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Artificial neural network based modeling for the degradation of tannery wastewater in sequential batch reactor

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ABSTRACT

Any wastewater treatment system must have a complete model to provide a tool for predicting the system's performance and to serve as the foundation for regulating the process's operation. This would save running expenses while also examining the stability of the environmental balance. This process is challenging and reaches a high degree of non-linearity due to the presence of bio-organic elements that are difficult to define using mechanistic techniques. Predicting plant operating characteristics using standard experimental approaches is time consuming and difficult, making it difficult to regulate such operations effectively. Using a radial function neural network, a research was successfully simulated to analyse the performance of sequential batch reactors on a lab scale. The information gathered is used in a neural network to treat tannery waste water in a sequential batch reactor. Degradation of organic compounds is represented in this method by a trained neural network. The degradation investigations used different dilutions such as 25%, 50%, 75%, and 100% for an initial substrate concentration of 6,240 mg COD/L and at different hydraulic retention times (5, 4, 3, and 2 d). The neural network-based model is thought to have been effective in establishing the system's properties with high precision. This research uses an artificial neural network (ANN) modelling technique to obtain the knowledge base of a genuine SBR, which is then used as a process model.

Keywords: Wastewater treatment; Artificial neural network (ANN); Multiple linear regression and absolute standard deviation; Radial basis

1. Introduction

Due to the growth in population and increased demand for leather, which was formerly manufactured on a small scale to suit local demands for footwear, drums, and musical instruments during ancient times, large commercial tanneries were built. The two most frequent processes for tanning raw hide/skin are vegetable tanning and chrome tanning. The production of high-intensity effluent in the region of 30 m^3 during the treatment of 1 tonne of skin/hide [1] has positioned tanneries as a high-polluting process. The qualities of the hide in its raw state and the end product in its needed form determine the various methods used in tanneries, resulting in a variety of tannery waste water. Tannery procedures are one of the most dangerous pollution-producing industries, with 300 kg of chemicals added per tonne of hide processing [2]. Heavy metals, hazardous compounds, chloride, lime with high dissolved and suspended salts, and other contaminants are all present in tannery effluent [4–7].

The artificial neural network (ANN) has established itself as a method of fast computing, and it is generating a lot of attention in the field of environmental engineering [8–12]. ANN has been successfully used to

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handle environmental engineering difficulties. In an effluent degradation research, using an artificial neural network reduces the number of trials required to define the system. The information processing methodologies used by the human brain inspired ANN, which is proving useful in a variety of engineering applications [13–17]. They are parallel computing tools made up of highly organised processing units called neurons that manage whole processing systems by making connections between objects in response to their environment. ANN has a remarkable capacity to extract meaningful information from complicated or inaccurate input. The ANN [18] can successfully extract huge, intricate trends for other computational approaches. An artificial neural network (ANN) is a mathematical model of human cognition or brain biology that has been generalised. Their primary benefit is that they can tackle issues that are too tough for standard technologies to address, such as those that lack an algorithmic solution or are too complicated to discover one. Back propagation and radial basis function (RBF) networks are two widely used networks in engineering systems for simulating non-linear situations.

Traditional feed forward back propagation networks require more neurons and take longer to train than radial basis networks [19]. The radial basis network function was effectively applied in this study to anticipate the degradation of tannery wastewater in SBR. The proposed radial basis function approach uses only a limited quantity of experimental data to anticipate the system's behaviour. The radial basis network function was successfully used to anticipate the organic matter breakdown of tannery effluent treated in SBR in this study. The suggested approach of applying radial basis function requires only a limited quantity of experimental data to predict the system's behaviour. A basic well-trained neural network can be utilised to address reactor modelling challenges without previous knowledge of the correlations between the process variables under investigation.

ANN, which is based on the concept of biological neurons, has proved successful in predicting the outcomes of chemical processes. ANN can successfully simulate non-linear models with numerous inputs. In addition, the ability of an ANN tool to cope with inconsistent and inaccurate data, as well as fault tolerance and sturdiness, are often used [20]. The ANN tool has been successfully used for prediction and simulation processes not only because of its ability to establish the link between input and output variables, but also because of its ability to anticipate the response precisely.

