of the students, r is a random coefficient between [0,1], and f_i is the knowledge level of *i*th student. The smaller objective function in the minimization problem expresses the higher knowledge of the student (Safarinejadian *et al*. 2014).

2.3. Artificial Neural Networks (ANN)

The superior qualities of the brain have forced scientists to work on it. With the studies made in this direction, the mathematical model was tried to be inspired by the neuro-physical structure of the brain. Various artificial cell and network models have been developed with the idea that the physical components must be modeled correctly in order to be able to fully model all behaviours of the brain.

ANNs are defined as complex systems in which the artificial neural cells connected to each other with different connecting geometries, inspired by human brain structure. Artificial neural networks, which can be characterized as an information processor, are possible to simulate a black box that produces output against a given input (Kohonen 1988).

Neural networks can detect similarities in inputs; although it does not have certain input values and it has never seen it before. This feature provides excellent interpolation capabilities, especially when some of the input data is not exact (Singh *et al*. 2003).

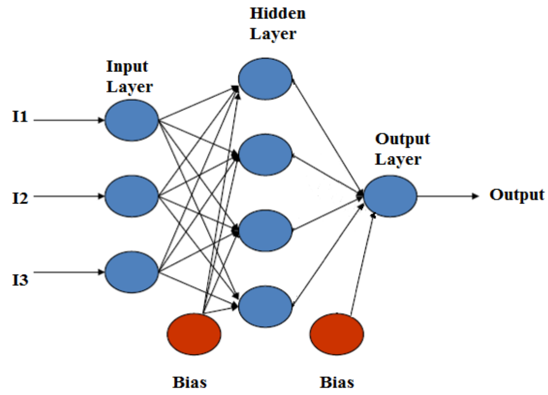

Fig. 1 The model of artificial neural network

Table 1 Variables used in ABC-ANN and TLBO-ANN model

ABC-ANN Parameters						TLBO-ANN			
NP		SN (NP/2)		MCN	Limit Interval	NMI	SP		
50	100	25	50	2000	[-1,1]	2000	50	100	200

ANN can understand the variability in information and offer a harmonious solution. ANN consists of artificial nerve cells that bind to each other in various forms and are usually organized in layers. It can be implemented as hardware in the electronic circuitry or as software in the computers. In accordance with the brain information processing method, ANN is a parallel distributed processor with the ability to collect information after a learning process, store connection weights between cells, store and generalize this information. The learning process includes learning algorithms that allow the renewal of ANN weights to achieve the desired goal. However, there are some disadvantages of ANN. These are briefly; hardware dependence, unexplained behaviour of the network, determination of proper network structure, difficulty of showing the problem to the network, and the duration of the network is unknown.

In this study, ANN architecture was established by using the multilayer feed forward NN and a three-layer network with one hidden layer was selected. The number of neurons was changed from five to 20. The number of maximum epoch was selected as 15 000.

2.4. ANN training with the ABC or TLBO algorithm

It has been proposed to apply the ABC or TLBO algorithm for training of the feed-forward neural networks to cope with some disadvantages caused by back propagation. By this means, the ABC or TLBO algorithm was used to find optimal weight and bias in the training process of feed forward neural networks (NNs). Weights and biases are constantly updated until the error value below the desired value is reached. The reliability of the models was evaluated according to R^2, RMSE and MAE.

Optimization of the coefficients is difficult because the magnitudes of the independent variables used in the

Table 2 Variables used in ABC-ANN and TLBO-ANN models

Number of members in the hidden layer	Population Volume	Limit	The Number of Iteration
5, 10, 15 and 20	50	100	500
		1000	2000
	100	500	2000
		1000	2000

Table 3 Variables used in ML-ANN models

Number of members in the hidden layer	Learning Coefficient	Coefficient of Momentum
5, 10, 15 and 20	0.1	0.1
		0.5
		1
	0.5	0.1
		0.5
		1
	1.00	0.1
		0.5
		1

analysis are in different intervals. In order to facilitate optimization, observed values are normalized between [0.1 -0.9] with Equation 8. After the analyses were done, the normalized values obtained as the result of the equation are again normalized so that the equations obtained are compared with the other methods and the raw data can be obtained more easily.

$$\text{Normalised Value} = \left[\frac{\text{Measured Value - Minimum Value}}{\text{Maximum Value - Minimum Value}}\right] x(0,9-0,1)+0,1 \qquad (8)$$

The ABC and TLBO algorithms were created with the maximum number of cycles (MCN) as 2 000, population size 50 and 100. ANN's weights are assigned as random values between [-1, +1]. The training process re-runs the network with a set of input vectors and ensures that the network is continuously updated until certain stopping criteria are met. The variables used in the forecasting models established are summarized in the Table 1, Table 2 and Table 3.

