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Modeling of Activated Sludge Process Using Multi-Layer Perceptron Neural Networks

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ABSTRACT

Mathematical Modeling of the activated sludge process (ASP) enhances the understanding of the process and improves the quality of the effluent released. However, as the process is complex and nonlinear, mathematical modeling of the process has been a challenge. In this study, multi-layer perceptron neural networks (MLP-ANN) are investigated to predict water quality parameters for better control of wastewater treatment plants employing an activated sludge process. The study area selected was in a central district of the southern state of India. The parameters to be investigated are biochemical oxygen demand (BOD), suspended solids (SS), and pH. The model is evaluated based on statistical parameters of correlation coefficient R and mean square error (MSE). The neural network toolbox of MATLAB 2015b is used for modeling and simulation study. It has been found that effluent biochemical oxygen demand was predicted with a maximum correlation coefficient of 0.927 and minimum mean square error of 0.0022, effluent suspended solids were predicted with a maximum correlation coefficient value of 0.947 and minimum mean square value of 0.0058, effluent pH was predicted with a maximum correlation coefficient value of 0.8299 and minimum mean square value of 0.0132.

INTRODUCTION

India has finished at the bottom of the Environment Performance Index-2022 released by the World Bank. This means India is among those countries in the world that have the worst environmental health. Out of 180 countries that have been ranked, India is in the bottom five with a score of 18.9. The study area selected is in a central district of the southern Indian state of Kerala.

Water resources management and planning require the development of the evaluation system and processes for the maintenance of effluent water quality parameters and conforming to health and environmental standards. (Hamed et al. 2004). Treatment of wastewater using biological processes has been found very promising and the activated sludge process (ASP) is one of the most preferred processes among them. It utilizes microorganisms like bacteria to remove contaminants by digesting them. Mathematical models are required for better control of treatment plants so that treated effluent conforms to environmental standards. Also tuning of operating parameters can be studied more effectively by models and alternate control strategies can be developed on computers without the need for actual systems. (Pai et al. 2011). Simulations of models using operating parameters lead to rapid responses in the event of unforeseen changes in processes, (Nair et al. 2016); Several mechanistic models were developed and used as the mechanistic models can predict beyond the range of data, but these techniques require a large amount of data and have complex nonlinear interaction between variables, (Fu & Poch 1995). Also, several factors which affect plant performance and are part of mechanistic model representation are routinely not monitored in actual plants. (Henze et al. 1987). Also, unpredictable conditions such as toxic material release, and explosions, (Manfred et al. 2002) are difficult to model.

Artificial Intelligence (AI) approaches mimic the human ability of learning and rational problem solving for better control of complex engineering systems. Artificial neural networks (ANN) are employed to model wastewater treatment processes due to high accuracy, less time for model development, and a limited amount of data required, (Pareek et al. 2002). Artificial neural networks require no explicit knowledge of processes and parameters and develop knowledge through historical observations of input-output data. They learn by examples and with suitable design, accurate predictions are obtained. However, the

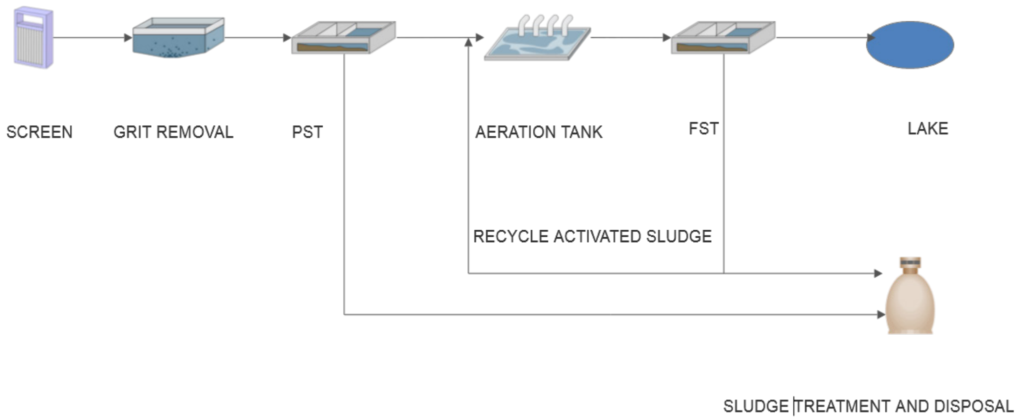

Fig. 1: Schematic of the sewage treatment plant.

limitation of the artificial neural network is that they do not compute outside the range of training data, (Vos & Rientjes 2005).

In the activated sludge process many variables are utilized to evaluate plant operation. These variables include biochemical oxygen demand (BOD), chemical oxygen demand (COD), total suspended solids (TSS), pH, etc. The literature survey done in this study area has used these variables and found that modeling sewage treatment plants using artificial neural networks is an effective tool in predicting effluent parameters.

The outcome of this research was to find the best model which represents the activated sludge process in terms of BOD, SS, and pH prediction. The data collected were fluctuating under different seasons and periods of the year. The study was conducted to model STP performance by using soft computing techniques of feed-forward multilayer perceptron artificial neural networks (FFMLP). The main aim was to find the best network structure of the artificial neural network for predicting effluent parameters.

MATERIALS AND METHODS

Study Area

The sewage treatment plant studied is situated in a central district of the southern state of Kerala in India. The plant which started its operation in 1970 can treat wastewater at 5 million liters per day.

As shown in Fig. 1, the plant consists of a typical STP in which influent wastewater passes through a screen, grit chamber, primary settling tank, aeration tank, and final settling tank. Secondary treatment is done in the aeration tanks after which the treated water is discharged into a nearby lake.

Data Collection and Analytical Methods

Data were analyzed from October 2008 to January 2022 and sampled and investigated once every month when the plant received good flow. The data for the influent stream was collected at the line after the grit chamber and that of the effluent stream was collected at the effluent line after the final settling tank. The influent and effluent parameters were stipulated as per the environmental regulations in force in the sewage treatment plant. The inputs were pH, oil and grease OG, suspended solids SS, and biochemical oxygen demand BOD and the output parameters modelled in this study were pH, SS, and BOD (Hamada et al. 2018). All influent and effluent parameters were measured according to IS 3025. A total of 113 data points were used for this study.

Further data normalizing was done according to equation (1)

$$Y_{Norm} = (Y - Y_{Min})/(Y_{Max} - Y_{Min}) \qquad \ldots(1)$$

Where Y represents the variable studied. The statistical parameters of the variables of STP are given in Table 1 where, Y_{max} = maximum value, Y_{min} = minimum value, Y_{mean} = mean value Sd = standard deviation and Cv = variance

Mathematical Modeling

Artificial neural networks (ANNs): The development of ANNs as a computational tool similar in working to the human brain started in 1940 (Lippmann 1988). Generally, artificial neural networks consist of layers of neurons in a connected structure from which output is generated. ANNs due to their ability to represent highly non-linear systems, high learning speed, and data processing are used in pattern recognition, classification, and problem-solving. ANN is a good tool for modeling relationships between several variables based on training data.

Table 1: Statistical indices of parameters.

	pH_{Inf}	SS_{Inf}	BOD_{Inf}	OG_{Inf}	pH_{Eff}	SS_{Eff}	BOD_{Eff}	OG_{Eff}
Y_{Max}	66	624	937	56	8.2	139	79	8.4
Y_{Min}	5.1	16	42.6	0.8	5.8	4	5.6	0
Sum	801.06	14757	38069.8	1330.4	803.91	4456.8	2344.23	216.34
Y_{Mean}	7.089	130.592	336.90	11.773	7.11	39.44071	20.74	1.91
Cv	31.79	7585.58	100565	85.959	0.24	2066.724	437.89	360.45
Sd	5.63	87.0952	317.12	9.2714	0.49	45.46124	20.925	18.98

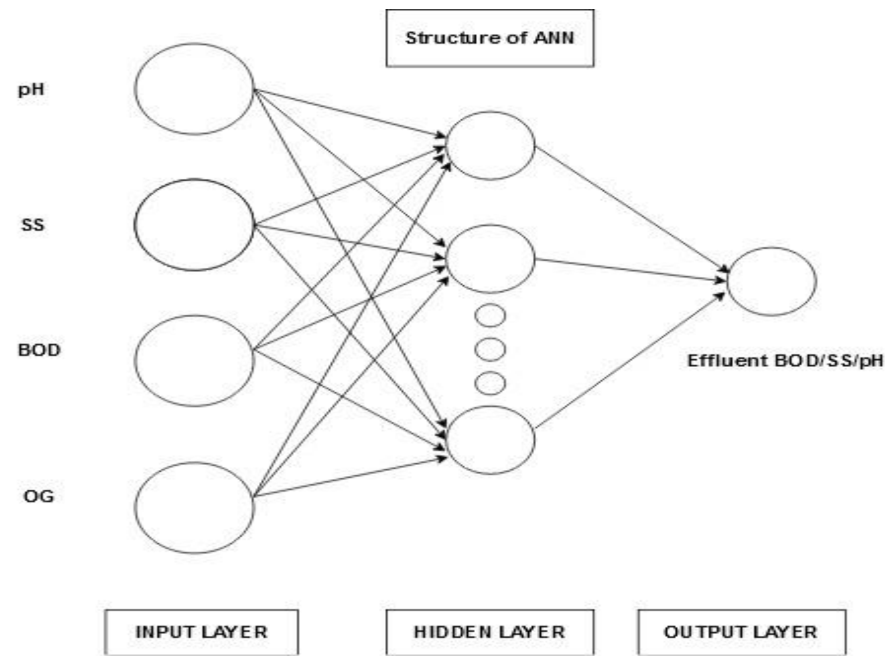

Fig. 2: Structure of ANN.

