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# Performance prediction and control for wastewater treatment plants using artificial neural network modeling of mechanical and biological treatment

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**Abstract:** Biological treatment in wastewater treatment plants appears to be one of the most crucial factors in water quality management and planning. Though, measuring this important factor is challenging, and obtaining reliable results requires significant effort. However, the use of artificial neural network (ANN) modeling can help to more reliably and cost-effectively monitor the pollutant characteristics of wastewater treatment plants and regulate the processing of these pollutants. To create an artificial neural network model, a study of the Samsun Eastern Advanced Biological WWTP was carried out. It provides a laboratory simulation and prediction option for flexible treatment process simulations. The models were created to forecast influent features that would affect effluent quality metrics. For ANN models, the correlation coefficients $R_{TRAINING}$ and $R_{ALL}$ are more than 0.8080. The MSE, RMSE, and MAPE were less than 0.8704. The model's results showed compliance with the permitted wastewater quality standards set forth in the Turkish water pollution control law for the environment where the treated wastewater is discharged. This is a useful tool for plant management to enhance the quality of the treatment while enhancing the facility's dependability and efficiency.

## Introduction

Wastewater treatment is a critical component of smart cities and is essential for maintaining the hygiene and health of municipal populations. The most practical wastewater treatment method currently used in municipal wastewater treatment is biological wastewater treatment. Water quality soft-sensing of WWTP is a difficult challenge due to its complex nonlinear dynamics with significant disturbances and an unpredictable time delay (Iratni & Chang, 2019) (Guo et al. 2015). Accurate soft--sensing models for wastewater water quality are essential under tight environmental requirements (Zeinolabedini & Najafzadeh, 2019). The necessity for extremely effective treatment techniques, in addition to the growing volume of wastewater released, is another justification for the use of AI in WWTP (Borgulat et al. 2022). The quantity of parameters is another key drawback of using statistical models. It would be challenging to estimate the model as the number of parameters rose (Tumer & Edebali, 2015). Artificial neural networks (ANNs) are among the several statistical techniques that can be directly used for wastewater treatment plant (WWTP) modeling (Yuchao Zhao et al. 2015). Particularly ANN-based models have been applied in a number of fields, including engineering, dynamic process modeling, pattern recognition, and process control and prediction. A quick and precise soft-sensing model provides an alert reference for the next course of action in advance if any aberrant operation takes place in addition to giving specific descriptions of dynamics. Consequently, it is essential to create an effective approach to assess the safety of the water environment, which includes an efficient and accurate soft-sensing model for WWTP (Wang et al. 2019). Artificial neural networks (ANNs) are the most widely used methods for forecasting water quality parameters among the existing soft-sensing models of WWTP. They have been particularly crucial in the simulation of industrial WWTPs, which shows the viability of additional practical applications (Oliveira-Esquerre et al. 2002).

In the past years, many studies concentrated on the creation of ANNs for the prediction of sludge volume using the Batna wastewater treatment plant's operating and influent quality parameters. With R = 0.8784 and RMSE = 0.443, the best neural network model for forecasting sludge volume has an input layer with 15 input variables, a hidden layer with 13 nodes, and an output layer with 1 output variable. The outcomes show how effective the right neural network models are in forecasting sludge volume index (SVI). This offers a very helpful tool that WWTP operators may utilize in their everyday operations to improve the effectiveness of the treatment process and the dependability of the WWTP (Bagheri et al. 2015). These tests investigated the connections between

COD and trace metals using an AI-based prediction model with ANNs integrated into MATLAB. The ANNs were trained using a supervised learning technique, which also connected input and output data. By minimizing the error function, the training was intended to estimate, validate, and predict the parameters. It was discovered that ANN models were a reliable technique for forecasting WWTP performance. Environmental management and other developing technologies can be predicted using the predictive methodologies (Matheri et al. 2021). Moreover, modeling the electrocoagulation removal of contaminants from wastewater by pulping processes was done using ANNs. Pseudo-first order and second-order models were used to simulate the process' kinetics. With an ideal pH of 6.83, a current density of 22.06 $mA/m^2$, and a reaction time of 45 minutes, it was discovered that the removability of the COD, TDS, and turbidity was 76.4, 57.0, and 97.13%. The $R^2$ of 0.999 and MSE of 0.00753 indicated that the ANN model provided a better fitting (Adeogun et al. 2021). A dynamic nonlinear autoregressive network with an exogenous input nonlinear autoregressive with exogenous inputs model (NARX) was created in a prior study to anticipate effluent quality. To enhance performance, several time-delay factors and training methods were employed. A PCA-NARX hybrid model was then created for high performance and compared with two static ANN models. The BR algorithm outperformed the other four training approaches for the NARX model. The dynamic PCA-NARX model performed significantly better in effluent quality simulations than static models. (Yang et al. 2022). Another instance given by researchers involved simulating an anaerobic fermentation process for biogas production in conjunction with wastewater purification in a modern WWTP with a designed nominal capacity of 27,000 $m^3$/day using (ANNs). Neural models were constructed, validated, and tested while taking into account both the technical features of the process and the quality of the treated effluent, using actual industry data from three years of continuous plant operation. The operating process parameters (COD, $BOD_5$, TSS, Pg, Ng) were more important for the biogas yield than for the wastewater quality, according to a parameter sensitivity analysis. The provided ANN model is a prediction tool that can be used to improve or steer complex processes such as steering/control methods (Sakiewicz et al. 2020). The predicted and experimental responses, on the other hand, are comparable, and the backpropagation ANN model successfully predicted plant performance. ANN can therefore be used to define the complete effluent and waste disposal process in the detergent business, handled by a number of procedures including air flotation, chemical coagulation, sedimentation, and biological treatment (Jana et al. 2022). Furthermore, in Matlab software, modeling of the Konya wastewater treatment plant was investigated using artificial neural networks with various designs. By combining output values of TSS with input values of pH, temperature, COD, TSS, and BOD, the treatment effectiveness of the plant was calculated. After going through a number of trial-and-error processes, the ideal neural network model design has been found. A correlation coefficient (R) between the observed and anticipated output variables that reaches up to 0.96 indicates that the ANN can forecast the plant performance, according to the modelling study (Paquin et al. 2015). According to several research studies, ANN was used to forecast the effluent chemicals performance of the Touggourt WWTP over the next 10 months. The outcomes demonstrated that, during the learning, validation, and testing phases, the ANN model could accurately predict the experimental findings with high correlation coefficients of 0.89, 0.96, and 0.87, respectively. Overall findings showed that the method to ANN modeling can offer a useful tool for simulating, regulating, and forecasting the performance of WWTP (Bekkari & Zeddouri, 2019). Another study that underlines the advantages of the self-organizing map technique in choosing key input variables for ANN modeling of WWTP efficiency performance made use of an ideal ANN design. The increased performance of the model in relation to several indicators is also highlighted in this study (Sharghi et al. 2019). Also, the seasonal ANN models were created to boost the capacity of WWTP in Harbin, northeast China, to purify wastewater. The ANN models found a connection between the quality of raw water, the amount of energy used, and the effluent water quality. The effluent water quality may be predicted by the models. As a result, it might give managers more precise data to monitor and plan WWTP processes, enhancing wastewater purification (Ying Zhao et al. 2016). In a previous study, the forecasting of three important water quality indices in the Gaza wastewater treatment plant was done using an ANN model. The treatment effectiveness of the plant was determined by comparing influent input data for pH, temperature, BOD, COD, and TSS with effluent output values for these parameters. The performance of the model was compared using the root mean squared error (RMSE), mean absolute percentage error (MAPE), and correlation coefficient (R). It was found that BOD, COD, and TSS at the outflow of the Gaza wastewater treatment facility could be precisely estimated using the ANN model (Hamada et al. 2018).