2.5. Assessment of model performance

The performance of the trained ANN model was derived from the following equations using the root mean square error (RMSE), the mean absolute error (MAE), and determination coefficients (R^2).

Where: BOD_{so}, the observed value of the BOD; BOD_{sp}, represents the modeled value of the BOD; N, represents the number of data; $\overline{BOD}_{so}$, the mean of the observed values of the BOD; $\overline{BOD}_{sp}$, represents the mean of the modeled values of the BOD.

$$\text{RMSE} = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(BOD_{s_o} - BOD_{s_p})^2} \qquad (9)$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|BOD_{s_o} - BOD_{s_p}\right| \qquad (10)$$

$$R^2 = \frac{(BOD_{s_o} - \overline{BOD}_{s_p})(BOD_{s_o} - \overline{BOD}_{s_p})}{\left[\sum_{i=1}^{N}\left(BOD_{s_o} - \overline{BOD}_{s_p}\right)^2\right]^{1/2}\left[\sum_{i=1}^{N}\left(BOD_{s_o} - \overline{BOD}_{s_p}\right)^2\right]^{1/2}} \qquad (11)$$

Fig. 2 The Location of Hurma WWTP

2.6. Description of the study area

The input data for the present study were collected between June 2015 and May 2016 from the Hurma Waste Water Treatment Plant (WWTP), which is in Antalya, Turkey (Fig. 2). The WWTP could serve 1.4 million people. Hurma WWTP is located about 16 km far from Antalya on Kemer highway and between 30°35'11.0"E 36°50'11.4"N coordinates.

Domestic wastewater is transported to the treatment plant by over 750 km of sewage network operating in various diameters, specifications and 9 pumping stations located in various parts of the city.

The treatment plant has different units and stations like; preliminary treatment, biological treatment units, sludge dewatering, sludge drying, UV disinfection and filtration unit, discharge pumping station, deodorization system units and it was designed according to existing pollution values and wastewater streams. The purified water is delivered to the sea at a depth of 50 meters with a discharge line of 5 km in total length.

2.7. Data used in the ANN approach

In this study; input flow (Q), pH, chemical oxygen demand (COD), suspended sediment quantity (SS), wastewater temperature (t), total phosphorus (TP), total nitrogen (TN), electrical conductivity (EC) were used as independent variables to prediction of the biochemical oxygen demand (BOD) of Hurma WWTP inlet pool. These variables have been used commonly in the literature to forecast BOD (Ozel 2011, Sinan 2010).

Mathematical models are widely used in the design and operation of wastewater treatment systems under optimum conditions. At the first stage, the model should be calibrated by means of the data obtained from the treatment plant, so that the dynamic input and the behaviour of the plant under environmental conditions can be examined (Yoo *et al.* 2003).

In this paper, daily analysis data of Hurma WWTP was used. The measurements were made daily in the inlet pool. Due to official holidays, weekends and technical maintenance days, it was not possible to carry out measurements on these certain days. Within the measured data between the years 2015-2016; due to measurement errors, missing or incorrect measurement or extreme values, 232 data were used in the model estimation by eliminating the anomalies given.

The statistical analysis results of the data set are given in Table 4. In this table, the mean values (x_{mean}), standard deviation (S_x), variation coefficient (C_v), skewness coefficient (C_{sx}), maximum value (x_{max}), minimum value (x_{min}) and maximum value to average ratio (x_{max} / x_{min}) are shown.

The data used in ANN models were divided into three parts. 60% of the data set was used for network training, 20% for network validation, and 20% for test of network; 140.46, and 46 are the number of elements in each set, respectively.

3. Results and discussion

The neural network must be well trained to get good predictive results. For this reason, the weights of the neural network were optimized.