2. Materials and methods

In a sequential batch reactor, salt-tolerant bacteria such as *Pseudomonas aeruginosa*, *Bacillus flexus*, *Exiguobacterium homiense*, and *Styphylococcus aureus* constantly decomposed tannery effluent in distinct stages (SBR). The microorganisms were used in various forms such as mixed cultures (MC), mixed cultures with sorbent (MCS), salt tolerant microorganisms (STM) and salt tolerant microorganisms with sorbent (STMS). The input layer is made up of organic materials in the influent, whereas the output layer is made up of two variables (COD and colour). 75% of data points were utilised to train the neural network and 25% were used to test the applicability of ANN at varied hydraulic retention lengths of 5, 4, 3, and 2 d and at different starting substrate concentrations of 1,560; 3,220; 4,680 and 6,240 mg COD/L. To obtain information about the measured spots and train the network, several trial runs were conducted. In order to test the success of SBR in lowering COD and colour in tannery effluent, the Radial Basis Function network was trained to predict SBR performance.

The study utilized the starting substrate concentration (6,240 mg COD/L) as a parameter, with various dilution factors such as 25% (1,560 mg COD/L), 50% (3,120 mg COD/L), 75% (4,680 mg COD/L), and 100% (6,240 mg COD/L) at varied organic loading rates. The reactor was run for a total of 50 d, with the hydraulic retention time being kept at 5 d and an organic loading rate of 0.319 kg COD/m^{3}d being fed for 15 d. The OLR was then raised to 0.39 kg COD/m^3 on the 16th day while the hydraulic retention time was kept at 4 d. The OLR was maintained at 0.52 kg COD/m^3 from the 32nd to the 40th day, with a hydraulic retention time of three days. Finally, until the completion of the experiment, an OLR of 0.78 kg COD/m^3 was given with a hydraulic retention duration of 2 d, and COD was measured [21]. The lowering of colour was studied [22]. The pH was corrected to 7.6 by centrifuging the sample at 10,000 rev/min for 30 min. At 465 nm, the absorbance was measured and converted into colour units [23]. Experiments with various initial substrate concentrations were also conducted.

2.1. Artificial neural network (ANN)

Due to their greatest power of learning and categorising data, biological neurons are regarded the core defining structure of ANN. Each network is made up of biological neurons that are stacked in layers and interconnected with other layers based on their weights. ANN designs using a feed forward back propagation algorithm in the input layer and a sigmoid transfer function in the output layer are particularly popular [24].

3. Results and discussion

The structure of radial basis function network used in this work is given by:

net = newrb

[net,tr] = newrb (P,T,Goal,Spread,MN,DF)

Newrb adds neurons to the hidden layer of a radial basis network until it meets the specified mean squared error goal.

NEWRB (PR,T,GOAL,SPREAD,MN,DF) takes these arguments,

P RxQ matrix of Q input vectors.

T SxQ matrix of Q target class vectors.

Goal Mean squared error goal, default = 0.0.

Spread Spread of radial basis functions, default = 1.0.

MN Maximum number of neurons, default is Q.

DF Number of neurons to add between displays, default = 25 and returns a new radialbasis network.

Newrb is used to establish a two-layer network. The first layer comprises radbas neurons and determines its weighted and net inputs using dist and netprod. Purelin neurons make up the second layer, which employs netprod and netsum to compute its weighted and net inputs. Both layers have biases. At beginning, there are no neurons in