Fig. 2 shown below shows a feed-forward structure consisting of three layers of neurons. The first layer which receives the input data is called the input layer and sends these data to the second layer called the hidden layer. The hidden layer and the output layer perform the computations before producing the output.

The basic processing elements are the neurons that receive the input. The inputs are processed by activation functions to produce an output signal. Also, the connecting weights between neurons and the activation functions used to determine the output from each neuron. The mathematical expression of the neural network is given in Equation (2) below.

$$Y_i = f\left(\sum_{j=1}^{M} W_{ij} X_j + b_i\right) \quad \ldots(2)$$

Where, Y_i is the predicted output, f is the activation function, W_{ij} is the weight assigned to each input j, X_j is the input, M is the total number of inputs and b_i is the bias.

For predicting the effluent parameters in the STP, a three-layer feed-forward ANN structure was developed. The number of neurons in the input layer was equal to the number of influent parameters considered for training. The number of neurons in the hidden layer was found by trial and error and the number of neurons in the output layer was one which is the effluent parameter predicted in the study. The network needs to be optimized in terms of statistical parameters and avoid overfitting. (Geman et al. 1992)

ANN training and testing: The available data is divided into three parts. The first part is the training set, which is used for computing the difference between predicted and actual outputs and updating the weights and biases of the network. The second part is called the validation set which is used to find out the stopping point of neural network training. The training error and validation error are found during the training and it is generally seen that both errors tend to decrease initially. But when the network starts overfitting, the validation error starts to increase and training is stopped. The network parameters corresponding to minimum validation error are fixed and the optimum number of neurons in the hidden layer is returned. The third part of the data is called the testing data which is used to test the ability of the model to generalize to new data. Ideally, the testing error should be a minimum.

The performance of neural networks is determined by the number of hidden layers, the number of neurons in hidden layers, the transfer functions used in neurons, and the algorithms used in training. When the number of hidden layer neurons and subsequently the number of parameters in the network are less than the number of training data points over-fitting problems can be avoided.

The ANN network used the Levenberg-Marquardt back-propagation algorithm for training with one hidden layer. The backpropagation algorithm returns the error produced by neural networks to modify the connection weights and biases. The tangent hyperbolic function (Haykin 2009) Equation (3) is used in the hidden layer and the linear activation function Equation (4) is used in the output layer.

$$f(x) = \frac{2}{1+e^{-2x}} - 1 \quad \ldots(3)$$

$$f(x) = x \quad \ldots(4)$$

The performance of the model was determined by the correlation coefficient R equation (5) and mean square error (MSE) equation (6) calculated between predicted and measured data.

$$R = \frac{\left[\sum_{i=1}^{N}(Y_i - Y_{Mean})(P_i - P_{Mean})\right]}{\sqrt{\sum_{i=1}^{N}(Y_i - Y_{Mean})^2 \ \sum_{i=1}^{N}(P_i - P_{Mean})^2}} \quad \ldots(5)$$

$$MSE = \sum_{i=1}^{N} \frac{(Y_i - P_i)^2}{N} \quad \ldots(6)$$

Where, Y_i and P_i are the predicted and measured data, Y_{mean} and P_{mean} are the average values of predicted and measured data and N is the total number of data points. When the mean square error was at a minimum and the correlation coefficient was at a maximum the model was considered to be optimum.

ANN software: The software MATLAB 8.6 (Version–R2015b) (Math Works, Inc., USA) is used to perform neural network modeling and simulation. The ratio of 60:20:20 is used for data division, 60 per cent for training, 20 per cent for validation and 20 per cent for testing. The multilayer perceptron ANNs (MLP-ANNs) were used due to their simplicity and ease of coding.

The ANN is trained using a different combination of inputs containing up to a maximum of four inputs for each of the three output parameters used in this study. Table 2 shows the different combinations used. The data is normalized before training. To find the optimum number of hidden layer neurons, the performance of each network is evaluated by trial and error.

In the present study, the Levenberg-Marquardt (LM) back-propagation training algorithm is used as it is the fastest algorithm and converges quickly. The convergence of the network is also determined by the learning rate parameter which prevents the network from being trapped in a local minimum than the global minimum. The learning rate parameter was fixed as 0.01. Figs. 3, 4, 5 show ANN training for biochemical oxygen demand BOD, suspended solids SS and pH prediction.

RESULTS AND DISCUSSION

Correlation Matrix (CM)

The correlation matrix is a table showing the relationship between several variables. In Table 3, there exists a positive correlation between BOD_{Eff} and SS_{Inf}, BOD_{Inf}, and OG_{Inf} and a negative correlation between BOD_{Eff} and $pH_{Inf.}$ This is because the decomposition of suspended solids and oil and grease at the inlet stream will demand more oxygen leading to a positive correlation between BOD_{Eff} and SS_{Inf}, BOD_{Inf} and OG_{Inf} (Lelie et al. 2021) The negative correlation between BOD_{Eff} and $pH_{Inf.}$ is due to the fact that when pH goes above the normal range of 6-8, organisms which decompose organic materials may not survive and BOD_{Inf} will not decrease.

Table 2: Input parameter used in the study.

Input	Input parameter combination
Input1	pH_{Inf}
Input2	SS_{Inf}
Input3	BOD_{Inf}
Input4	OG_{Inf}
Input5	$pH_{Inf} + SS_{Inf}$
Input6	$pH_{Inf} + BOD_{Inf}$
Input7	$pH_{Inf} + OG_{Inf}$
Input8	$SS_{Inf} + BOD_{Inf}$
Input9	$SS_{Inf} + OG_{Inf}$
Input10	$BOD_{Inf} + OG_{Inf}$
Input11	$pH_{Inf} + SS_{Inf} + BOD_{Inf}$
Input12	$SS_{Inf} + BOD_{Inf} + OG_{Inf}$
Input13	$pH_{Inf} + SS_{Inf} + OG_{Inf}$
Input14	$pH_{Inf} + BD_{Inf} + OG_{Inf}$
Input15	$pH_{Inf} + SS_{Inf}\ BD_{Inf} + OG_{Inf}$