One of the most well-known machine learning methods, which is a subset of AI, is ANN. Neural networks fall under the category of „black box" models since knowledge of the process's physical characteristics is not necessary. It establishes a connection between the variables affecting the output. the quantity of studies employing the ANN approach to model the aforementioned membrane processes According to the growing body of research over the years, the tendency appears to be moving more in the direction of ANN models (Jawad et al. 2021). ANN models have projected the complete and fecal coliform eradication for an intermittent cycle extended aeration-sequential batch reactor. Some of the metrics used to build the network were pH, BOD, COD, TSS, oil & grease, total kjeldahl nitrogen (TKN), ammonical nitrogen (AN), total phosphorus (TP), fecal coliform, and total coliform. The most effective ANN models for total and fecal coliform were selected using the trial-and-error method. The output of the simulation was within 5% of MAPE for both total and fecal coliform. ANN models can regulate the amounts of fecal coliform and total coliform in the treated wastewater effluent, lowering the dangers to the public's health (Khatri et al. 2020).

In order to choose the best method for the prediction of the wastewater quality data, the major objective of the current paper is to determine the optimum topology of the ANN and compare the resulting prediction results with real data. In order to generate models with different ANN topologies, the neurons in the hidden layer were modified. The effectiveness of the created ANN was evaluated using the correlation coefficient, MAD, RMSE, and MAPE for training and independent validation. This is because there are many problems with how wastewater quality is measured and recorded, including BOD, TN, TP, and TSS. It is believed that the findings of this study will aid in the creation of strategies and policies to lessen the pollution the WWTP produces and enhance its effectiveness as a case study for predicting the performance of the WWTP. The error was reduced to provide the optimal operating points by comparing the output data to the real training data and ANN data. The results would have been more precise and thorough if data that were measured on a daily or weekly basis had been collected, even though the data obtained on a monthly basis was somewhat adequate.

## Materials and methods

### *The Plant Description*

The largest wastewater treatment facility in the Black Sea region, the Samsun Eastern Advanced Biological Wastewater Treatment Plant and Deep-Sea Outfall Project was constructed on the coastal portion of the Tekkekoy District's Industrial Zone in Turkey. The location of the Samsun Eastern Advanced Biological Wastewater Treatment Plant is shown in Figure 1.

The facility's project flow rate for the first phase in 2018 was 105,000 $m^3$/day, and for the second phase, it is 120,000 $m^3$/day. In Samsun Province, the Treatment Plant provides services to 44% of the populace. The facility also removes nitrogen and phosphorus as part of the lengthy aeration-activated sludge treatment process. Following the advanced treatment, the wastewater is discharged as a deep-sea outfall (23.5 m) at the end of a 250 m diffuser and a 2.45 km long, 1600 mm diameter HDPE pipeline. In terms of capacity, the facility is the biggest treatment facility in the Black Sea area. The Samsun Eastern Advanced Biological WWTP features bio-disc and UV disinfection units with a capacity of roughly 1,000 $m^3$/day, and it has been discovered that the facility's green spaces are watered with treated wastewater. Figure 2 includes a picture of the facility.

The Urban Wastewater Treatment Regulation states that in facilities with a project flow rate of 20,000 $m^3$/day or more, the $BOD_5$ concentration shall be 25 mg/L, the TSS concentration 35 mg/L, the total nitrogen concentration 10 mg/L, and the total phosphorus concentration less than 1 mg/L. is required. The dissolved oxygen (DO) was determined using INSTRUMENTATION – Membrane Sensor (Model 1056


**Fig. 1.** Location of Samsun eastern advanced biological wastewater treatment plant

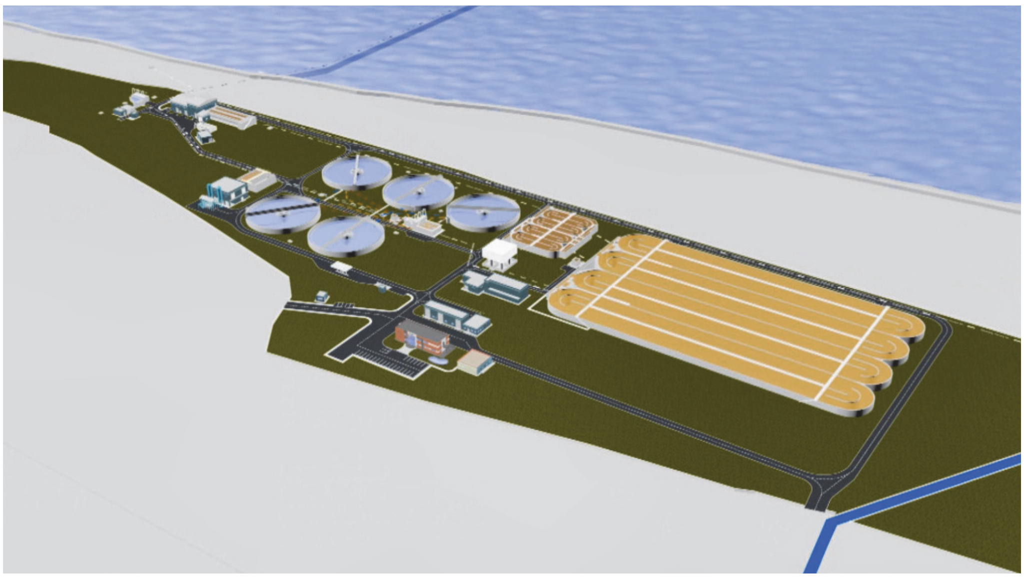

**Fig. 2.** Photograph of Samsun eastern advanced biological wastewater treatment plant

Dissolved Oxygen Analyzer), and after data analysis, the mean, standard deviation, and variance were 1.68, 0.33, and 0.11, respectively. These values are roughly within the range for wastewater treatment.

Samsun eastern advanced biological wastewater treatment plant consists of pretreatment units (Coarse screen (2+1), screen unit capacity of 4,250 $m^3$/h, screen opening 30 mm and chain type screen, Inlet transfer unit (3+1), pump unit capacity of 2892 $m^3$/h and submersible pump, fine screen (2+1), screen unit capacity of 4,250 $m^3$/h, screen opening 6 mm aperture and perforated type screen, ventilated sand and grease removal unit, final hydraulic capacity of 10,000 $m^3$/h, 2 units equipped and final unit capacity of 5,000 $m^3$/h), advanced biological treatment units anoxic–anaerobic–oxic (A2O)(Bio-P tanks (4 units), unit tank volume of 2,625 $m^3$ and retention time (HRT) of 0.7 hours (anaerobic), activated sludge tanks (4 units), the volume of each tank is 39,198 $m^3$, the air flow rate is 38,439 $Nm^3$/h, number of blowers is 3+1 and blower pressure is 750 mbar (oxic and anoxic), secondary sedimentation tanks (5 units), tank diameter 48.5 m, the volume of each tank is 6,848 $m^3$ and double-sided V-type weir and recirculation and effluent pumping station), and sludge units (sludge dewatering) (1%), total pool volume 2,250 $m^3$, total air volume 2.96 $Nm^3$/h and number of mixers 2, concentration (5%), concentrator drum power is 1.1 kW, concentrator drum capacity is 70 $m^3$/h and a number of drums is 3+1, centrifugal type decanter (25%), decanter power 30 kW, decanter capacity 22 $m^3$/h and number of decanters 2+1).

Domestic wastewater is transported to Samsun eastern advanced biological wastewater treatment facility by a collector line with a 2,000 mm diameter from communities in the southern part of the city. The initial stage of treatment for incoming wastewater involves the pre-treatment units.