In the ML-ANN model generated for Hurma WWTP, 36 analyses were performed in total using different number of hidden layers, learning coefficient and momentum coefficients. The best prediction result in ML-ANN, is obtained in the model where the number of hidden layers in the network architecture is 10, the learning coefficient is 1 and the momentum coefficient is 0.5.

For the ABC-ANN model totally 16 analyses were performed with different number of hidden layers, population volumes and limit values. The best NN architecture was achieved where the number of hidden layers is 10, the population volume is 50 and the limit is 1000.

For the TLBO-ANN model, a total of 16 analyses were carried out by selecting different numbers of hidden layers, population volume and limit values. The best estimation was obtained with values of 10, 50, 100, respectively, number of hidden layers, population volumes and limit values. The results of analysis shown at Figure 3.

Table 5 shows the training error values for each of the ANNs used in this study. The accuracy of the established models was obtained with RMSE, MAE and R^2. All error values are calculated by comparing with actual values. To identify the most appropriate model, observed values and the results of the ML-ANN, ABC-ANN, and TLBO-ANN models were given in Fig. 4.

The scatter diagrams and time series graphs of BOD estimation with ML-ANN, ABC-ANN and TLBO-ANN models are given in Fig. 3. As explained in the figures, while ML-ANN and TLBO-ANN estimate the observed values with a high accuracy, ABC-ANN was inadequate to estimate peak values.

Table 4 Basic statistics of Hurma WWTP's analysis data

		x_{min}	x_{max}	S_x	C_{sx}	C_v (S_x/X_{ort})	x_{mean}	x_{max}/x_{mean}
BOD	Tra.	120.00	500.00	101.53	-0.05	0.30	329.28	1.51
	Val.	160.00	490.00	85.52	-0.65	0.22	386.95	1.26
	T.	240.00	500.00	73.04	-0.06	0.18	393.91	1.26
Q	Tra.	115.73	259.38	19.08	1.86	0.11	164.56	1.57
	Val.	134.49	220.71	15.30	1.46	0.09	166.31	1.32
	T.	141.59	196.96	9.24	1.31	0.05	161.14	1.22
pH	Tra.	7.33	8.81	0.17	0.29	0.02	7.95	1.10
	Val.	7.55	8.22	0.14	0.84	0.02	7.80	1.05
	T.	7.09	7.84	0.19	-1.62	0.02	7.63	1.02
t	Tra.	10.10	30.60	5.15	-0.48	0.24	20.91	1.46
	Val.	11.60	18.80	3.35	-0.33	0.21	15.72	1.19
	T.	14.70	25.00	2.17	-0.43	0.11	19.72	1.26
COD	Tra.	226.00	1340.00	250.96	0.58	0.38	659.06	2.03
	Val.	385.00	1063.00	148.63	-0.16	0.21	700.37	1.51
	T.	408.00	1273.00	169.810	0.62	0.23	726.15	1.75
SS	Tra	48.00	853.00	166.63	0.95	0.53	313.27	2.72
	Val	80.00	1288.00	218.13	2.28	0.57	377.69	3.41
	T	40.00	1052.00	227.15	1.27	0.58	387.56	2.71
TN	Tra.	17.50	64.00	8.29	0.27	0.21	38.34	1.66
	Val.	23.10	59.90	7.39	0.36	0.19	38.94	1.53
	T.	29.30	65.80	8.82	0.88	0.20	43.46	1.51
TP	Tra.	3.24	25.90	2.20	6.17	0.37	5.84	4.43
	Val.	3.51	6.53	0.62	0.13	0.12	4.95	1.31
	T.	3.81	27.00	6.31	2.50	0.85	7.41	3.64
EC	Tra.	1392.00	2080.0	130.03	-1.27	0.07	1875.2	1.10
	Val.	1532.00	2030.0	117.07	-1.42	0.06	1886.9	1.07
	T.	1625.00	2045.0	116.64	-0.86	0.06	1917.7	1.06

*Tra: Training; Val: Validation; T:Test Series

Table 5 The test performances of the ML-ANN, ABC-ANN, TLBO -ANN models in BOD estimation

	R2		RMSE (mg/l)		MAE (mg/l)	
The Name of Models	Training	Test	Training	Test	Training	Test
ML-ANN	0.892	0.844	46.137	41.301	36.698	30.364
ABC-ANN	0.847	0.655	55.708	44.724	67.918	51.785
TLBO-ANN	0.854	0.782	54.125	43.828	46.018	38.211

The accuracy of these three methods were ranked as; ML-ANN, TLBO-ANN and ABC-ANN respectively for training test.