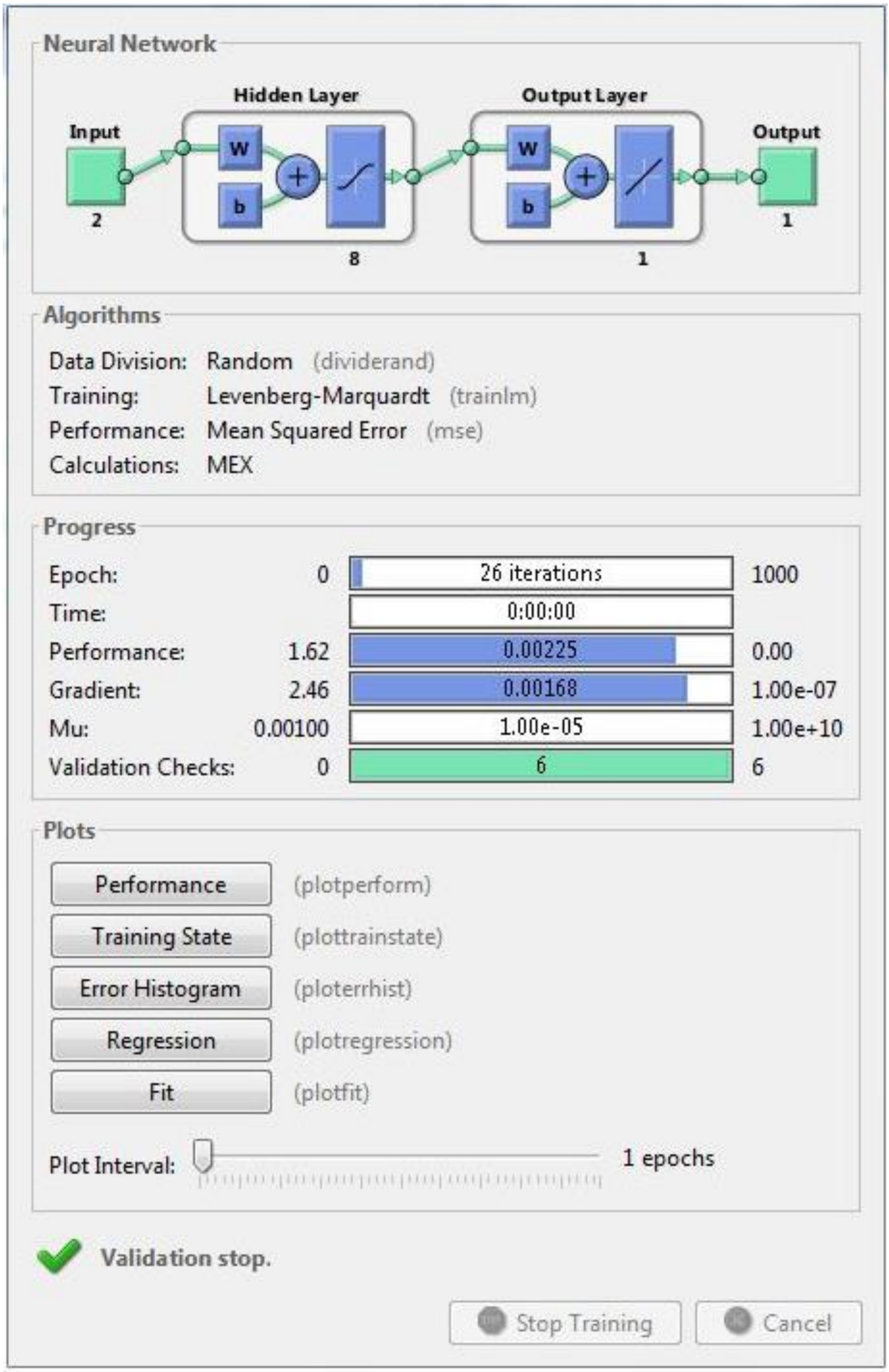

Fig. 3: ANN training for BOD prediction.

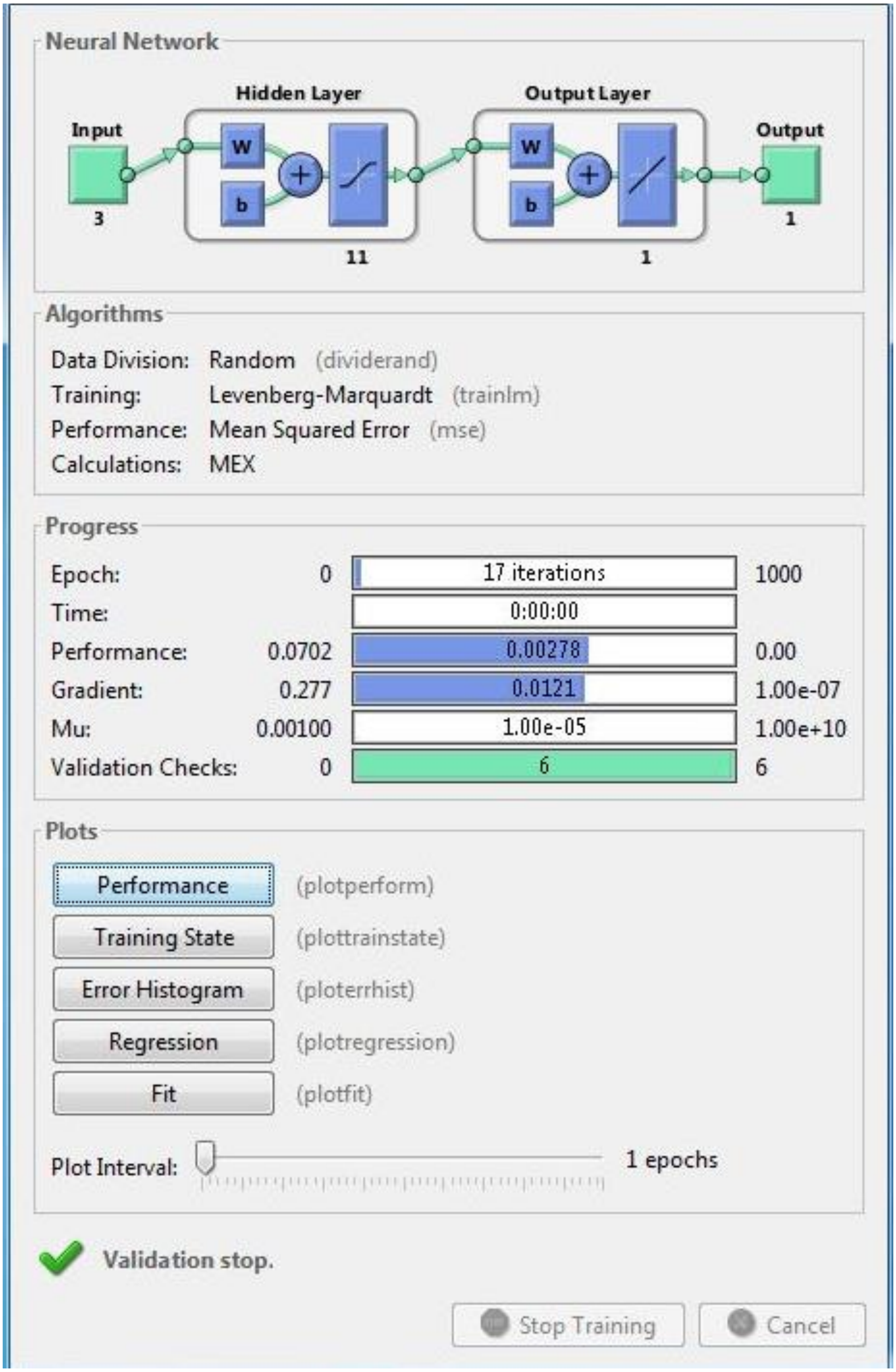

Fig. 4: ANN training for SS prediction.

Fig. 5: ANN training for pH prediction.

Table 3: Correlation matrix.

Parameter	pH_{Eff}	SS_{Eff}	BOD_{Eff}	OG_{Eff}
pH_{Inf}	0.18784	-0.0351	-0.1018	-0.0016
SS_{Inf}	-0.0925	0.61159	0.57309	0.62197
BOD_{Inf}	-0.1848	0.85927	0.54389	0.52597
OG_{Inf}	0.2057	0.29457	0.47785	0.26874

Similarly, there exists a positive correlation between SS_{Eff} on one hand and SS_{Inf} BOD_{Inf} and OG_{Inf} and a negative correlation between SS_{Eff} and pH_{Inf} respectively. The positive correlation is because oil and grease and particles contributing to biochemical oxygen demand may be themselves suspended in water. (Giokas et al. 2002) The weak negative correlation between SS_{Eff} and pH_{Inf} is because the acidic or basic nature of a substance doesn't influence its settling characteristics.

Parameters showing a positive correlation should be included in the modeling of BOD_{Eff} and SS_{Eff}. The meaning of a positive correlation coefficient is that the increase of one variable causes the other variable also to increase and vice versa. While $pH_{Eff\ is}$ positively correlated to pH_{Inf} and OG_{Inf}, it is negatively correlated to SS_{Inf} and BOD_{Inf}.

ANN Model Development

The performance of networks is evaluated by finding the optimum number of neurons in the hidden layer. A trial and error procedure is adopted to find out the optimum number of neurons. The performance of the network was compared using mean square error MSE and correlation coefficient R values. When the correlation coefficient was maximum and the mean square error was minimum, a model was considered to be the best. The results of developing one input, two inputs, three inputs, and four input models' model, (Mjalli et al. 2006) for the estimation of BOD, SS, and pH in terms of R and MSE are summarized in Tables 4, 5 and 6.