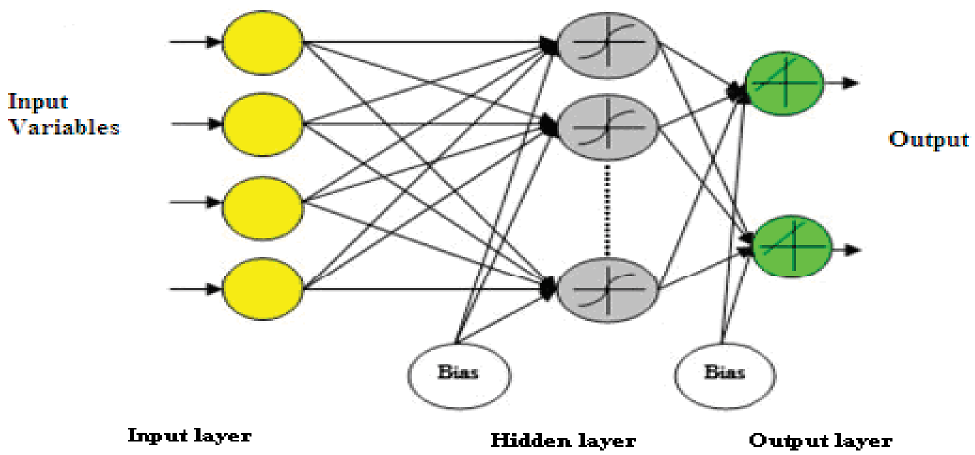

Fig. 1. ANN structure.

the radbas layer. The following steps are performed until the network's mean squared error falls below the target or the maximum number of neurons is reached:

- The network is simulated
- The input vector with the greatest error is found
- A radbas neuron is added with weights equal to that vector.
- The purelin layer weights are redesigned to minimize error.

The neural network projected data is compared to the experimental findings at the midway point of the experiment. The overall absolute error and root mean square error (RMSE), which is defined as the difference between the desired and actual outputs, are used to assess the network's performance. ABSD and RMSE differences between experimental and neural network ABSD and RMSE the predicted values for tannery effluent treatment in SBR are shown in Table 1.

Absolute standard deviation

$$\text{ABSD} = \frac{\sum\left|\left(\text{ANN value} - \text{Experimental value}\right)\right|}{\text{number of data points}} \quad (1)$$

Root mean square error

$$\%\text{RMSE} = \sqrt{\frac{\sum\left(\frac{\text{Experimental value} - \text{NN value}}{\text{Experimental value}}\right)^2}{\text{number of data points}}} \times 100 \quad (2)$$

Figs. 2–9 depict the link between experimental data and ANN predicted outcomes. At different operational parameters of the reactor, the artificial neural network model-based outputs were found to match the experimental findings exactly, as shown in the figures. The validity and robustness of using a neural network to forecast SBR performance has been established, reducing the need for complex mathematics and calculations in SBR performance modelling. These results mirrored those of prior research [25,26].

Table 1
ABSD and RMSE between experimental and neural network predicated values for the treatment of tannery effluent in SBR

Microorganism		Data	COD
MC	ABSD	Training	96.44
		Test	127.09
	%RMSE	Training	6.997
		Test	8.719
	R^2	Training	0.9942
		Test	0.9899
MCS	ABSD	Training	89
		Test	143.51
	%RMSE	Training	6.1416
		Test	9.4202
	R^2	Training	0.9982
		Test	0.9864
STM	ABSD	Training	108.9
		Test	139.30
	%RMSE	Training	8.7611
		Test	11.072
	R^2	Training	0.9921
		Test	0.9866
STMS	ABSD	Training	124.6
		Test	141.21
	%RMSE	Training	10.46
		Test	13.207
	R^2	Training	0.9970
		Test	0.9842

3.1. Multiple linear regression

The parameters observed in SBR were modelled using the multiple linear regression approach in this study. Minitab 15 was used to do regression analysis. Table 2

