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Modeling wastewater treatment plant (WWTP) performance using artificial neural networks: Case of Adana (Seyhan)

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Abstract

In this study, performance estimation of biological wastewater treatment plants (WWTP) was made by applying Artificial Neural Network (ANN) techniques. As material, 355-day data from Adana Metropolitan Municipality Seyhan wastewater treatment plant for 2021 were used. Of the data used, 240 were evaluated as training data and 115 as test data. In the establishment of the ANN model, the daily chemical oxygen demand (COD), daily water flow (Qw) and daily suspended solids (SS) parameters at the entrance of the WWTP were used as input parameters. The daily biological oxygen demand (BOD) parameter was determined as the output parameter. In the study, feed forward back propagation ANN model (FFBPANN) was used to estimate the daily BOD amounts at the entrance of the WWTP. In the statistical analysis, the correlation (R^2) values of the input parameters with BOD were found to be 0.906 for COD, 0.294 for Qw and 0.605 for SS. The R^2 value was determined as 0.891, the MAE value was 10.32% and the RMSE value was 722.21 in the network structures where the best results were obtained for the test and training data (in the 4-4-1 ANN model). As a result of the study, it was concluded that the ANN model was successful in estimating the BODs of the WWTPs in obtaining reliable and realistic results, and that effective analyzes with the simulation of their nonlinear behavior could be used as a good performance evaluation tool in terms of reducing operating costs.

Keywords: Artificial neural network, Biological oxygen demand, Modeling, Waste water treatment plant

INTRODUCTION

Artificial neural networks collect information about examples, make generalizations, and then make decisions about new examples using the information they have learned when compared to examples they have never seen. Due to these learning and generalization features, artificial neural networks find wide application in many fields of science today and reveal the ability to successfully solve complex problems (Ergezer et al., 2003). In other words, they are computer programs that imitate biological neural networks, which are parallel and distributed information processing structures that are inspired by the human brain, connected to each other through weighted connections, and composed of processing elements, each of which has its own memory (Elmas, 2003).

In addition to factors such as global warming and seasonal changes, the damage to the environment is increasing rapidly due to unsustainable resource consumption. The water used for various vital activities is sent to wastewater treatment plants through different methods. The estimation of the operating parameters of the plant in the treatment of water with conventional methods takes a long time and constitutes a significant obstacle in terms of efficiency. In addition to the difficulty of the treatment process in the wastewater treatment plants established to purify the wastewater and deliver it to the receiving environments, various models are needed for the efficient operation of the treatment plants (Khatae, 2009). Recently, computer aided methods have found wide application in environmental issues. These methods can be defined as a complex system formed as a result of the interconnection of processors, such as many neurons in the human brain, by various methods. Artificial neural networks have a high approximation capability and have the advantage of solving problems in a short time (Kologirou, 1999; Bechtler et al., 2001). Especially in fields such as agriculture and industry, expressing physical systems with equations and solving mathematical models with computer aid is one of the problems encountered (Hanbay et al., 2006). In a study conducted in Canada, two ANN models, back propagation network and radial basis function, were developed to estimate the nitrogen content in sewage waters. In this developed model, a simulation of nitrogen concentration in wastewater was applied. In this simulation applied, it has been shown that wastewater has fertilizer potential (Sharma et al., 2003). Biological oxygen demand (BOD) is of great importance in terms of water quality in treatment plants. However, it is important to measure and correctly estimate this parameter from an environmental point of view (Hamed et al., 2004; Aguilera et al., 2001). The fact that the BOD measurement process takes up to five days naturally increases the cost. Regression analysis used in the measurement is an important parameter in defining water quality. However, due to non-linear relationships, obtaining effective results does not provide a good modeling opportunity compared to traditional methods. Various methods that can be used for nonlinear cases are widely used today (ANN, BM, ASBS). With the back propagation algorithm, which is one of these methods, it is possible to adjust the weights in order to bring the margin of error to the desired value. This process can be repeated until the optimum solution is reached (Yurtoglu, 2005).