### *Creating the neural network*

A typical neural network structure used in this study is shown in Figure 3. The graphic shows the hidden layer (hidden variables), output layer (dependent variables), and input layer (independent variables) of the ANN structure. These layers are connected via connections with different weights. The input and output layers are joined by the hidden layer. One or more neurons may be present in the buried layers. Nonlinear equations can be obtained from provided data that correspond to a hidden layer in a network. The topological structure of an artificial neural network depends on the number of layers, the number of nodes in each layer, and the type of transfer functions (F. Golzar et al. 2020).

The input ($I_i$) is multiplied by the weights ($W^I_{i,j}$), added with the hidden layer's biases ($B^H_j$), and then collected as the neurons in the hidden layer ($N_j$). The resulting values are then multiplied by the weights of the hidden layer and transmitted to the output layer by means of a transfer function ($F^H$) ($W^H_{1,j}$). The final value of the ANN model output is given by the sum of output layer bias.

For all different kinds of networks, the ANN's essential operating concept remains the same. The basic processing unit, the neuron, accepts signals as input, processes them using an activation function, and then outputs a signal. The weight of each neuron and the transfer functions are additional factors that help signals move from one layer to the next layer. The underlying mathematical idea of the neural network is expressed in Equation (1).

$$Y_i = f(\sum_{j=1}^{M} W_{ij}X_j + b_i \tag{1}$$

where $Y_i$ represents the projected output's value $i$. $W_{ij}$ is the weight given to each input $j$, $M$ is the total number of inputs, and bi is the bias for each output. $f$ is the activation function.

The sigmoid function is the most prevalent kind of activation function(Haykin, 2009). The tan-sigmoid function and the log-sigmoid function, which are represented by Equations (2) and (3), respectively, are examples of the sigmoid function(Gangi Setti & Rao, 2014).

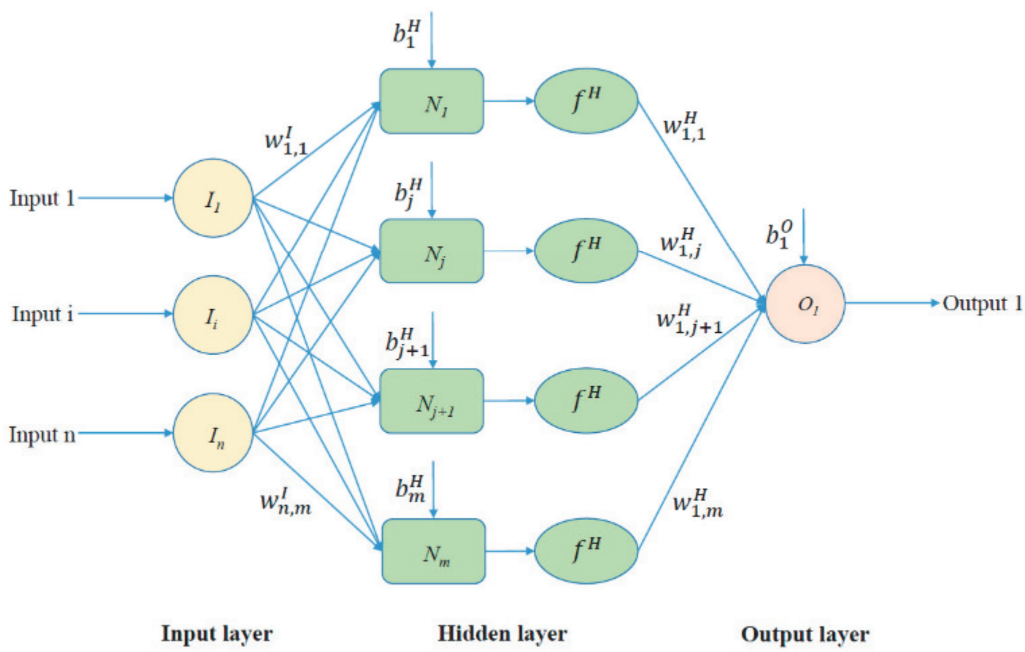


**Fig. 3.** The structure of an artificial neural network (ANN) is depicted schematically

$$f(x) = \frac{2}{1 + \exp(-2x)} - 1 \tag{2}$$

$$f(x) = \frac{1}{1 + \exp(-x)} \tag{3}$$

where $x$ is the activation function's input.

The dataset must be split into three sets: training (70% of the available data), validation (15% of the available data), and testing (15% of the available data) in order to create the ANN model (K. Golzar et al. 2016).

### Neural network training (learning)

In other words, realization occurs when input/output data are processed, with the training algorithm adjusting the synapses' weights based on the data until convergence is attained. Learning occurs by training using examples. Similar to a real neural network, learning in artificial neural networks involves altering the weight values between neurons to achieve a certain goal. Values for the initial weight are selected at random. Examples are shown in artificial neural networks as their weight values vary. The goal is to identify the weight values that will result in the appropriate outputs for the network's examples (Agatonovic-Kustrin & Beresford, 2000). It is clear that the network can generalize about the events that the samples reflect when the weight values of the network are accurate. Network learning is the process of enabling artificial neural networks to generalize about unknowable situations by extracting specialized information from prior experiences. Attempts to determine whether the network learns (performs) after the training are referred to as „testing" the network. Examples that the network has never seen before are utilized for testing. The connection weights calculated during training are used by the network to produce outputs for these occurrences that it is not aware of. The generated outputs' accuracy metrics provide details about the network's learning. The more successful the training, the better the results. The „test set" is a sample set used for testing, while the „training set" is a sample set used in education (NEGNEVITSKY, 2005). The objective of model training is to iteratively modify the network through numerous data presentations. The two primary methods of model training are unsupervised and supervised. Unsupervised training occurs when the model is solely provided with input data and uses these to change the connection weights. While working with supervised data, values from both the input and the target data are given to the model. It was used in this experiment because supervised training takes less time than unsupervised training.

### Evaluation of predicting performance

ANN learning of the relationship in the data structure can be characterized as the process of selecting the most acceptable values for the network weights using problem cases. For any weight(W);

$$W_{new} = W_i \mp \Delta W \tag{4}$$

The equation illustrates the mathematical process of learning. The amount of change in the present weight values is indicated by the $\Delta W$ in Equation (4), which is calculated in accordance with a predetermined rule. The phrase „learning algorithms" refers to the principles used for determining $\Delta W$. To assist in locating the ideal weight set, numerous learning techniques have been proposed (Chang et al. 2001).

The ability of various ANN models to predict outcomes was evaluated using the correlation coefficient (R) for the training set and all datasets, mean absolute error (MAE), root mean square error (RMSE), and mean absolute percentage error (MAPE).

$$R = \frac{\sum_{i=1}^{n}(x_{o,i} - \bar{x}_{o,i}) \times (x_{p,i} - \bar{x}_{p,i})}{\sqrt{\sum_{i=1}^{n}(x_{o,i} - \bar{x}_{o,i})^2 x \sum_{i=1}^{n}(x_{p,i} - \bar{x}_{p,i})^2}} \tag{5}$$

$$MAE = \frac{1}{n}\sum_{i=1}^{n}\left|x_{p,i} - x_{o,i}\right| \tag{6}$$

$$RSME = \sqrt{\frac{\sum_{i=1}^{n}(x_{p,i} - x_{o,i})^2}{n}} \tag{7}$$

$$MAPE = \frac{1}{n}\sum_{i=1}^{n}\left|\frac{x_{p,i} - x_{o,i}}{x_{o,i}}\right| \tag{8}$$

Where: $x_{p,i}$: correlated value; $x_{o,i}$: observed value; n: number of observations; and $\bar{x}_{o,i}$: average of observed values.