It is seen that two input models of pH and biochemical oxygen demand BOD are giving a maximum correlation coefficient R values of 0.927 and minimum MSE of 0.0022 with eight hidden layer neurons for effluent BOD prediction. The optimum network structure is given in Table 4. The regression curves of training, validation, testing, and total regression are shown in Fig. 6, the best neural network for predicting BOD is shown in Fig. 7, plots of measured and predicted BOD is shown in Fig. 8, and plot of error between predicted and measured BOD is shown in Fig. 9. The developed model performs to accepted standards of model development with a correlation coefficient greater than 0.9 and low mean square values.

It is seen that three input models of pH, biochemical oxygen demand, and oil and grease are giving a maximum correlation coefficient R values of 0.947 and minimum MSE of 0.0058 with seventeen neurons in the hidden layer for effluent SS prediction. The optimum network structure is given in Table 5. The combined regression curves are presented in Fig. 10, the best neural network for predicting SS is shown in Fig. 11, plots of measured and predicted BOD is shown in Fig. 12, and plot of error between predicted and measured BOD is shown in Fig. 13. The developed model performs to accepted standards of model development with a correlation coefficient greater than 0.9 and low mean square error values.

It is seen that three input models of pH, suspended solids and biochemical oxygen demand are giving a maximum correlation coefficient R values of 0.8299 and minimum MSE of 0.0132 with twenty-one neurons in the hidden layer for effluent pH prediction. The optimum network structure is given in Table 6. The combined regression curves are presented in Fig. 14, the best neural network structure for pH prediction is shown in Fig. 15, plots of measured and predicted BOD is shown in Fig. 16, and plot of error between predicted and measured BOD is shown in Fig. 17. Prediction of pH requires the study of more input parameters affecting pH for better correlation coefficient and mean square error values.

Most of the literature survey on the application of ANNs for modeling WWTPs utilized these variables and found that the ANN-based models provide an efficient and robust tool in predicting WWTP performance. For modeling wastewater treatment plants using ANN, (Hamoda et al. 1999) found a correlation coefficient of 0.74 for BOD prediction and .72 for TSS. Mjalli et al. (2004) predicted BOD with a correlation coefficient of 0.951 and TSS with a correlation coefficient R of 0.987. Abyaneh (2014) found RMSE = 25.1 $mg.L^{-1}$ and R = 0.83 for the prediction of BOD and Nasr et al. (2012) found that the ANN can predict the plant performance with a correlation coefficient of 0.903. Hamada et al. (2018) predicted BOD with a correlation coefficient of 0.786 and TSS of 0. 765. Alsulaili (2021) showed that the ANN model developed to predict the BOD concentration performed the best among the three outputs. The top-performing ANN models yielded R^2 values of 0.752 and 0.631 for the prediction of the BOD and TSS concentrations, respectively. Only a study done by Mjalli et al. (2004) gives a better prediction of BOD and TSS although the number of neurons used in that study was comparatively higher.

Sensitivity of Input Parameters

Analysis of the sensitivity of input factors for each predicted output was carried out by keeping the number of neurons in the hidden layers constant and using the same network

Table 4: Optimized neural network structure for BOD prediction.

Input parameter	ANN	Epoch	MSE	Train	Valn	Test	Reg	Train	Valn	Test
pH Inf	1-9-1	13	0.0064	0.0072	0.0035	0.0054	0.7707	0.7907	0.5514	0.7204
SS Inf	1-13-1	10	0.0069	0.0086	0.0026	0.0031	0.7508	0.7401	0.8621	0.7513
BOD Inf	1-10-1	10	0.0028	0.0023	0.0024	0.0054	0.91	0.9367	0.854	0.8456
OG Inf	1-3-1	408	0.0078	0.0049	0.0254	0.0037	0.7143	0.7709	0.8024	0.6349
pH Inf + SS Inf	1-10-1	11	0.007	0.0081	0.0048	0.004	0.747	0.767	0.7572	0.6369
pH Inf+ BOD Inf	1-8-1	6	0.0022	0.0025	0.0021	0.0009	0.927	0.92	0.954	0.8801
pH Inf + OG Inf	1-13-1	9	0.0059	0.0026	0.0058	0.0209	0.8302	0.8103	0.9361	0.9119
SS Inf + BOD Inf	1-11-1	10	0.0031	3.60E-03	0.0021	0.0017	0.9057	0.9079	0.9094	0.9366
SS Inf + OG Inf	1-8-1	13	0.0063	0.0076	0.0053	0.0016	0.783	0.7444	0.8632	0.8523
BOD In f+ OG Inf	1-14-1	15	0.0036	0.0021	0.013	0.0008	0.8806	0.861	0.8748	0.9445
pH Inf + SS Inf + BOD Inf	1-10-1	8	0.0043	0.0053	0.002	0.0023	0.8579	0.8604	0.8911	0.8062
SS Inf + BOD Inf + OG Inf	1-11-1	25	0.0026	0.0021	0.003	0.0046	0.9139	0.932	0.7715	0.9395
pH Inf + SS Inf + OG Inf	1-9-1	15	0.0029	0.0029	0.0024	0.0036	0.9071	0.9072	0.777	0.9653
pH Inf + BD Inf + OG Inf	1-7-1	21	0.0027	0.0032	0.0014	0.0013	0.9111	0.9182	0.8663	0.7995
(pH + SS + BOD + OG)$_{Inf}$	1-7-1	11	0.0028	0.0023	0.0013	0.0066	0.9079	0.9277	0.9205	0.9229

Table 5: Optimised neural network structure for SS prediction.

Input parameter	ANN	Epoch	MSE	Train	Valn	Test	Reg.	Train	Valn	Test
pH Inf	1-10-1	27	0.017	0.0168	0.0176	0.0173	0.8312	0.8241	0.8822	0.788
SS Inf	1-13-1	35	0.0181	0.015	0.022	0.028	0.821	0.845	0.833	0.7033
BOD Inf	1-16-1	10	0.0093	0.0082	0.0192	0.0049	0.9115	0.933	0.83	0.95
OG Inf	1-14-1	15	0.0203	0.0183	0.0358	0.014	0.794	0.806	0.737	0.827
pH Inf + SS Inf	1-10-1	7	0.0167	0.0151	0.0196	0.0215	0.8385	0.867	0.823	0.6889
pH Inf + BOD Inf	1-13-1	9	0.9182	0.9213	0.934	0.9159	0.0086	0.0075	0.0087	0.0138
pH Inf + OG Inf	1-6-1	25	0.0124	0.0096	0.0052	0.0324	0.881	0.8988	0.9539	0.789
SS Inf + BOD Inf	1-11-1	9	0.0109	0.0119	0.0149	0.0051	0.8988	0.905	0.877	0.952
SS Inf + OG Inf	1-2-1	29	0.0127	0.0146	0.0114	0.0048	0.8788	0.873	0.879	0.938
BOD Inf + OG Inf	1-4-1	18	0.0081	0.0097	0.0056	0.0031	0.9238	0.919	0.946	0.9341
pH Inf + SS Inf + BOD Inf	1-7-1	24	0.0067	0.0055	0.0126	0.0063	0.9383	0.946	0.9381	0.9289
SS Inf + BOD Inf + OG Inf	1-7-1	20	0.0079	0.0068	0.0114	0.009	0.9259	0.9251	0.892	0.8926
pH Inf + SS Inf + OG Inf	1-5-1	32	0.0082	0.007	0.0043	0.0178	0.9226	0.9334	0.9742	0.8307
pH Inf + BD Inf + OG Inf	1-11-1	17	0.0058	0.0039	0.0041	0.0161	0.947	0.959	0.969	0.9044
(pH+ SS+BOD+OG)$_{Inf}$	1-7-1	6	0.0057	0.005	0.0072	0.0073	0.9473	0.957	0.941	0.863

Table 6: Optimized neural network structure for pH prediction.