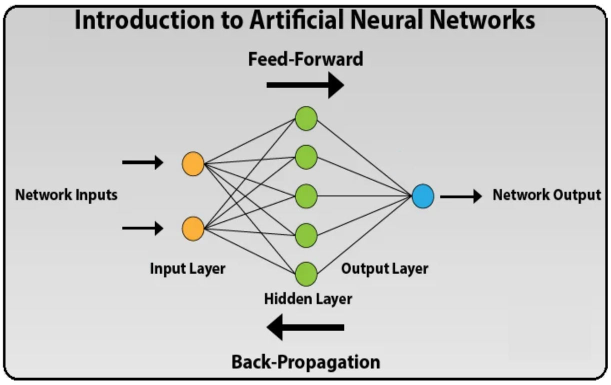
In recent years, ANN-based models with one or more inputs and one or two outputs have been used to predict WWTP performance and ensure plant efficiency. The learning process takes place by training the samples and processing the input and output data. In other words, learning takes place by repeating the training algorithm until a convergence is achieved by using these data (Keskin et al., 2007). In this study, with the help of Artificial Neural Network (ANN) techniques, the performance of Adana Seyhan biological wastewater treatment plant (WWTP) was estimated. In addition, in this estimation, alternative methods have been tried to be determined to reduce BOD measurement costs.

Artificial Neural Networks (ANNs)

ANNs mimic the working functions of the human brain. They are logical software developed to produce new information by generalizing. They are also artificial systems that model the functions of the human brain (Öztemel, 2012). ANNs can establish connections between memorization and information, together with learning as self-learning mechanisms (Elmas, 1994) [14]. The success of modeling various systems by training existing data with ANN has increased the usability of ANN (Haykin, 1994; Özcalık et al., 2003).

According to the algorithm of ANN, nerve cells are arranged in multiple layers to correlate between inputs and outputs. In an ANN model, there are three layers as input, hidden and output layers, and a network can have more than one hidden layer (Yaldız, 2006). A typical ANN model is given in Figure 1 (URL, 2019).

Figure 1. Artificial Neural Network Model



Feed Forward Back Propagation ANN Model (FFBPANN)

Feedforward neural networks allow for one-way signal flow, and most are organized in layers (Weatherford et al.,2003). The outputs of cells in one layer are given as inputs to the next layer over weights. The input layer transmits the information it receives from the external environment to the hidden layer without making any changes. The network output is determined by processing the information in the hidden and output layer (Öztemel, 2012). In Feedback Artificial Neural Networks (ANNs), at least one cell's output is given as an input to itself or to other cells, and usually the feedback is done through a delay element (Kebalcı, 2014).

MATERIALS AND METHODS

Collection of Data

In the study, 355-day data from Adana Metropolitan Municipality Seyhan wastewater treatment plant for 2021 were used as material. Of the data used, 240 were evaluated as training data and 115 as test data. In the establishment of the ANN model, the daily chemical oxygen demand (COD), daily water flow (Q_w) and daily suspended solids (SS) parameters at the entrance of the WWTP were used as input parameters. The daily BOD parameter was determined as the output parameter. Biological oxygen demand (BOD) is shown as one of the most important parameters in the management and planning of water quality. The flow chart of Adana Metropolitan Municipality Seyhan Wastewater Treatment Plant is given in Figure 2 (URL, 2019).

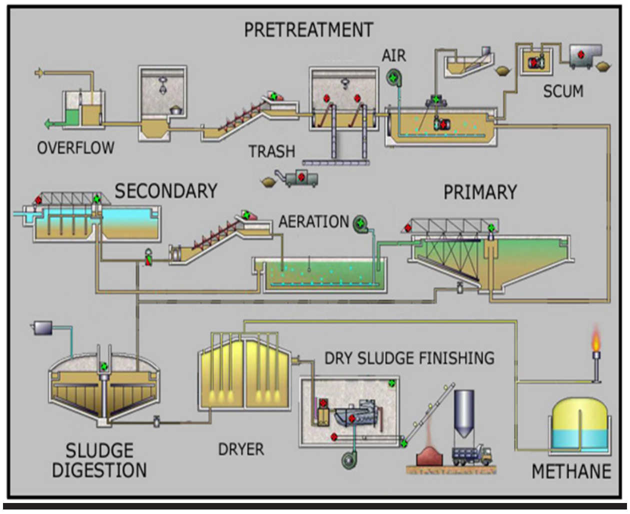


Figure 2. Wastewater Treatment Process Step by Step

The statistical analysis results of the data obtained from the treatment plant used as the material in the study are given in Table 1. In the table, the Xave, Sx, Cv, Csx, xmin, and xmax parameters show the mean, standard deviation, variance, skewness, minimum and maximum values of each data, respectively. As seen in Table 1, while the most variable data was seen in SS, the relationship between COD and BOD parameters changed linearly. It is seen that the water flow rate (Qw) is inversely proportional to the BOD (R^2=-0.294).