### Applying of ANN model on WWTP

The historical data used in this study came from investigations made in the WWTP laboratory. BOD, TN, TP, TSS, T, DO, pH, HRT, Q, and conductivity for both raw influent wastewater and treated effluent were recorded in the plant laboratory for a period of about 4 years (from September 2014 to December 2018). Wastewater entering the treatment plant was tested on a monthly basis for a period of four years. The information gathered was carefully reviewed. After assessing the numerous modeling options for treatment plant performance, it was decided to relate the quality of the raw influent wastewater to the quality of the final treated effluent. The treated effluent and influent operational data are included in Table 1 together with the descriptive statistical analysis. The MATLAB® (R2022b) (MATLAB, 2022) software neural network toolbox, a high-performance interactive software program for scientific and engineering computation, was used to design, build, train, and test the neural networks. Data pre-processing and organization operations have also been carried out using Microsoft® Excel® for Microsoft 365 MSO. The effluent water quality of the WWTP is the output of the ANN models, while the inputs are raw water quality parameters. The outputs were identified as Biochemical Oxygen Demand (BOD), Total Nitrogen (TN), Total Phosphorus (TP), pH and Total Suspended Solids (TSS) effluent water based on a thorough review of the data that was available. Twelve raw wastewater parameters made up the input variables. BOD, TN, TP, TSS, T, DO, pH, HRT (Bio-phosphorus pons, aeration pond and final settling tanks), Q, and conductivity were the raw wastewater's parameters as shown in Figure 4. The data were separated into a training set, a validation set, and a test set using an early stopping strategy to increase the network's generalization capacity.

**Table 1.** A summary of the results obtained from WWTP

| | INPUTS | | | | | | | | | | | | | OUTPUTS | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| | Ta (ºC) | DO (mg/L) | HRT (H) | | | conductivity µs/cm | Q ($m^3$/day) | pH | BOD (mg/L) | TN (mg/L) | TP (mg/L) | TSS (mg/L) | BOD (mg/L) | TN (mg/L) | TP (mg/L) | TSS (mg/L) | pH |
| | | | Bio-phosphorus pons (anaerobic) | aeration pond (anoxic-oxic) | Final settling tanks | | | | | | | | | | | | |
| 1 | 20.30 | 1.23 | 2.31 | 46.55 | 9.02 | 2336.40 | 109296.57 | 7.38 | 116.98 | 36.89 | 3.51 | 174.70 | 3.20 | 5.96 | 0.71 | 13.90 | 7.13 |
| 2 | 16.50 | 1.54 | 1.92 | 38.77 | 7.51 | 2208.87 | 131236.61 | 7.33 | 180.33 | 39.98 | 3.90 | 177.71 | 3.49 | 7.52 | 0.71 | 15.23 | 7.08 |
| 3 | 12.70 | 1.82 | 1.94 | 39.19 | 7.60 | 2017.57 | 129814.43 | 7.80 | 231.03 | 39.24 | 3.93 | 223.23 | 4.24 | 8.48 | 0.98 | 17.57 | 7.55 |
| 4 | 9.40 | 1.93 | 2.79 | 56.24 | 10.90 | 2152.52 | 90461.68 | 7.25 | 132.00 | 34.01 | 3.48 | 157.26 | 6.16 | 8.07 | 0.90 | 16.40 | 7.00 |
| 5 | 7.20 | 2.06 | 1.72 | 34.74 | 6.73 | 1248.81 | 146457.68 | 7.96 | 135.12 | 36.32 | 3.70 | 170.03 | 5.22 | 8.09 | 0.62 | 16.32 | 7.71 |
| 6 | 7.20 | 2.13 | 1.72 | 34.72 | 6.73 | 1339.93 | 146532.11 | 7.35 | 125.26 | 36.66 | 3.60 | 153.57 | 8.15 | 8.87 | 0.71 | 12.96 | 7.10 |
| 7 | 8.10 | 1.94 | 1.62 | 32.72 | 6.34 | 1557.06 | 155486.65 | 7.70 | 124.73 | 37.62 | 3.54 | 152.81 | 9.61 | 8.68 | 0.32 | 11.23 | 7.45 |
| 8 | 11.30 | 1.86 | 1.43 | 28.90 | 5.60 | 1355.20 | 176068.90 | 7.15 | 116.44 | 35.15 | 3.31 | 167.10 | 10.07 | 8.22 | 0.47 | 9.80 | 6.90 |
| 9 | 15.60 | 1.75 | 2.09 | 42.28 | 8.19 | 1724.65 | 120352.52 | 7.16 | 159.53 | 43.61 | 4.63 | 212.45 | 10.94 | 6.76 | 0.53 | 11.94 | 6.91 |
| 10 | 20.20 | 1.19 | 1.67 | 33.63 | 6.52 | 1987.17 | 151272.80 | 7.76 | 189.79 | 43.89 | 4.73 | 195.27 | 11.86 | 6.94 | 0.40 | 12.70 | 7.51 |
| 11 | 23.20 | 1.06 | 1.62 | 32.76 | 6.35 | 2128.71 | 155321.29 | 6.98 | 138.14 | 39.25 | 4.25 | 139.97 | 11.63 | 6.76 | 0.45 | 10.90 | 6.73 |
| 12 | 23.60 | 1.04 | 1.74 | 35.05 | 6.79 | 1991.77 | 145172.84 | 7.03 | 152.84 | 38.13 | 4.82 | 204.65 | 11.47 | 6.94 | 0.85 | 10.39 | 6.78 |
| 13 | 20.30 | 1.07 | 1.79 | 36.19 | 7.01 | 1884.57 | 140601.97 | 7.90 | 139.93 | 36.21 | 4.42 | 160.10 | 11.55 | 6.76 | 0.85 | 10.40 | 7.65 |
| 14 | 16.50 | 1.35 | 1.76 | 35.55 | 6.89 | 1367.03 | 143115.71 | 7.54 | 125.57 | 33.70 | 4.14 | 134.39 | 11.99 | 6.47 | 0.84 | 9.23 | 7.29 |
| 15 | 12.70 | 1.49 | 1.82 | 36.82 | 7.14 | 1702.10 | 138194.60 | 7.53 | 120.10 | 31.78 | 3.98 | 141.80 | 12.17 | 6.39 | 0.85 | 10.90 | 7.28 |
| 16 | 9.40 | 1.96 | 1.67 | 33.63 | 6.52 | 1462.97 | 151272.45 | 7.48 | 117.06 | 31.60 | 3.56 | 140.68 | 17.29 | 8.51 | 0.64 | 17.29 | 7.23 |
| 17 | 7.20 | 2.07 | 1.88 | 37.96 | 7.36 | 1314.90 | 134028.61 | 7.36 | 131.70 | 30.72 | 3.81 | 144.81 | 10.67 | 5.50 | 0.44 | 12.58 | 7.11 |
| 18 | 7.20 | 2.25 | 1.87 | 37.84 | 7.33 | 1339.34 | 134453.69 | 7.18 | 127.30 | 31.13 | 4.22 | 130.59 | 9.27 | 4.78 | 0.42 | 9.59 | 6.93 |
| 19 | 8.10 | 1.98 | 1.62 | 32.70 | 6.34 | 1440.26 | 155603.77 | 7.67 | 103.00 | 29.97 | 3.62 | 109.10 | 9.17 | 4.71 | 0.50 | 10.00 | 7.42 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 20 | 11.30 | 1.86 | 1.50 | 30.19 | 5.85 | 1581.17 | 168521.70 | 7.58 | 143.80 | 30.19 | 4.21 | 156.73 | 10.13 | 4.42 | 0.68 | 8.87 | 7.33 |
| 21 | 15.60 | 1.78 | 1.56 | 31.60 | 6.12 | 2097.29 | 161022.48 | 7.25 | 134.00 | 29.51 | 3.68 | 162.00 | 10.24 | 5.22 | 0.52 | 10.50 | 7.00 |
| 22 | 20.20 | 1.36 | 1.52 | 30.70 | 5.95 | 1987.63 | 165721.77 | 7.39 | 134.00 | 29.34 | 3.88 | 162.00 | 10.43 | 4.99 | 0.56 | 9.20 | 7.14 |
| 23 | 23.20 | 1.21 | 1.55 | 31.27 | 6.06 | 1845.00 | 162706.39 | 7.43 | 147.35 | 30.54 | 3.91 | 152.55 | 10.05 | 5.35 | 0.60 | 9.23 | 7.18 |
| 24 | 23.60 | 1.11 | 1.89 | 38.20 | 7.40 | 1696.32 | 133192.03 | 7.48 | 153.77 | 33.19 | 4.55 | 180.55 | 8.82 | 6.31 | 0.69 | 8.06 | 7.23 |
| 25 | 20.30 | 1.35 | 1.94 | 39.24 | 7.61 | 1602.70 | 129658.27 | 7.32 | 147.45 | 35.96 | 4.78 | 176.53 | 9.90 | 5.51 | 0.71 | 9.13 | 7.07 |
| 26 | 16.50 | 1.68 | 2.06 | 41.58 | 8.06 | 1704.03 | 122358.52 | 7.25 | 151.82 | 38.05 | 4.43 | 194.94 | 9.62 | 5.24 | 0.68 | 8.26 | 7.00 |
| 27 | 12.70 | 1.97 | 2.02 | 40.78 | 7.90 | 1655.70 | 124775.83 | 7.16 | 177.62 | 39.34 | 4.95 | 200.90 | 10.84 | 5.64 | 0.65 | 11.93 | 6.91 |
| 28 | 9.40 | 1.99 | 2.50 | 50.43 | 9.77 | 1438.03 | 100897.29 | 7.02 | 144.03 | 35.96 | 4.43 | 156.71 | 9.67 | 4.74 | 0.66 | 11.80 | 6.77 |
| 29 | 7.20 | 2.12 | 2.31 | 46.59 | 9.03 | 1197.10 | 109210.81 | 7.50 | 142.12 | 36.03 | 4.08 | 177.16 | 9.04 | 4.48 | 0.67 | 8.52 | 7.25 |
| 30 | 7.20 | 2.16 | 2.33 | 46.97 | 9.10 | 1394.18 | 108329.43 | 6.97 | 139.36 | 34.00 | 4.14 | 160.96 | 8.66 | 4.94 | 0.64 | 7.29 | 6.72 |
| 31 | 8.10 | 2.05 | 2.04 | 41.26 | 8.00 | 1274.03 | 123323.58 | 7.03 | 137.85 | 36.37 | 4.60 | 174.26 | 9.04 | 5.39 | 0.35 | 7.35 | 6.78 |
| 32 | 11.30 | 1.94 | 1.86 | 37.57 | 7.28 | 1424.17 | 135422.27 | 7.25 | 138.04 | 35.67 | 4.52 | 170.90 | 8.79 | 4.90 | 0.23 | 8.27 | 7.00 |
| 33 | 15.60 | 1.73 | 2.51 | 50.58 | 9.80 | 1220.58 | 100593.97 | 7.96 | 147.48 | 35.87 | 4.53 | 182.84 | 9.36 | 5.35 | 0.60 | 7.32 | 7.71 |
| 34 | 20.20 | 1.38 | 2.06 | 41.67 | 8.08 | 1502.27 | 122106.93 | 7.65 | 152.61 | 35.72 | 4.48 | 158.33 | 10.53 | 6.22 | 0.59 | 7.80 | 7.40 |
| 35 | 23.20 | 1.26 | 1.89 | 38.25 | 7.41 | 1485.42 | 133032.58 | 7.87 | 155.44 | 37.01 | 4.77 | 173.94 | 10.05 | 4.83 | 0.34 | 8.16 | 7.62 |
| 36 | 23.60 | 1.21 | 1.83 | 37.04 | 7.18 | 1513.97 | 137377.81 | 7.83 | 161.77 | 37.21 | 5.09 | 189.29 | 10.06 | 4.68 | 0.39 | 9.00 | 7.58 |
| 37 | 20.30 | 1.46 | 2.07 | 41.83 | 8.11 | 1514.63 | 121632.87 | 7.57 | 159.84 | 37.17 | 4.88 | 186.13 | 10.61 | 5.93 | 0.62 | 8.80 | 7.32 |
| 38 | 16.50 | 1.58 | 1.88 | 37.96 | 7.36 | 1392.16 | 134038.52 | 8.03 | 152.64 | 37.23 | 4.63 | 186.10 | 10.60 | 5.65 | 0.41 | 8.42 | 7.78 |
| 39 | 12.70 | 1.67 | 2.26 | 45.69 | 8.85 | 1431.67 | 111369.90 | 7.89 | 153.94 | 36.02 | 5.10 | 201.63 | 11.23 | 5.43 | 0.60 | 8.50 | 7.64 |
| 40 | 9.40 | 1.84 | 2.45 | 49.50 | 9.59 | 1433.55 | 102792.42 | 7.77 | 147.67 | 35.76 | 4.56 | 193.00 | 12.63 | 6.49 | 0.75 | 9.58 | 7.52 |
| 41 | 7.20 | 1.98 | 1.93 | 38.90 | 7.54 | 1179.00 | 130794.77 | 7.36 | 133.33 | 32.84 | 3.99 | 180.00 | 11.14 | 5.72 | 0.58 | 9.74 | 7.11 |
| 42 | 7.20 | 2.03 | 1.96 | 39.60 | 7.68 | 1493.89 | 128470.46 | 7.65 | 151.02 | 34.81 | 4.43 | 210.00 | 10.54 | 5.69 | 0.47 | 8.36 | 7.40 |
| 43 | 8.10 | 2.01 | 1.70 | 34.34 | 6.65 | 1655.10 | 148172.32 | 7.89 | 153.40 | 33.94 | 4.45 | 214.52 | 10.35 | 5.43 | 0.30 | 8.29 | 7.64 |
| 44 | 11.30 | 1.87 | 1.90 | 38.26 | 7.42 | 1877.10 | 132974.83 | 7.45 | 152.58 | 35.42 | 4.77 | 192.80 | 10.25 | 5.34 | 0.47 | 8.70 | 7.20 |