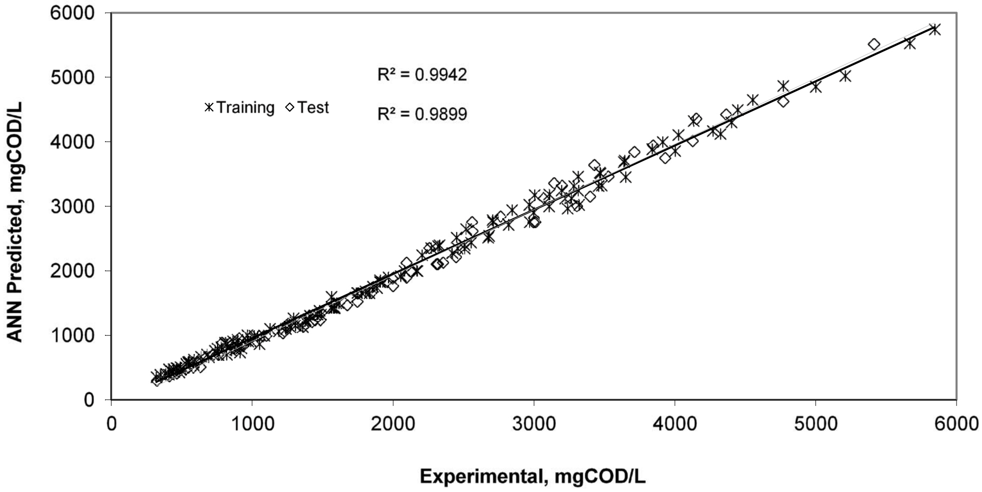

Fig. 2. Comparison of ANN predicted values with experimental values of COD reduction in SBR using MC.

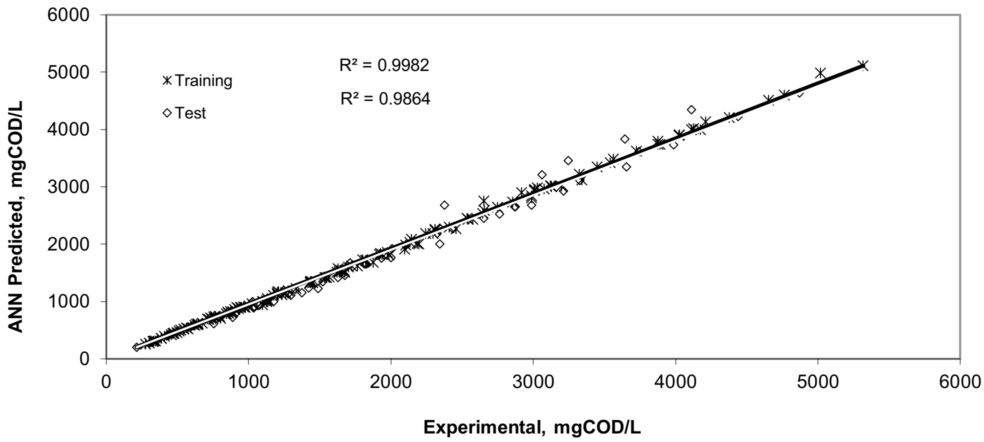

Fig. 3. Comparison of ANN predicted values with experimental values of COD reduction in SBR using MCS.

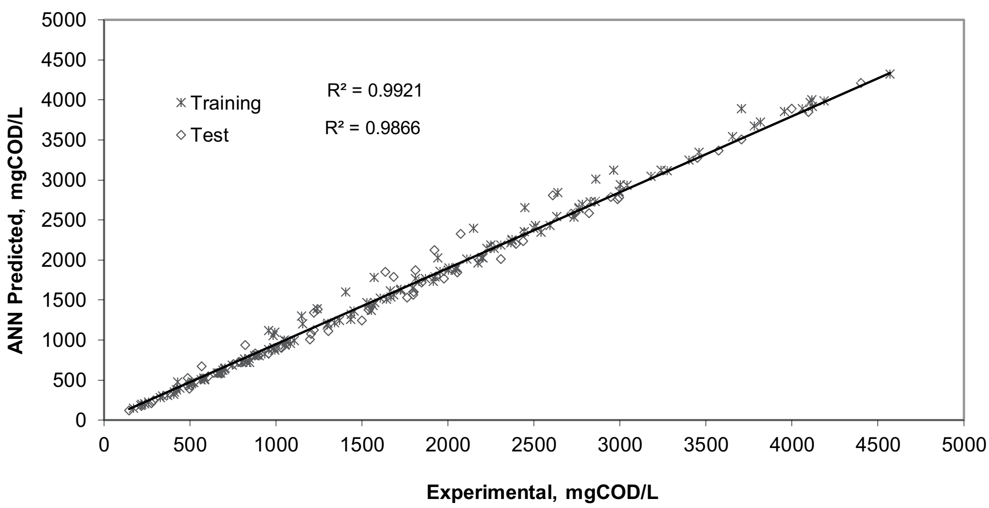

Fig. 4. Comparison of ANN predicted values with experimental values of COD reduction in SBR using STM.