The ML-ANN method is the most successful model in the established methods for prediction of BOD regards to RMSE and MAE values for test set. Similarly, ML-ANN method gave highest correlation coefficient value for both training and test sets. It can be seen in Table 5.

As seen in Fig. 4 and Fig. 5, when all methods compared with each other, ML-ANN predicted peak values more accurately than other methods.

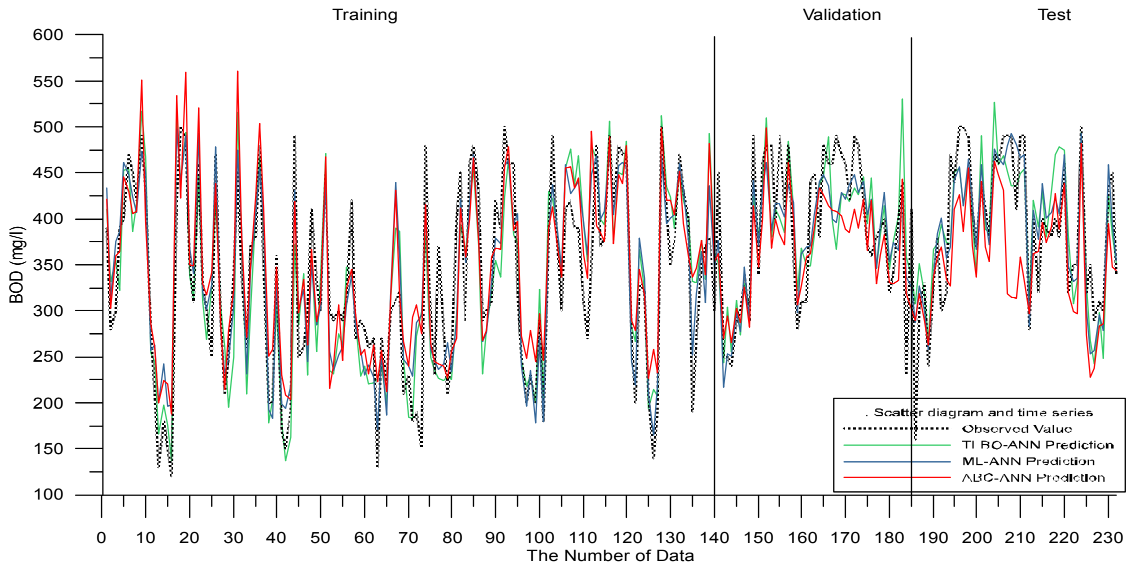

Fig. 3 Time series of ML-ANN, ABC-ANN, TLBO-ANN models in BOD estimation

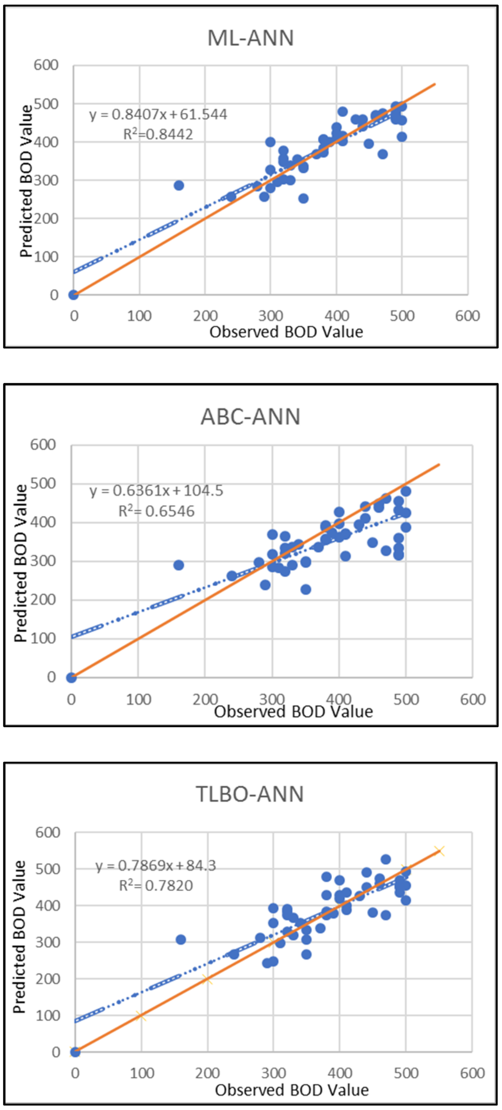

Fig. 4 Scatter diagram of ML-ANN, ABC-ANN, TLBO-ANN models in BOD estimation

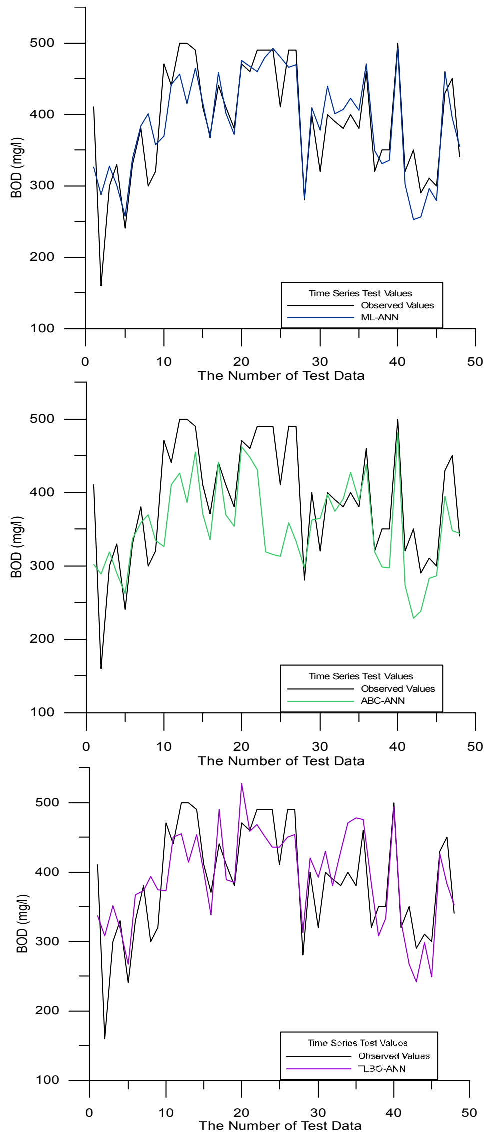

Fig. 5 Time series of ML-ANN, ABC-ANN, TLBO-ANN models in test sets

4. Conclusion

It is very important to estimate of the BOD accurately because it is extremely critical in the management and planning of water quality process and the estimation of the amount of the BOD plays an important role in determining the environmental effects of the water quality. However, the measurement of this parameter, which is important, is difficult and it takes five days to obtain the measurement results. Measuring difficulties and long duration of the process also increase the cost of measurement.