| | | | | | | | | | | | | | | | | | |
|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|---|
| 45 | 15.60 | 1.77 | 1.97 | 37.85 | 7.33 | 1653.74 | 134435.90 | 7.49 | 165.33 | 37.87 | 4.81 | 197.03 | 10.86 | 5.36 | 0.38 | 8.68 | 7.24 |
| 46 | 20.20 | 1.54 | 1.90 | 38.32 | 7.43 | 1783.17 | 132773.77 | 7.66 | 159.33 | 37.54 | 4.83 | 198.83 | 11.42 | 4.58 | 0.42 | 9.03 | 7.41 |
| 47 | 23.20 | 1.43 | 2.00 | 40.29 | 7.81 | 1629.71 | 126288.39 | 7.09 | 158.33 | 37.29 | 4.65 | 196.42 | 10.40 | 5.35 | 0.36 | 8.52 | 6.84 |
| 48 | 23.60 | 1.38 | 1.86 | 37.59 | 7.29 | 1754.65 | 135347.90 | 7.80 | 157.31 | 38.46 | 4.74 | 172.39 | 10.31 | 4.91 | 0.33 | 8.71 | 7.55 |
| 49 | 20.30 | 1.43 | 2.12 | 42.82 | 8.30 | 1710.93 | 118811.93 | 7.68 | 159.04 | 37.04 | 4.60 | 182.33 | 10.20 | 5.52 | 0.65 | 8.70 | 7.43 |
| 50 | 16.50 | 1.69 | 2.82 | 56.95 | 11.04 | 1522.00 | 89338.23 | 7.99 | 153.17 | 36.22 | 4.57 | 175.16 | 10.14 | 5.30 | 0.67 | 9.06 | 7.74 |
| 51 | 12.70 | 1.83 | 2.55 | 51.55 | 9.99 | 1503.77 | 98709.30 | 7.89 | 149.40 | 36.29 | 4.22 | 182.60 | 9.85 | 5.82 | 0.39 | 8.90 | 7.64 |
| 52 | 9.40 | 1.94 | 1.67 | 33.67 | 6.53 | 1461.74 | 151094.77 | 7.36 | 149.11 | 36.17 | 4.48 | 198.32 | 10.68 | 6.15 | 0.66 | 8.90 | 7.11 |
| Min | 7.20 | 1.04 | 1.43 | 28.90 | 5.60 | 1179.00 | 89338.23 | 6.97 | 103.00 | 29.34 | 3.31 | 109.10 | 3.20 | 4.42 | 0.23 | 7.29 | 6.72 |
| Max | 23.60 | 2.25 | 2.82 | 56.95 | 11.04 | 2336.40 | 176068.90 | 8.03 | 231.03 | 43.89 | 5.10 | 223.23 | 17.29 | 8.87 | 0.98 | 17.57 | 7.78 |
| Mean | 14.62 | 1.68 | 1.95 | 39.33 | 7.62 | 1618.77 | 132500.82 | 7.50 | 146.75 | 35.69 | 4.31 | 174.77 | 9.90 | 5.99 | 0.57 | 10.21 | 7.25 |
| Standard Dev. | 5.77 | 0.33 | 0.32 | 6.37 | 1.23 | 279.80 | 19800.25 | 0.30 | 20.33 | 3.13 | 0.46 | 23.59 | 2.24 | 1.19 | 0.17 | 2.56 | 0.30 |
| variance | 33.34 | 0.11 | 0.10 | 40.52 | 1.52 | 78285.47 | 392049824.27 | 0.09 | 413.34 | 9.80 | 0.21 | 556.56 | 5.01 | 1.41 | 0.03 | 6.55 | 0.09 |