Input parameter	ANN	Epoch	MSE	Train	Valn	Test	Reg	Train	Valn	Test
pH Inf	1-10-1	7	0.023	0.0223	0.0314	0.018	0.6719	0.747	0.3944	0.44
SS Inf	1-11-1	55	0.0262	0.0262	0.0364	0.163	0.617	0.7638	0.7346	0.6221
BOD Inf	1-18-1	7	0.0275	0.0302	0.0192	0.0234	0.5902	0.5343	0.7445	0.6644
OG Inf	1-15-1	17	0.0325	0.0325	0.0508	0.014	0.475	0.525	0.182	0.55
pH Inf + SS Inf	1-5-1	26	0.0145	0.0093	0.0204	0.0327	0.809	0.8664	0.7585	0.6789
pH Inf + BOD Inf	1-15-1	15	0.0151	0.0135	0.0207	0.0165	0.8023	0.808	0.8405	0.707
pH Inf + OG Inf	1-9-1	12	0.019	0.0196	0.0149	0.0201	0.742	0.742	0.839	0.543
SS Inf + BOD Inf	1-9-1	8	0.0294	0.0295	0.0412	0.0174	0.5523	0.4351	0.449	0.5889
SS Inf + OG Inf	1-9-1	8	0.0346	0.0342	0.0512	0.0199	0.4207	0.483	0.959	0.324
BOD Inf + OG Inf	1-16-1	18	0.0235	0.0199	0.034	0.0295	0.6677	0.7277	0.5119	0.57
pH Inf + SS Inf + BOD Inf	1-21-1	11	0.0132	0.0116	0.0182	0.0153	0.8299	0.872	0.529	0.7374
SS Inf + BOD Inf + OG Inf	1-27-1	14	0.0235	0.0196	0.0299	0.0351	0.67	0.743	0.467	0.6313
pH Inf + SS Inf + OG Inf	1-21-1	9	0.0135	0.12	0.0155	0.0183	0.8244	0.8687	0.6142	0.6667
pH Inf + BD Inf + OG Inf	1-22-1	17	0.0134	0.0085	0.0254	0.024	0.826	0.8905	0.5978	0.6796
(pH+SS+BOD+OG)$_{Inf}$	1-14-1	13	0.0136	0.0075	0.04	0.0152	0.823	0.8966	0.3932	0.86

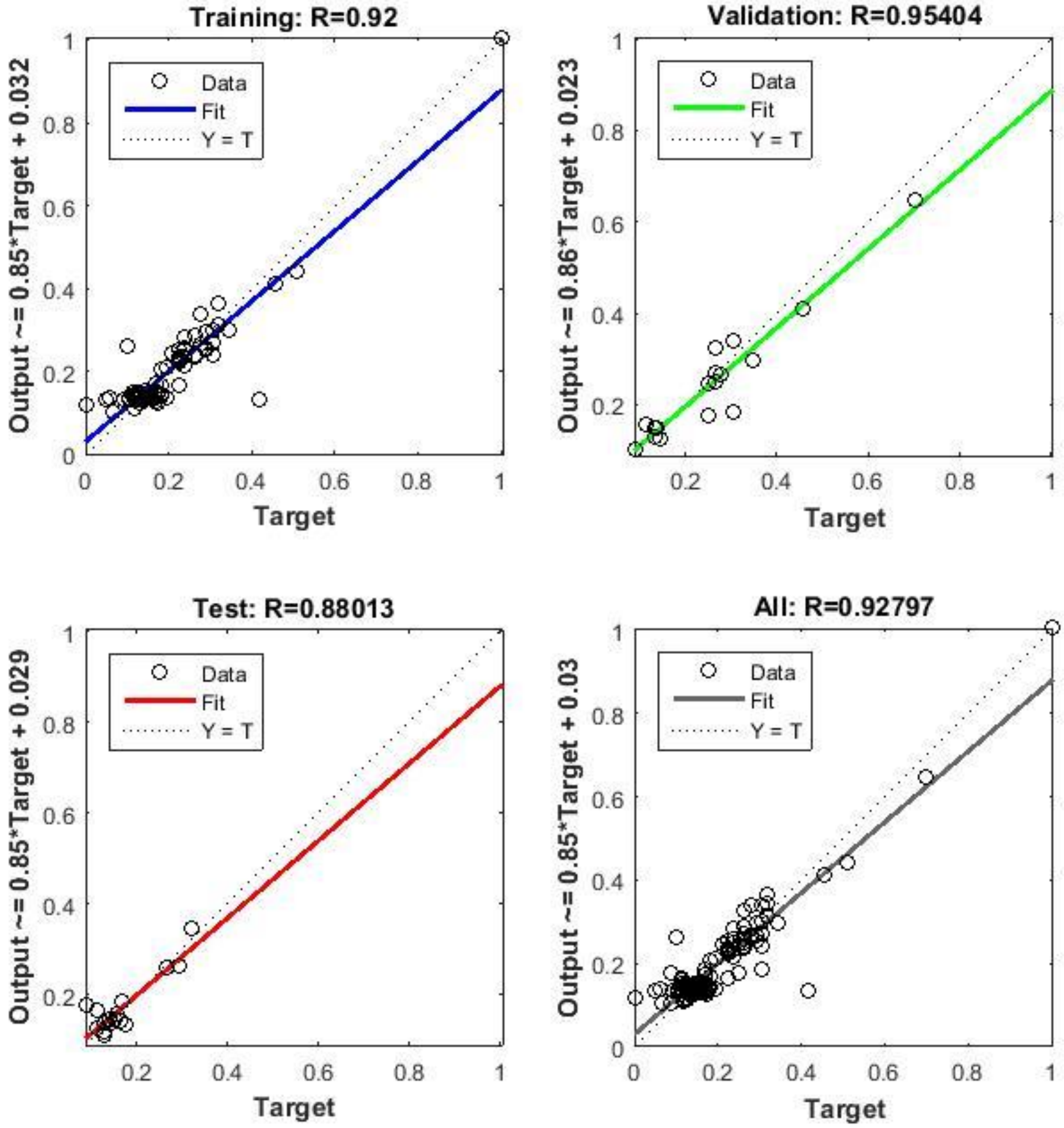

Fig. 6: Best regression curves of ANN for BOD prediction.

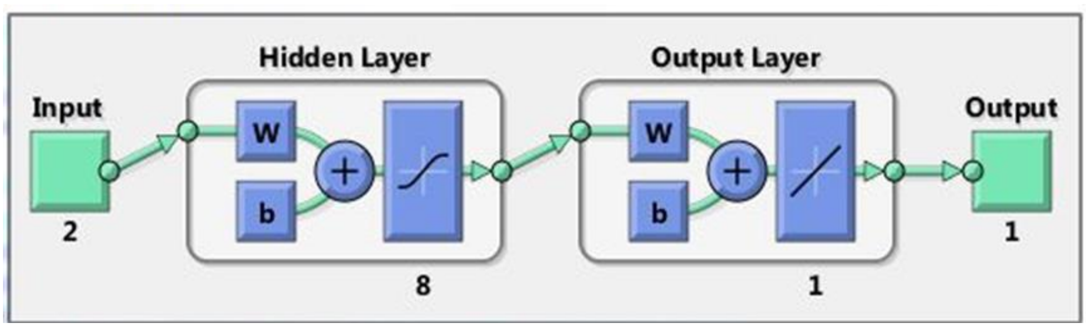

Fig. 7: Best ANN structure for BOD prediction.

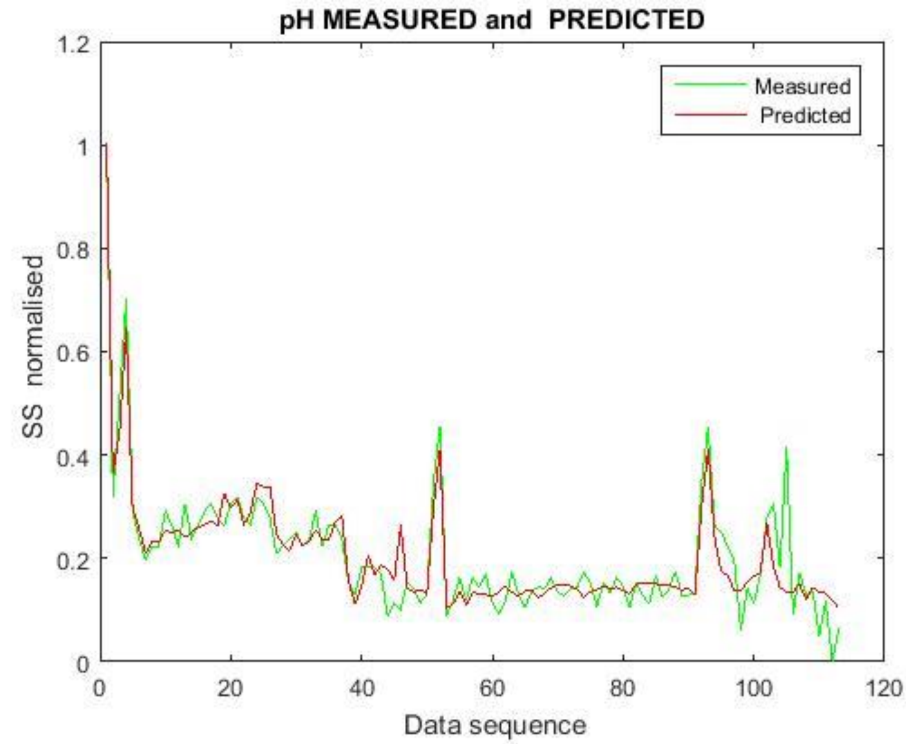

Fig. 8: Plot of measured and predicted BOD.