Application of the FFBP ANN Model

ining sets and 115 as test sets. The estimated network structure of the model applied in the study is given in Figure 3.

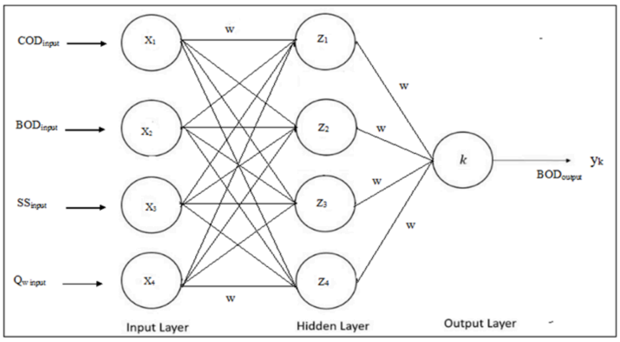


Figure 3. Network Structure Estimated in Artificial Neural Networks Model for WWTP Process Control

In the study, statistical functions of correlation coefficient (R^2), mean square error (RMSE) and mean absolute error (MAE) were used to evaluate the error levels of the data used (Landeras et al., 2008; Traore et al., 2010; Trejo-Perea et al., 2009; Yılmaz et al., 2008). The equations used in the calculation of the correlation coefficient (R^2), mean square error (RMSE) and mean absolute error (MAE) statistical functions are given below;

$$R^2 = \frac{\left[\sum_{i}^{m}(yi-\bar{y})(Oi-\bar{O})\right]}{\sum_{i=1}^{m}(yi-\bar{y})^2\sum(Oi-\bar{O})^2}$$

In the equation;
m, the number of data tested,
Oi, predicted data in neural network,
yi, the calculated amount of data.

Table 1. Data Used in the Study and Statistical Analysis

Data	BOD (mg/l)	COD (mg/l)	SS (mg/l)	Qw (m^3/day)
Xaverage	228.978	384.299	209.041	154494.274
Sx	74.197	136.920	104.294	7625.813
Cv(Sx/Xaverage)	0.324	0,356	0.499	0.049
CSX	-0.120	-0.576	0.433	-0.777
Xmin	63	131.000	58	106999
Xmax	474	880	766	178279
Correlation with BOD (R)	1.000	0.906	0.605	-0.294

Analysis of 355 data consisting of COD, SS and Qw and BOD from an output vector was considered in the study. The data used did not give very good results in predicting the ANN model. For this reason, the data were normalized and divided into two groups to form training and test sets between 0 and 1. In the study, 240 of the two groups formed from 355 data sets were used as tra-

$$X_n = \frac{\left(E_{gerçek} - X_{\min}\right)}{X_{\max} - X_{\min}}$$

In the equation;
Xn , Normalized data value,
Xmin, the min value of the data to be normalized,
Xmax, the max value of the data to be normalized.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}\left|y_i - y_i^{'}\right|$$

In this equation;

$\bar{y}$, the average of the calculated amount of data (yi).

$y = \alpha_1\, x + \alpha_0$

In the equation;
x, the argument (amount of data),
α0, intersection,
α1, denotes slope.

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}\left(yi - yi^{'}\right)^2}{N}}$$