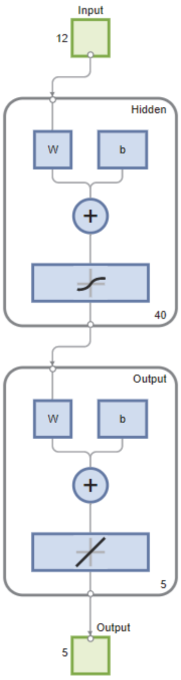


**Fig. 4.** Structure of ANN for WWTP

An ANN model's fundamental components are the input layer, where data are fed into the model and the weighted sum of the input is computed, the hidden layer or layers, where data are processed, and the output layer, where ANN outputs are produced. The effectiveness of a complex neural network forecast model is susceptible to insufficient training. It has been demonstrated that a Feed-Forward Back-Propagation (BP) neural network model with a single hidden layer may approximate nonlinear functions with a small number of discontinuities accurately if the hidden layer contains a sufficient number of neurons (Hong et al. 2003). Therefore, in this investigation, the BP model with a hidden layer was used. The number of neurons in a hidden layer can be counted in a variety of ways, according to the literature, however these approaches are all completely empirical and cannot be used generally. As a result, 40 neurons in the buried layer were selected from a large body of literature (Pai, 2008) and the neuron transfer function in the hidden layer was decided to be either hyperbolic tansig or logsig sigmoid functions. The optimum model structure has been discovered using the trial-and-error method. The output characteristic of the entire neural network can be significantly influenced by the transfer function in the last layer. The output layer's sigmoid function must be used to convert the estimated output back to the real world. A linear function, on the other hand, avoids remapping the outputs by estimating the output in the range from zero to infinity (Hanbay et al. 2008). As a result, a linear function was selected as the transfer function for the output layer's neurons. The neural network was trained using the training set. The training set's error was monitored using the validation set. The validation error of the validation set typically decreased along with the increase in training error at the start of training. However, if the network was overtrained, even when the training error was declining, the validation error would steadily rise. The network with the lowest validation error would be the best model at this point, and network training would be ended. The model was lastly validated using the test set. In this study, the target value of iterations was 1000, but the ANN model stopped at 7 iterations (minimum error) as shown in Figure 5.

## Results and discussion

To identify the best network architecture for BOD, TN, TP, TSS, and pH prediction for the treated effluent, a network with 12 inputs and 5 outputs was established. Table 2 compares the ANN and RSM's prediction responses to experimentally collected data. The model's statistical performance results are shown in Table 2. All configurations are calculated to get the values in the table (training, testing and validation) The error levels are reasonable and within the predicted range based on the statistical performance for the output prediction. As a result, it can be inferred that the ANN model generalizes the data effectively and is probably capable of making precise predictions when new data are presented.

The linear regression plot for the best-performing model from each configuration is shown in Figure 6. The comparison plot between the predicted and actual data is shown in Figure 7 based on the MSE values, and the ANN model shows an acceptable fit. As a consequence, it was agreed that the best design for output prediction would consist of an input layer with 12 neurons, a hidden layer with 40 neurons, and five output layer neurons. This study addresses the issue of how to apply an ANN model to diagnose the dynamic behavior of Samsun WWTP and capture the intricate interactions that exist between process variables. By creating an ANN model for projecting plant performance based on previous observations of some important product quality characteristics, the plant may be operated and controlled safely. The network's training window's regression button in MATLAB carries out a linear regression between the outputs of the network and their respective goals. The best model regression results are displayed in Figure 6. For testing (R-value= 0.88712), validation (R-value= 0.90496), and training (R-value= 0.98645), it is shown that the output closely follows the targets. These numbers can be translated into a five-output total response with an R-value of 0.95294. The ANN model's prediction results for the validation and testing data set were determined to be good (refer to Figure 7).

To predict BOD, TN,TP, TSS, and pH, a conventional ANN model with backpropagation integrated with the LM method is created. The best model for predicting the performance of the WWTP among the candidate models described above is the MLP one hidden layer-based outputs prediction model with 40 neurons in the hidden layer because, in contrast, the reason the R values are closer to each other for the training, validation, and test sets is minimal. The analysis of performance statistics is supported by the depiction of the measured output values in comparison to the predicted values of the MLP network. Figures 8 and 9 show the performance of MLP and RBF neural networks, respectively. The plot of MSE against the number of epochs for the training, validation, and test datasets is shown in Figure 8. The ANN simulation terminates when either the minimum MSE is reached or the maximum number of training epochs have been used, whichever comes first. When the training process reached epoch 2, the MSE gradually fell with increasing iteration numbers. Additionally, the MSE significantly decreased and peaked at epoch number 7, when its value was the lowest.