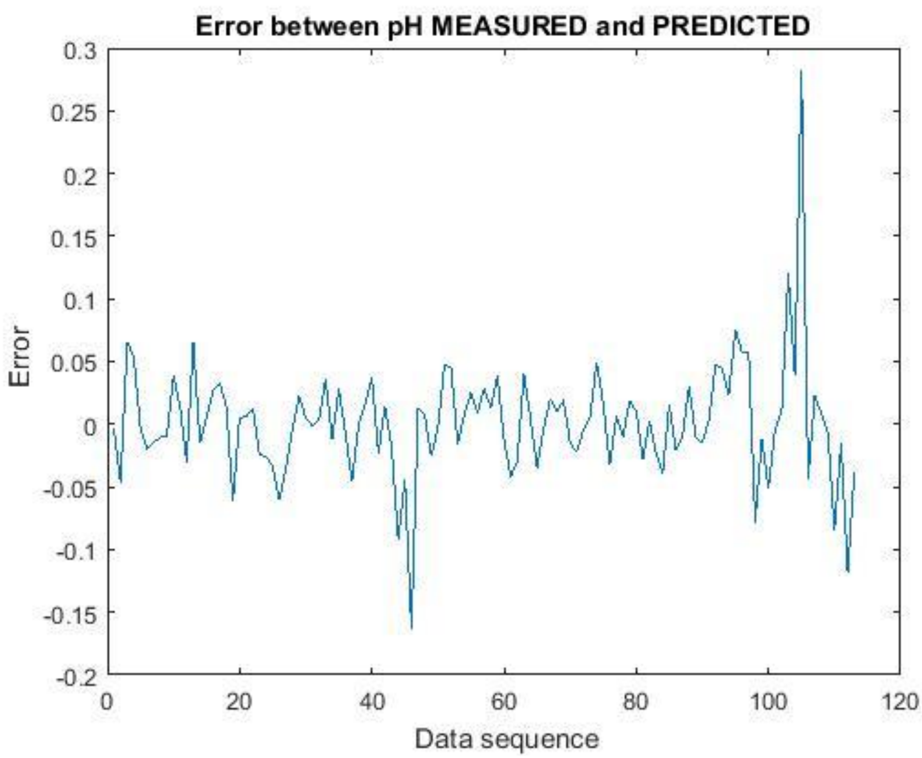

Fig. 9: Error between measured and predicted BOD.

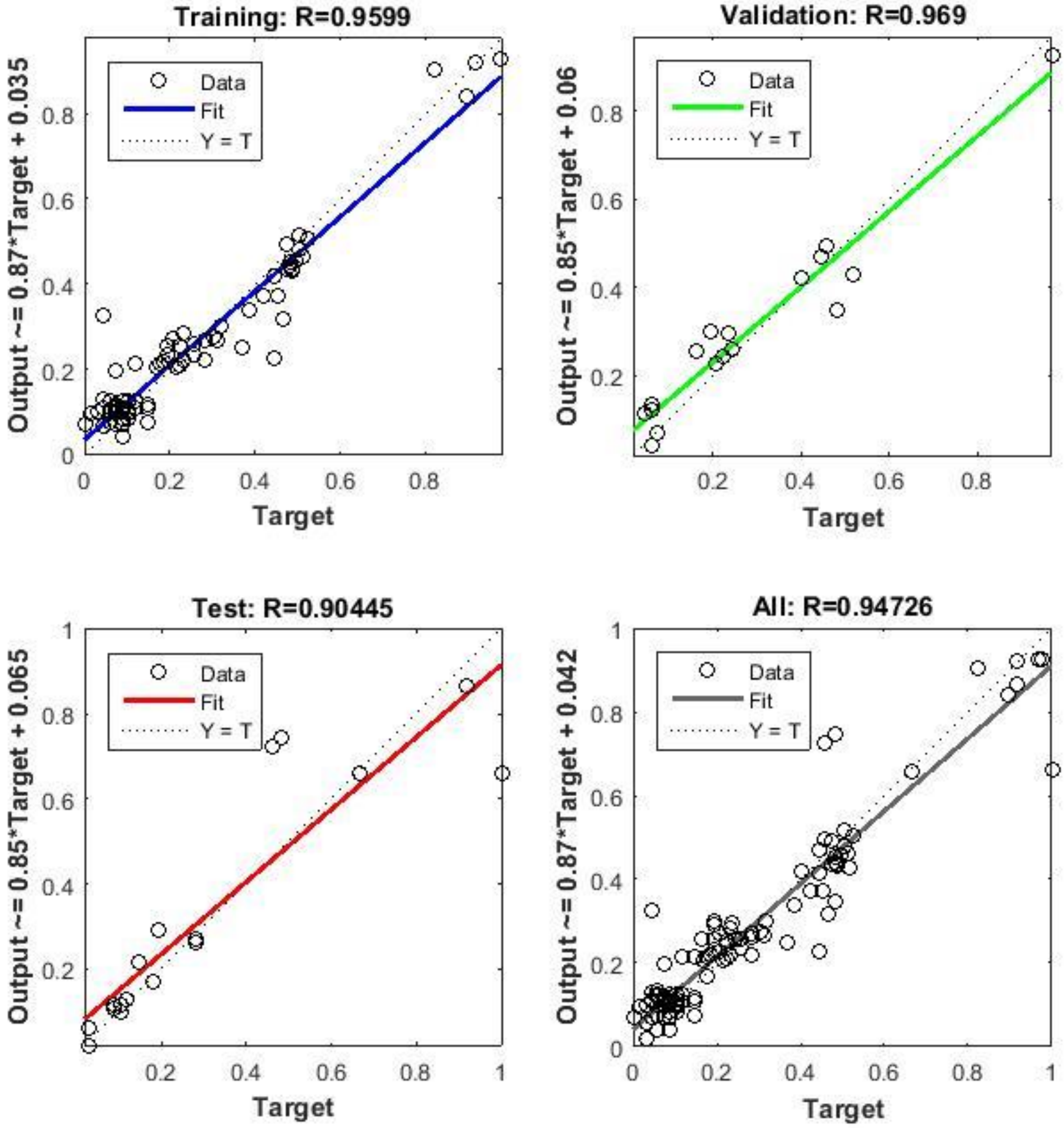

Fig. 10: Best regression curves of ANN for SS prediction.

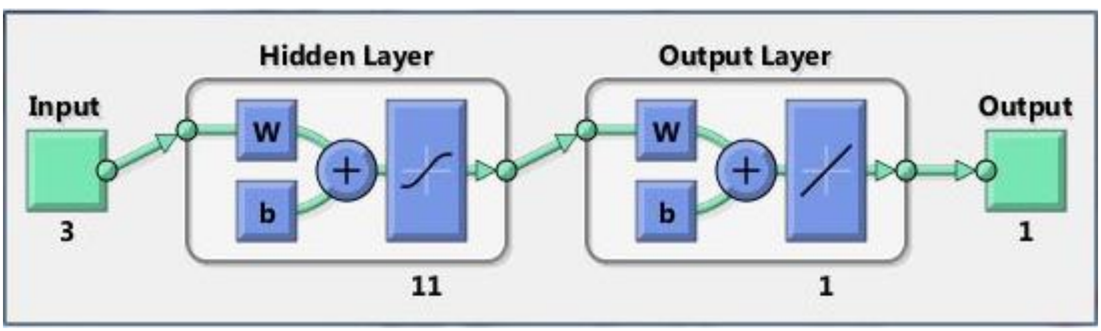

Fig. 11: Best ANN structure for SS prediction.