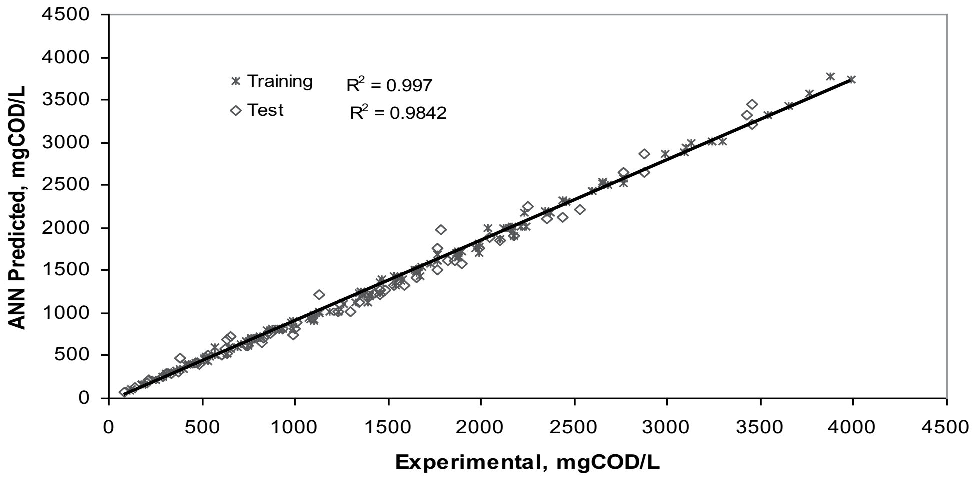

Fig. 5. Comparison of ANN predicted values with experimental values of COD reduction in SBR using STMS.

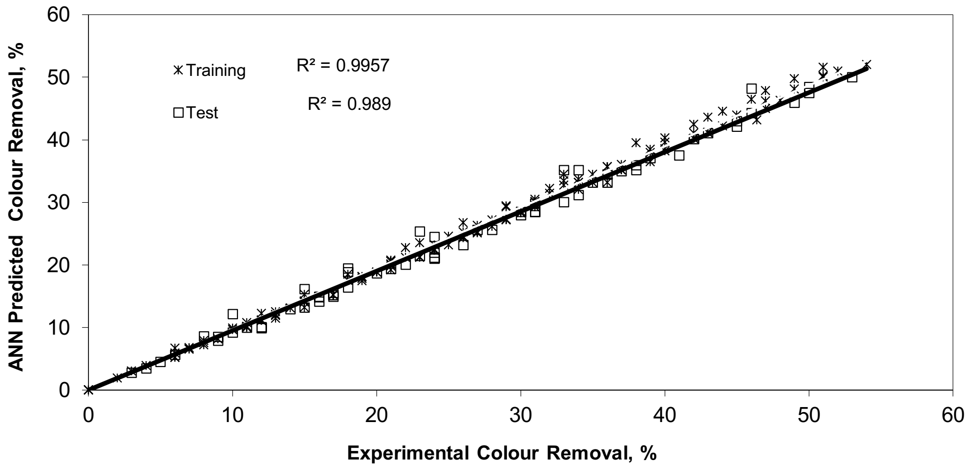

Fig. 6. Comparison of ANN predicted values with experimental values of colour removal in SBR using MC.