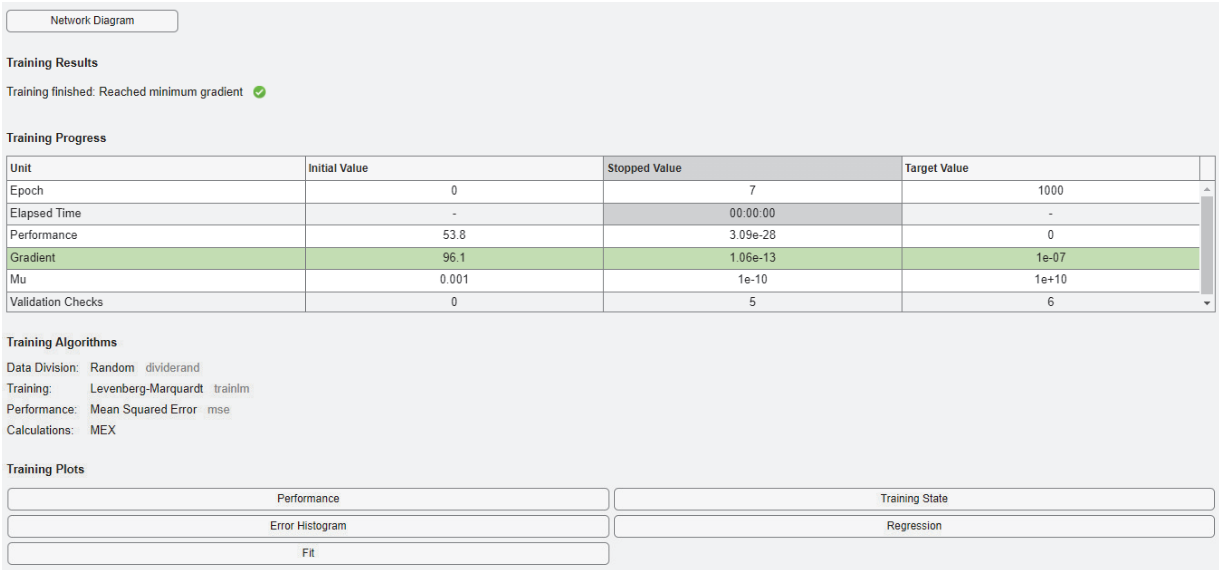


**Fig. 5.** Neural network training interface

**Table 2.** Performance statistics for the output's prediction models

| ERROR | The error between observation and ANN | | | | |
|---|---|---|---|---|---|
| | **BOD (mg/L)** | **TN (mg/L)** | **TP (mg/L)** | **TSS (mg/L)** | **pH** |
| **MAD** | 0.9492 | 0.4676 | 0.0904 | 1.0440 | 0.0913 |
| **MSE** | 1.8367 | 0.4432 | 0.0123 | 2.5914 | 0.0198 |
| **RMSE** | 1.3553 | 0.6657 | 0.1107 | 1.6098 | 0.1408 |
| **MAPE** | 0.1197 | 0.0800 | 0.1832 | 0.1020 | 0.0126 |

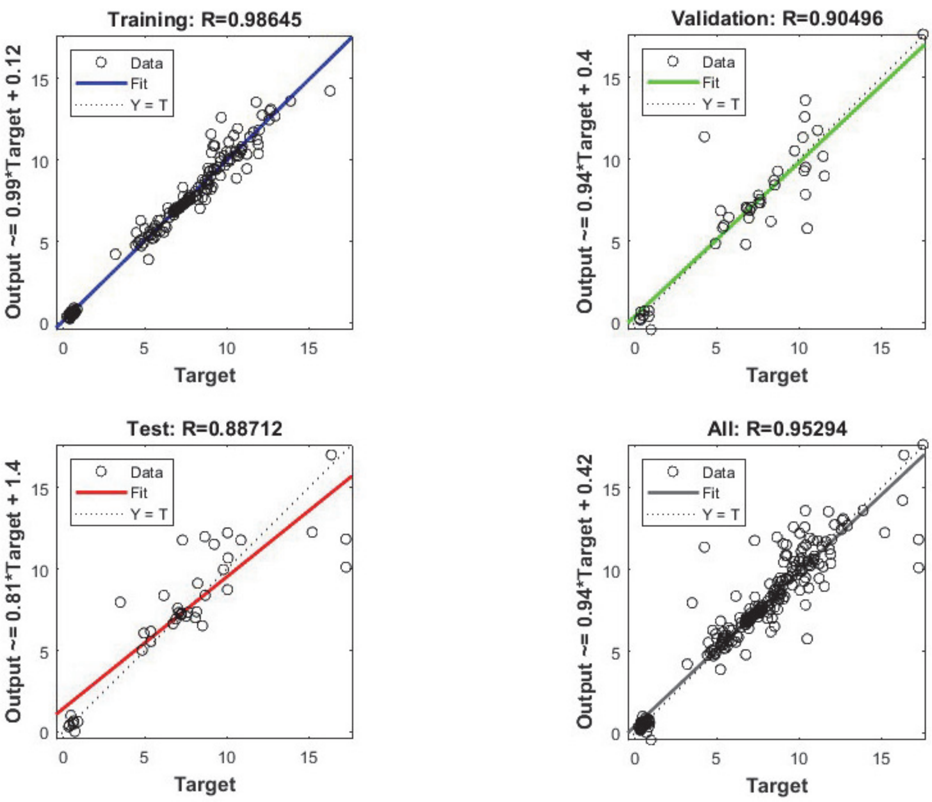


**Fig. 6.** The distribution of the measured data and predicted values for the ANN model (Regression plot for the best performing)

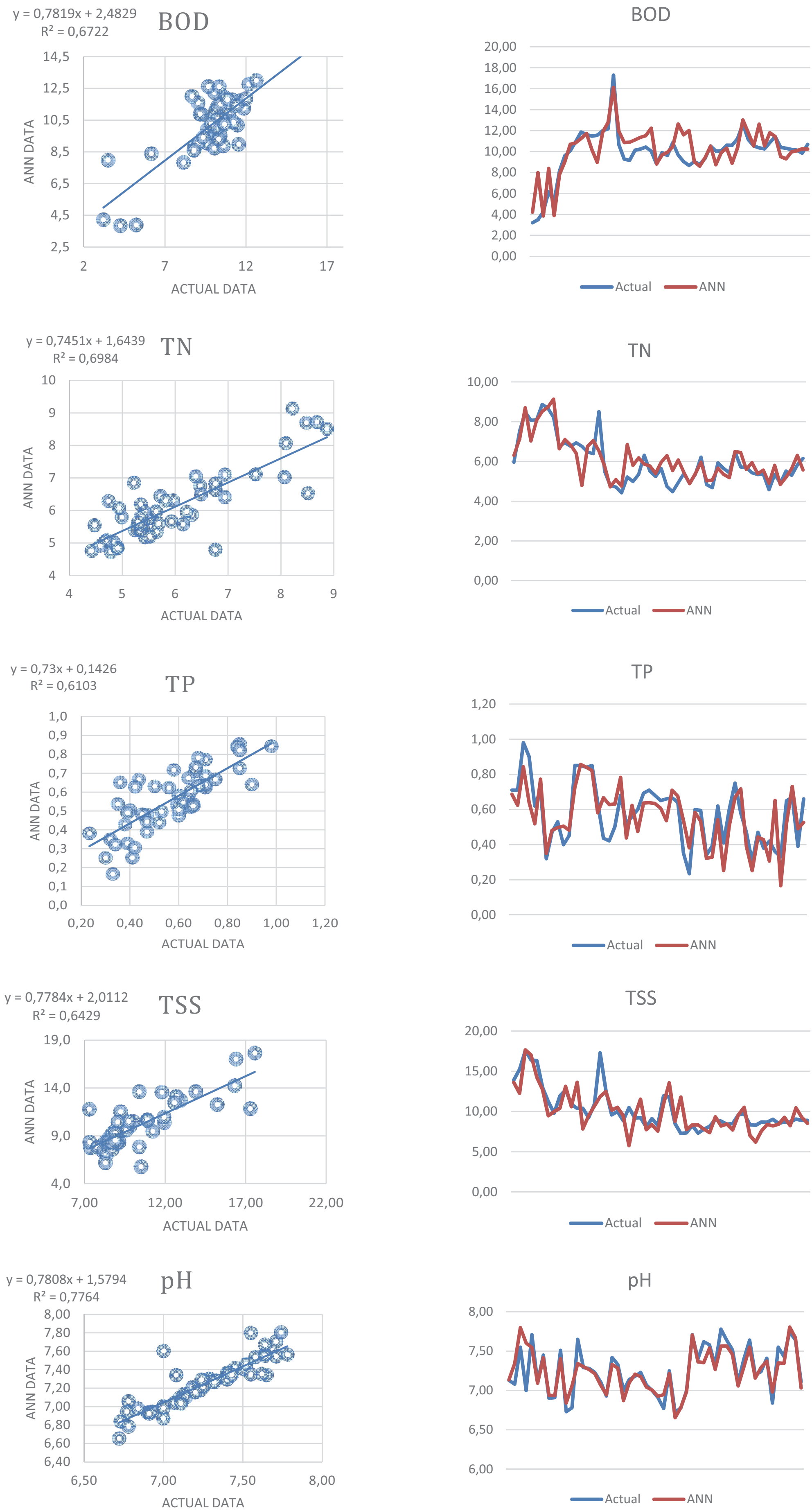


**Fig. 7.** A parity plot depicting the distribution of experimental and predicted percentage reduction values for BOD, TN, TP, TSS and pH