RMSE, the Root of Mean Squared Errors

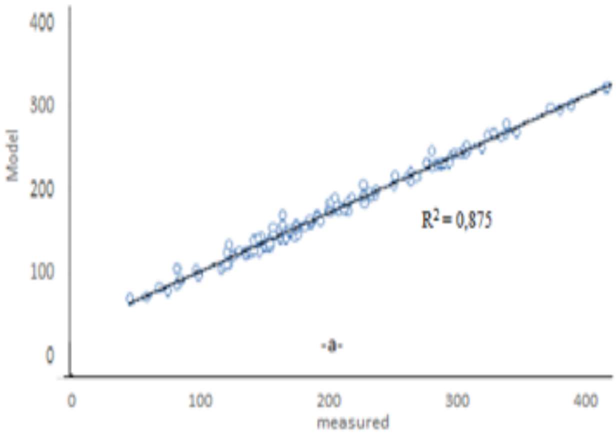
CONCLUSION

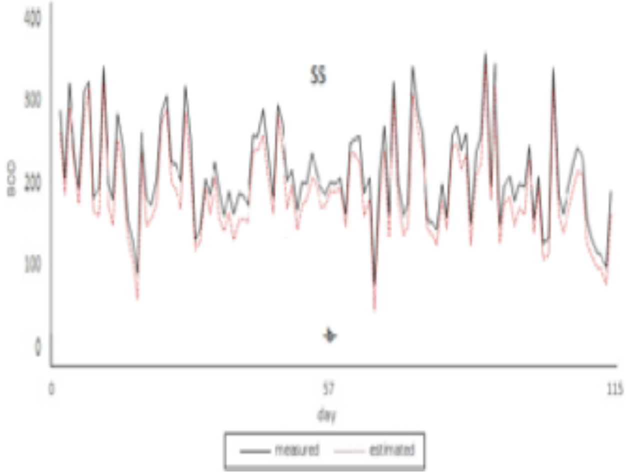
Performing Sensitivity Analysis Using FFBP ANN Model

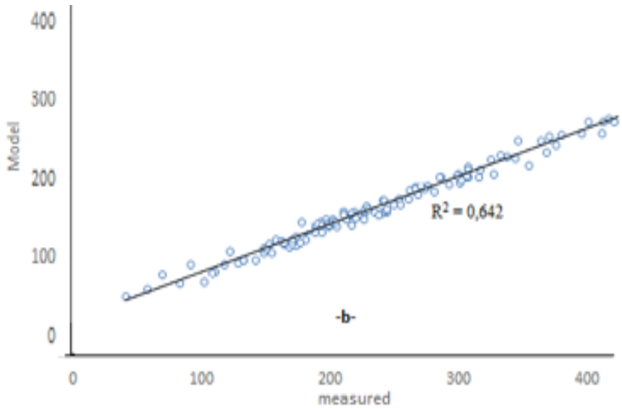
The selection of the input parameters to be used in the FFBP ANN model is important for the performance of the model (Elmas, 2007). Sensitivity analysis, which gives the BOD estimation and the most effective input combinations, was found using the IBGYYSA model (Table 2). In the BOD estimation, almost most of the input parameters were determined to be important compared to the stability analysis. As can be seen in Figures 4 a-b-c, as a result of the calculation of the efficiency degrees in the BOD estimation, it was determined that the most effective parameter was COD, while the least effective parameter was Qw.

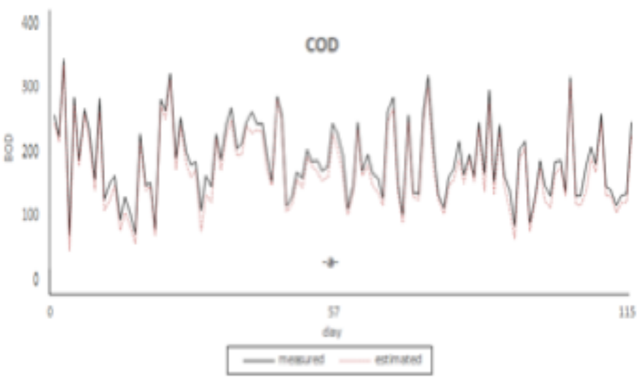
Table 2. Determining the Most Effective FFBP ANN Model Using Sensitivity Analysis

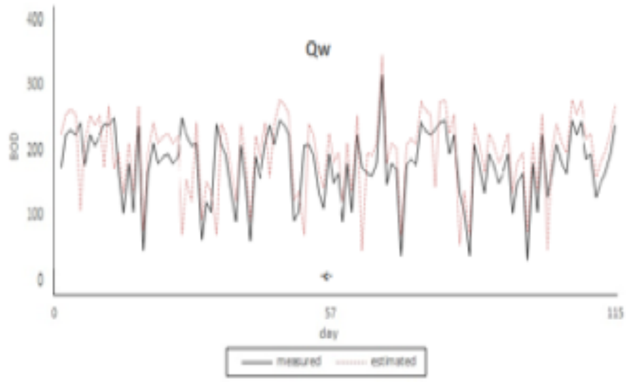
	MAE (%)	RMSE	R^2
COD+SS+Qw	10.32	722.21	0.891