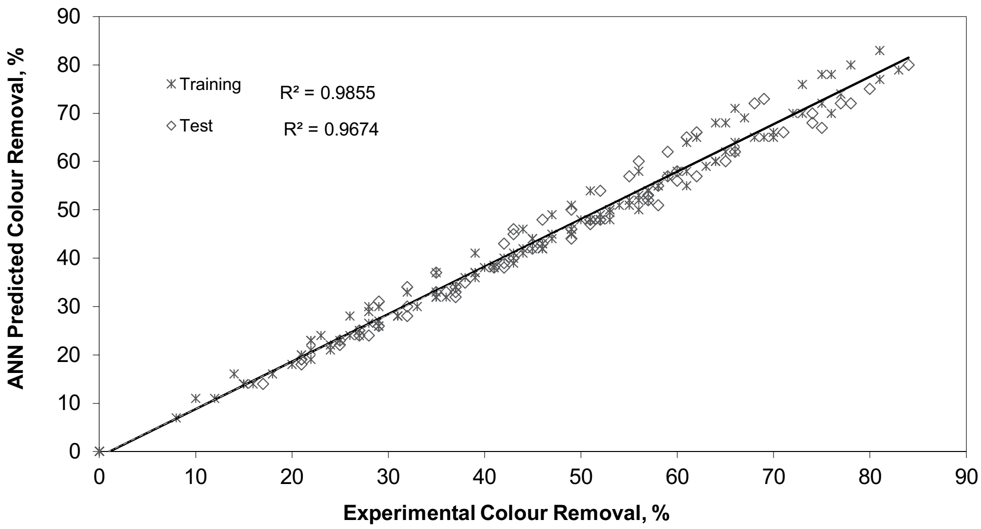

Fig. 7. Comparison of ANN predicted values with experimental values of colour removal in SBR using MCS.

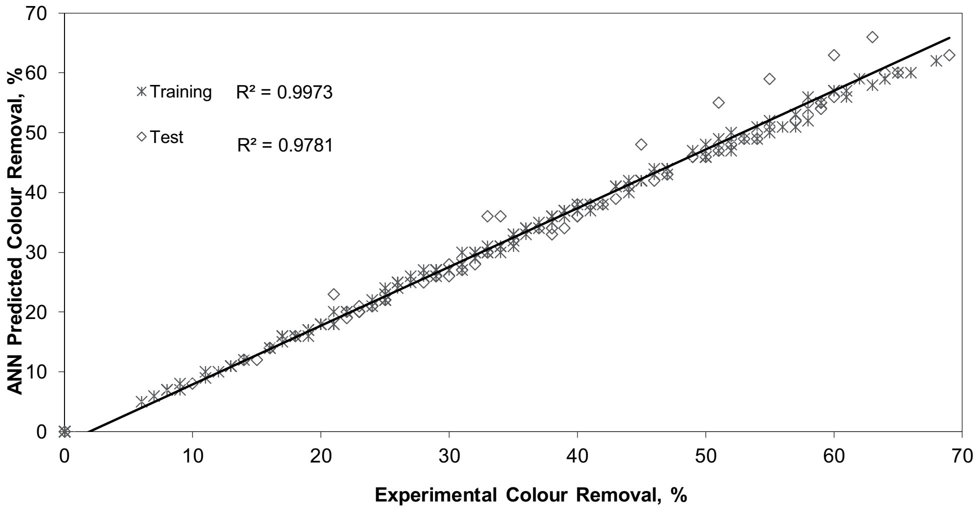

Fig. 8. Comparison of ANN predicted values with experimental values of colour removal in SBR using STM.