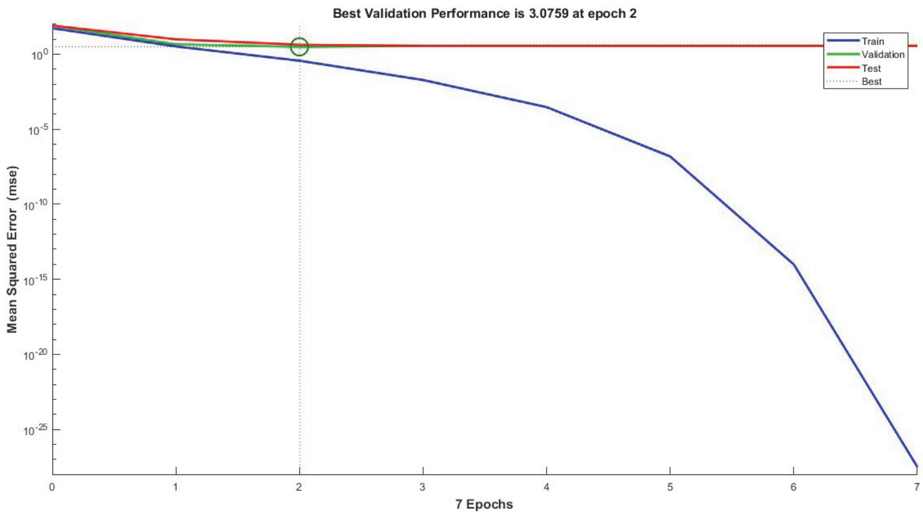


**Fig. 8.** MLP network training performance

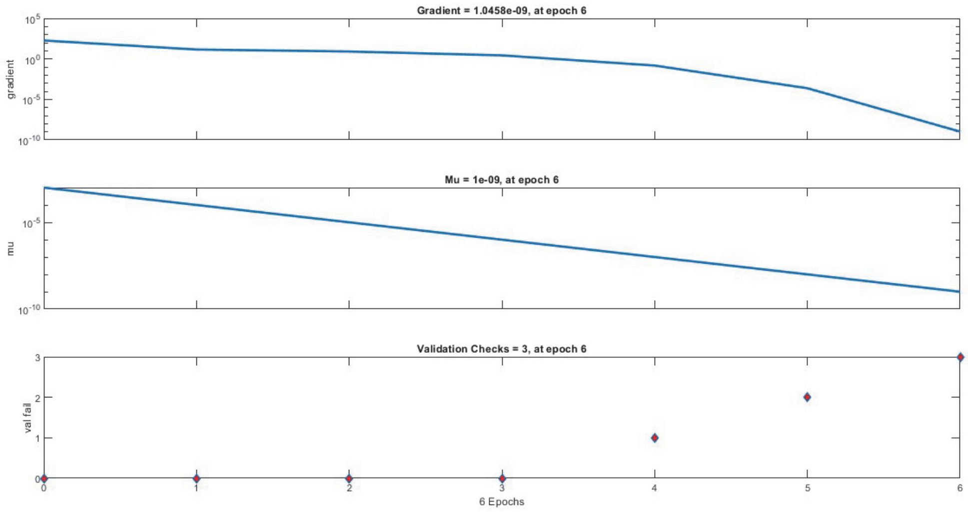


**Fig. 9.** RBF network training performance

How many data points are close to the bin value is indicated by the height of the bar in a bar plot, as seen in Figure 10. Yet, the output is very close to the target value and the NN model performs well because errors are almost zero. The bin number supplied in the histogram function (i.e., histogram(data,20)) determines the error values; if you use a different bin value, the error values may change. You can try bin numbers 50 or 100. The bin number that is closest to 0 becomes the wrong value. Since an error of zero suggests that the outputs are close to the target, the model performs well if the bin bars at zero are taller than higher error values (Alnajjar & Üçüncü, 2023).

This study differs from others in that it simultaneously predicted the values of five outputs while building and training neural networks using a sizable number of inputs. It can be said that the results of the model can be relied upon to predict the output values of wastewater treatment plants because the error values were low, with the MAD, MSE, RMSE, and MAPE being less than 0.6786, 0.7576, 0.8704, and 0.1276 respectively, and the coefficient of determination is 0.8838, 0.8080, 0.8099, 0.8876, and 09396 for each of BOD, TN, TP, TSS, and pH.

Given that a sufficient number of inputs and variables were used in the model's development, the neural network model that was built, trained, and tested using the data from the Samsun Eastern Advanced Biological Wastewater Treatment Plant was more accurate than that used in earlier studies. It could also be used to predict the output of other wastewater treatment plants. In contrast to earlier studies, the data acquired covered a considerable amount of time.

## Conclusions

The built ANN models successfully forecasted the WWTP performance based on the effluent BOD, TN, TP, TSS concentrations and pH in the treatment plant. The key factor contributing to the model's subpar performance was noise in the data used to develop the ANN. The results demonstrated the need for prior data preparation and analysis for ANN training. The complexity of the network setup (number of inputs, hidden layers, and neurons) should be steadily increased until no further development is seen. In this study, a design with twelve inputs and five outputs was sufficient; any more inputs would have caused the system to become overfitted.

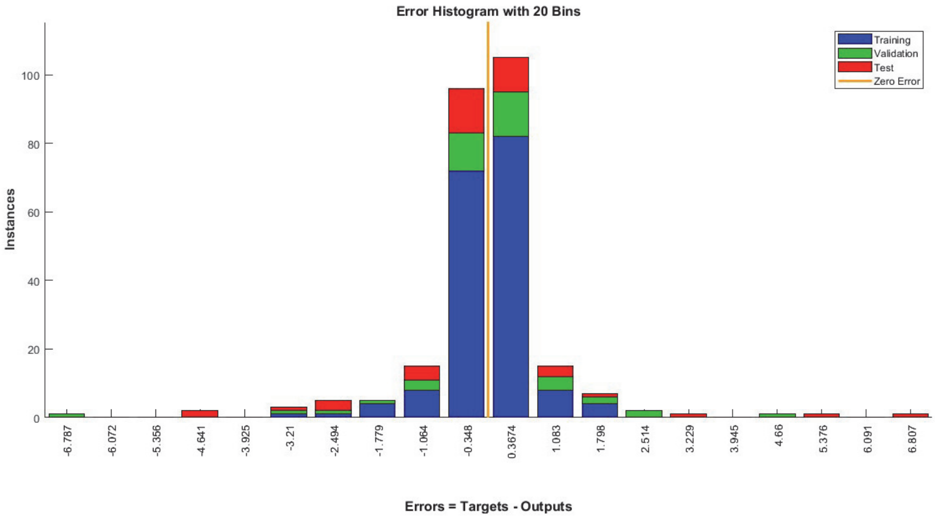


**Fig. 10.** Error histogram for ANN model to get zero error

The neural network's best models were created using the MLP-BP with three layers, the tansig activation function at a hidden layer with 40 neurons, the purelin activation function at the output layer, and the LM training method with seven iterations. According to the ANN forecast, the outputs from the experiment and the simulation were nearly identical. Having greater R and lower MSE values during ANN training with low experimental values of input data shows that the MLPANN produces accurate findings. The results demonstrate that this soft sensor model can be successfully applied to online control and management systems for WWTPs.

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