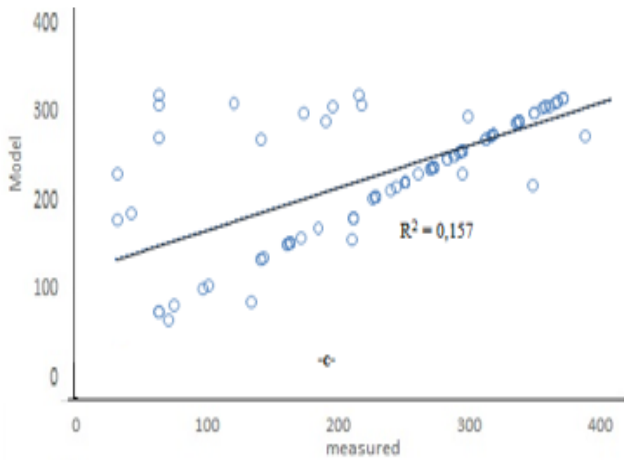












Figures 4 a-b-c. Determining the Performance of Input Parameters in Estimating BOD with FFBPANN

Determining the Most Appropriate FFBP ANN Model

RMSE and R^2 performance functions are used to determine the active FFBP ANN model. The number of hidden layer neurons was determined as 4 from the test set performance values as a result of various trials, as shown in Table 3. The ANN (4-4-1) model with the highest performance was determined.

Table 3. Determining the Most Effective FFBP ANN Model

ANN (Number of neurons in layers)	Number of Iterations	R^2	RMSE
ANN(4, 2, 1)	1000	0.887	743.12
ANN (4, 3,1)	1000	0.886	759.23
ANN (4, 4, 1)	1000	0.891	722.21
ANN (4, 5, 1)	1000	0.883	764.17
ANN (4, 2, 1)	2000	0.867	781.16
ANN (4, 3, 1)	2000	0.869	779.22
ANN (4, 4, 1)	2000	0.857	792.23
ANN (4, 5, 1)	2000	0.860	786.51

In the study, the model was tested after the FFBPANN model was trained. It can also be seen from the trend graphs that the estimated values of FFBPANN as a result of the tests performed with BOD are very close to the observed values (Figure 5).

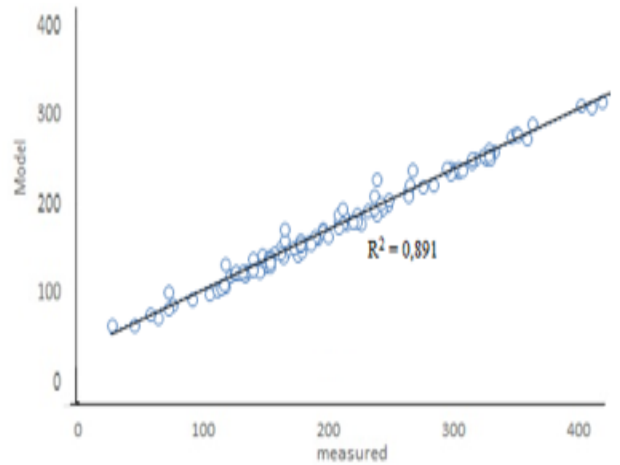


Figure 5. Comparison of BOD Estimates with Measured BODs in the FFBP ANN Model

RESULTS

In this study, using the FFBPANN model, the values of 355 daily BOD amounts (R2) for 2021 at the entrance of Adana-Seyhan wastewater treatment plant were found to be 0.906 for COD, -0.294 for Qw and 0.605 for SS. The R^2 value was determined as 0.891, the MAE value was 10.32%, and the RMSE value was 722.21 in the network structures where the best results were obtained for the test and training data (in the 4-4-1 ANN model). These values show that the ANN model used in the study gives very successful results. As a result of calculating the efficiency degrees in BOD estimation by using all of the inputs used for all models, it was determined that the most effective parameter was COD, while the least effective parameter was Qw. In addition, it was determined that the use of ANNs in BOD estimation of all input parameters (COD, SS and Qw) in the sensitivity analysis performed for the determination of the most effective model, because an effective FFBPANN model depends on the input parameters, gives much better results than the conventional models. Well-trained ANN parameters are important for the wastewater treatment processes used in WWTPs to give reliable estimates. In this study, it has been concluded that the ANN model is successful in estimating the BODs of WWTPs in terms of reliable and realistic results, and that effective analyzes with simulation of nonlinear behavior can be used as a good performance evaluation tool in terms of reducing operating costs.

COMPLIANCE WITH ETHICAL STANDARDS

Conflict of interest

The authors declared that for this research article, they have no actual, potential or perceived conflict of interest.

Author contribution

The contribution of the authors to the present study is equal. All the authors read and approved the final manuscript. All the authors verify that the Text, Figures, and Tables are original and that they have not been published before.

Ethical approval

Ethics committee approval is not required.

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Data availability

Not applicable.

Consent for publication

Not applicable.

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