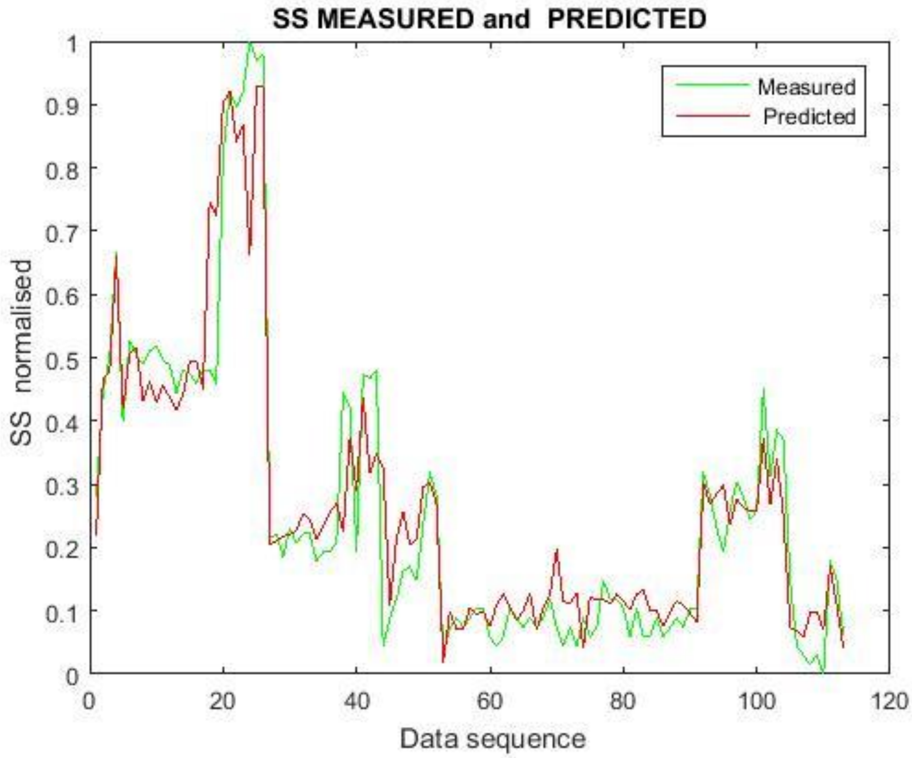

Fig. 12: Plot of measured and predicted SS.

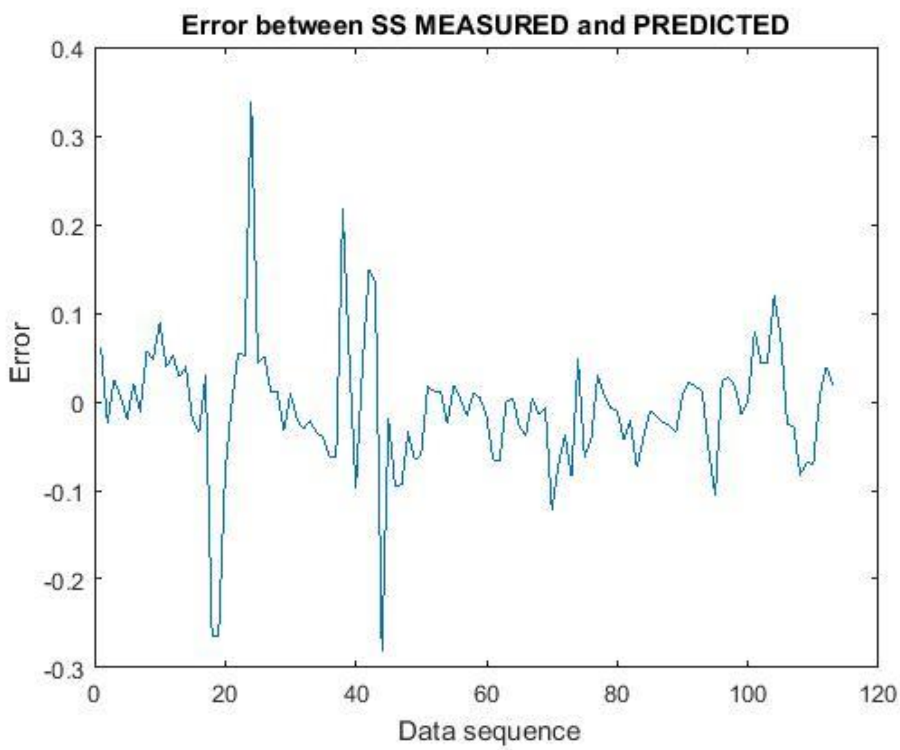

Fig. 13: Error between measured and predicted SS.

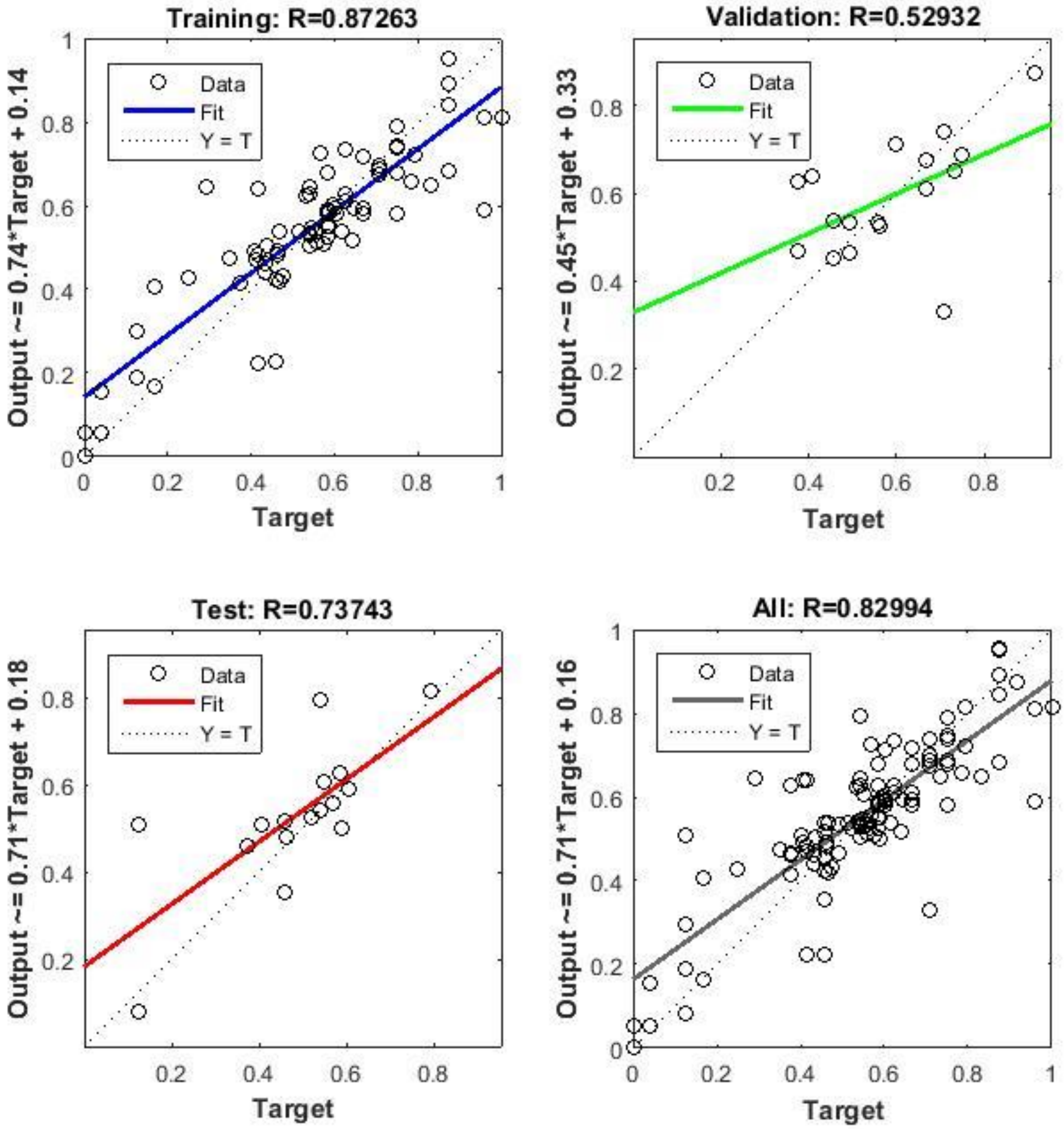

Fig. 14: Best regression curves of ANN for pH prediction.

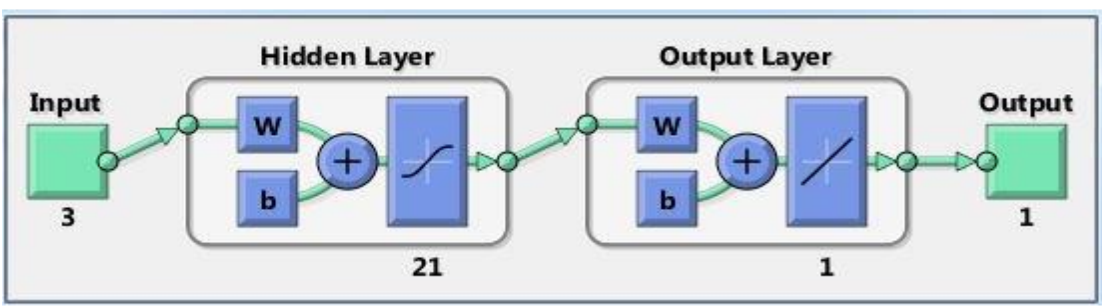

Fig. 15: Best ANN structure for pH prediction.