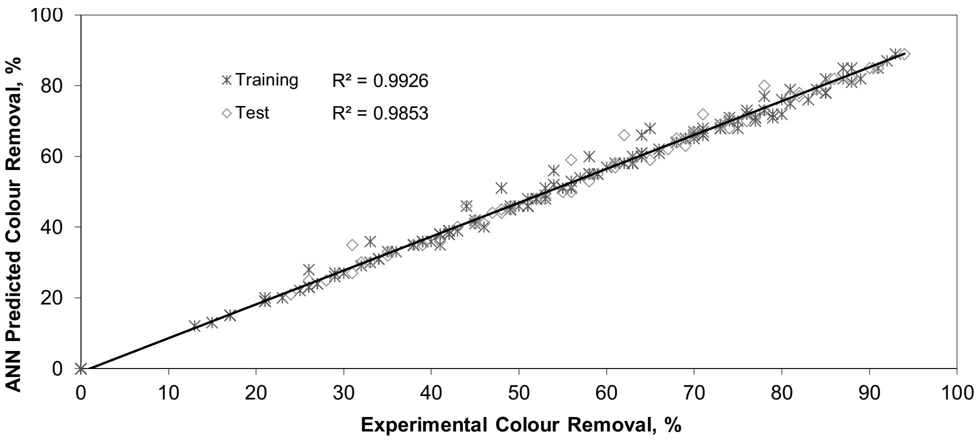

Fig. 9. Comparison of ANN predicted values with experimental values of colour removal in SBR using STMS.

Table 2
Multiple linear regression constants for modeling of SBR

Parameter	Microorganism	Constant	Influent COD, mg COD/L	HRT, d	OLR, kg COD/m^{3}d	R^2	Durbin–Watson Statistic
COD	MC	–1146	–0.516	209	–301	85.72	1.83
	MCS	–1348	–0.389	263	–576	86.83	1.89
	STM	–819	–0.319	163	–565	87.80	1.90
	STMS	–390	–0.318	59.4	–275	85.35	1.95
Colour	MC	29.0	–0.00278	1.86	–0.48	90.20	1.92
	MCS	59.6	–0.00269	0.02	–2.16	91.11	1.85
	STM	50.5	–0.00188	0.16	–5.32	90.81	1.87
	STMS	63.6	–0.00294	1.31	–0.15	90.55	1.95

displays the results collected. The R^2 value for colour prediction was found to be more than 90% in the table, indicating that the model is fit. The COD levels ranged from 85% to 90%. This was owing to a wide range of COD concentrations in the influent.

The Durbin–Watson statistic test was used to look for relationships between inaccuracies. It investigates if neighbouring residuals are linked. In conclusion, this decision was essential in evaluating whether the assumption of independent mistakes was justified. Uncorrelated residuals are indicated by a value of 2 in the test statistic, which ranges from 0 to 4. A number more than 2 indicates a negative correlation between neighbouring variables, whereas a value less than 2 indicates a positive correlation. The magnitude of the Durbin–Watson statistic is determined by the number of predictors in the model and the number of observations. According to a cautious rule of thumb, values less than 1 or larger than 3 are plainly cause for concern. In this study, the Durbin–Watson statistic values were found to be almost 2 in all cases.

According to Table 2, the negative indications of influent COD concentration and OLR coefficients reflect a negative impact on the reaction. This indicates that when the OLR and influent COD grow, the COD and colour reduction efficiency decreases. The positive indication of HRT shows that the reaction is having a beneficial impact. It indicates that increasing HRT improves COD and colour reduction efficiency. The factors influent COD concentration, HRT, and OLR have a significant influence on the responses, according to the P values (not reported). Based on the largest value of R^2 value, the best network architecture was found. The constructed ANN model's dependability is indicated by a correlation coefficient of such a high value. As a result, the best network topology of the ANN model created in this study consists of an input layer with four neurons, a hidden layer with ten neurons, and a single neuron output layer, and this architecture is known as ANN [27,28].

4. Conclusion

Radial basis function structure was used to predict SBR performance. The reduction in COD and colour in the tannery effluent was used as a criteria for assessing the reactor's effectiveness. Artificial neural network model-based parameters have been proven to match perfectly with experimental data at various reactor operating conditions. The validity and robustness of using a neural network to forecast SBR performance has been established, reducing the need for complex mathematics and calculations in SBR performance modelling. Multiple linear regressions were used to model the SBR. R^2 values greater than 0.90 suggest a well-fitting regression. With a high R^2 value and a very low RMSE, an ideal ANN model for predicting tannery wastewater (%) was successfully created. Using experimental data, the created ANN model could accurately estimate wastewater removal (%).

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