The applicability of different ANN techniques in the BOD estimation has been demonstrated in this paper. The estimation models were compared with each other. Based on the comparison results, in all the models, the ANN techniques were successful in the terms of reflecting the biochemical oxygen demand. ML-ANN and TLBO-ANN methods provide more successful result than ABC-ANN method regards to behaviour and estimation of the peak values. When the test results (RMSE, MAE and R^2) are taken into consideration, it is observed that the ML-ANN method has better predictions than the other methods.

This study proposes ML-ANN as a suitable model to sufficiently estimate the BOD for the Hurma WWTP. The ML-ANN model predicted the BOD better than the ABC-ANN and TLBO-ANN models. The model had root mean squared error (RMSE) 41.3006 mg/l and a mean absolute error (MAE) 30.3639 mg/l for testing set.

The ML-ANN model gave satisfactory prediction of BOD using the WWTP's water quality variables. This may mean that it may be a useful tool for predicting the BOD in different WWTP. For this reason, the ANN model can be of great convenience to water surveys and WWTP managers.

By means of this obtained method, instantaneous BOD value can be obtained with the instantly measured input values without waiting for the result of BOD test analysis. With this estimated value, it is possible to have an idea about the approximate value without waiting for 5 days for the analysis of the BOD. Thus, the operation of the treatment plant will be cheaper and done in a shorter time.

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