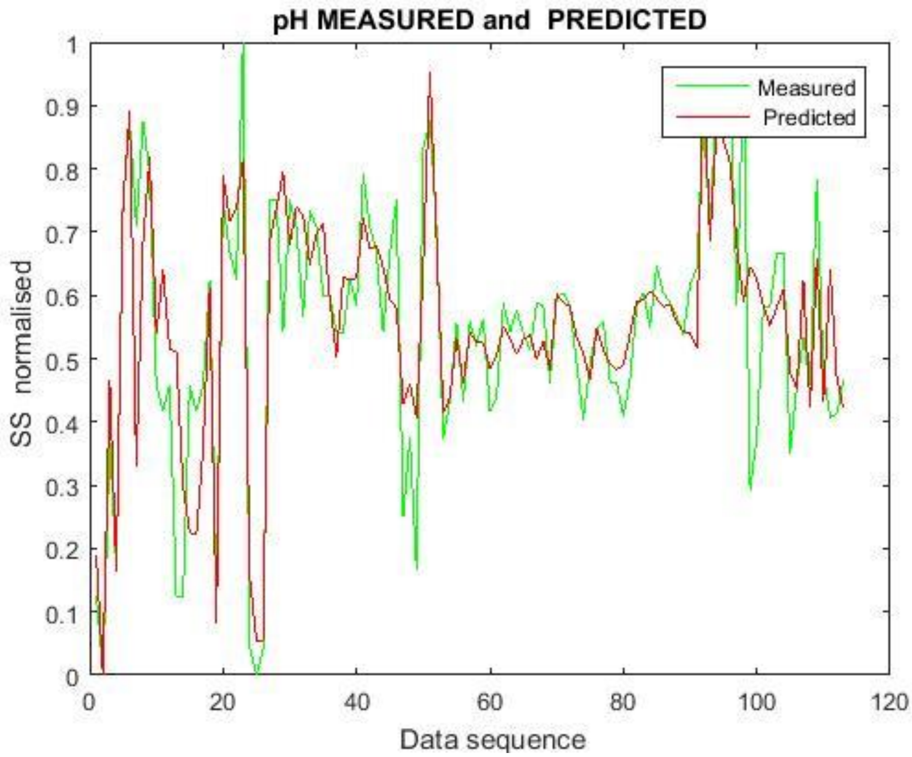

Fig. 16: Plot of measured and predicted pH.

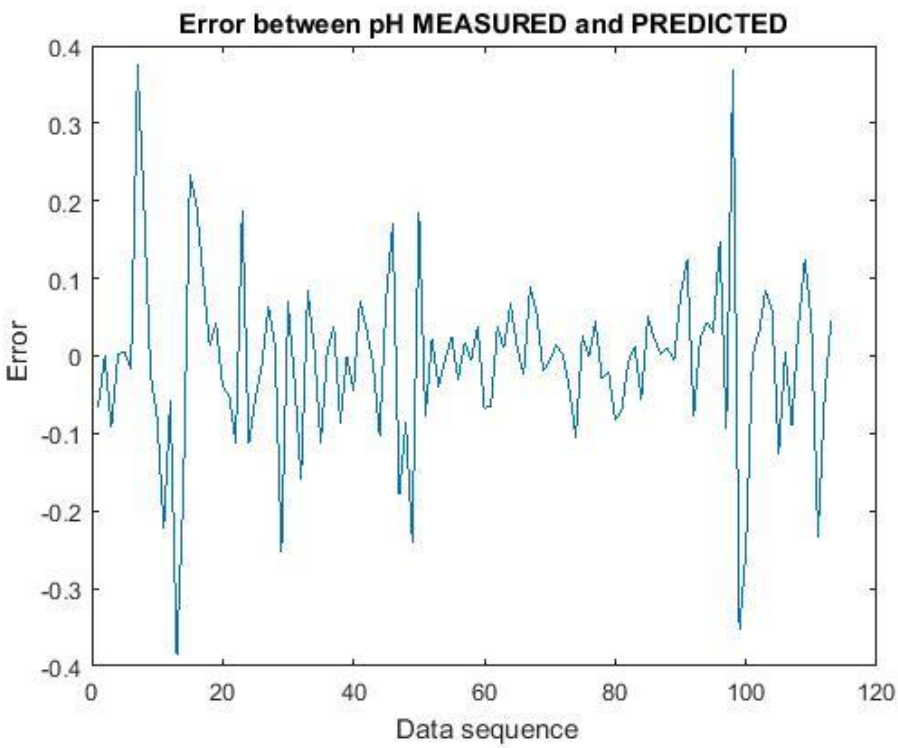

Fig. 17: Plot of error between measured and predicted pH.

parameters used in the network optimization study. For selecting the most important network input the periodic remove method was used where a particular input parameter was removed from the four different parameters and the mean square error was calculated.

The sensitivity analysis shows which input parameters are likely to have the greatest impact on the selected variables. This is done by error analysis where the individual variables are eliminated one by one from the input data. The greater the error computed after eliminating an input variable compared to the error computed with all the input variables together, the more sensitive the network becomes to the absence of this variable. The results of sensitivity analysis for biochemical oxygen demand, suspended solids and pH prediction are given in Tables 7, 8 and 9 respectively.

It has been found that for BOD prediction SS> pH >OG >BOD. It means that SS is the most sensitive parameter in BOD prediction followed by OG, pH and SS. This implies that suspended solids present in the influent stream are the biggest contributor to BOD at the outlet stream and is the most important parameter in predicting BOD (Hamada et al. 2018). For SS prediction pH >OG>SS>BOD and for pH prediction pH>SS. It means that for predicting suspended solids and pH with the least error pH at the influent stream is the most important parameter to be included in modeling.

Table 7: Sensitivity analysis for BOD prediction.

Input parameters for BOD prediction	Mean Square error
$pH_{Inf} + SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0028
$pH_{Inf} + BD_{Inf} + OG_{Inf}$	0.0027
$pH_{Inf} + SS_{Inf} + OG_{Inf}$	0.0023
$pH_{Inf} + SS_{Inf} + BOD_{Inf}$	0.0024
$SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0025

Table 8: Sensitivity analysis for SS prediction.

Input parameters for SS prediction	Mean Square error
$pH_{Inf} + SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0047
$pH_{Inf} + BD_{Inf} + OG_{Inf}$	0.0043
$pH_{Inf} + SS_{Inf} + OG_{Inf}$	0.0029
$pH_{Inf} + SS_{Inf} + BOD_{Inf}$	0.0061
$SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0142

Table 9: Sensitivity analysis for pH prediction.

Input parameters for pH prediction	Mean Square error
$pH_{Inf} + SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0217
$pH_{Inf} + BD_{Inf} + OG_{Inf}$	0.0262
$pH_{Inf} + SS_{Inf} + OG_{Inf}$	0.0193
$pH_{Inf} + SS_{Inf} + BOD_{Inf}$	0.0171
$SS_{Inf} + BOD_{Inf} + OG_{Inf}$	0.0341

CONCLUSION

Artificial neural networks-based modeling and simulation of any sewage treatment plant is effective in predicting its performance and controlling the operation of the plant resulting in the improved treated effluent. The modeling methodologies adopted with different combinations of input variables gave good predictions between the measured and predicted values.

Effluent biochemical oxygen demand BOD was predicted with a maximum correlation coefficient value of 0.927 and minimum mean square error of 0.0022 with eight neurons in the hidden layer. Effluent-suspended solids were predicted with a maximum correlation coefficient value of 0.947 and minimum mean square value of 0.0058 with seventeen neurons in the hidden layer. Effluent pH was predicted with a maximum correlation coefficient value of 0.8299 and minimum mean square value of 0.0132 with twenty-one neurons in the hidden layer.

From the sensitivity analysis, it has been found that the most important parameter for predicting biochemical oxygen demand is suspended solids followed by pH, oil and grease, and BOD at the influent stream. The most important parameter for predicting suspended solids is pH followed by oil and grease, suspended solids, and biochemical oxygen demand. Also, the most important parameter for predicting pH is pH followed by suspended solids at the influent stream.

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