Research Article

Journal of Environmental Nanotechnology

Utilizing Sophisticated Deep Learning Methods to Forecast Treatment Methods for Effluents Generated by the Paper and Pulp Industry

P. Kavitha[1], R. Ganesan[2], A. Latha[2*], B. Krishnakumari[3] and M. Mageswari[3]

[1]Department of Artificial Intelligence and Data Science, Panimalar Engineering College, Chennai, TN, India

[2]Department of Civil Engineering, Velammal College of Engineering and Technology, Madurai, TN, India

[3]Department of Civil Engineering, Panimalar Engineering College, Chennai, TN, India

Received: 18.11.2024 Accepted: 15.02.2025 Published: 30.03.2025

*lathaganesan.a@gmail.com

ABSTRACT

Industrialization has led to the contamination of water with industrial effluents and sewage, resulting in water scarcity issues in India and elsewhere. The effluents are characterized by a dark color, unpleasant scent, high organic content, and severe levels of COD, BOD, and pH. This study investigates the application of inexpensive absorbents and electrochemical oxidation to mitigate the environmental consequences of industrial wastewater treatment. The first procedure involves the usage of cabbage and betel leaf, while the secondary step utilizes Electrochemical Oxidation (EO), which achieves a COD elimination efficiency of 69.19%. This paper deals with the utilization of an artificial neural network model to provide a precise explanation of the EO process in wastewater treatment systems and effectively control and adjust it. The chemical oxygen demand (COD) of the effluent from an electrochemical oxidation wastewater treatment facility used in paper and pulp production was predicted using a neural network model. Testing demonstrates that the Back Propagation (BP) neural network simulation accurately predicts the changing tendency of the real value and possesses some predictive capability. Out of the 20 sample data groups used for simulation prediction, 9 sets have a prediction relative error that is less than 5%, with 45% of those falling within this range. Furthermore, 75% of the pairs had a prediction error of less than 10%, with 15 pairs within this range. The highest comparative error observed is 18.6%. The regression analysis yielded a correlation coefficient of 0.7431 between the real and projected values.

Keywords: Low-cost absorbent; Electrochemical oxidation; COD removal; Neural Network; Regression analysis.

1. INTRODUCTION

Water is an indispensable source for all kinds of life. Only a minuscule fraction of Earth's freshwater, less than 0.3%, exists in rivers, lakes, and the atmosphere. An even smaller portion, about 0.003%, is found within living organisms and manufactured goods. Water is a highly effective solvent for a diverse range of chemical compounds, making it extensively utilized in industrial operations. However, globalization, industrialization, and a few factors lead to the contamination of pure water. Water must be conserved for future generations (Abiola *et al.* 2010). These hazardous substances in wastewater disrupt the environment's natural balance. Paper has long been essential to our daily lives. Paper and pulp production harms the environment. Papermaking produces 60 m^3/ton of effluent. Paper is a versatile material with many uses. It is used for many purposes such as reading, writing, and packaging.

Due to increased population, failure of monsoon, and exploitation of water resources, scarcity in water has risen immensely. Moreover, human activities have had a detrimental effect on the water and the environment. Therefore, using the wastewater treatment process in the industry reduces water consumption because of the recycling of treated water and also avoids polluted water discharge into the water bodies (Calderón *et al.* 2021). Fluoride is a crucial element for tooth health and bone growth. However, an excessive amount of fluoride can negatively impact human health. Controlling the excessive concentration of fluoride (WHO) at a level of 1.5 mg/l was highly necessary. Researchers have employed several approaches and procedures over the years to regulate the presence of fluoride ions. A research report focuses on the use of *Phyllanthus emblica* (Amla) bark to measure fluoride levels. Techniques like Fourier transform infrared spectroscopy (FTIR), Scanning electron microscopy (SEM), and elemental analysis employing carbon, hydrogen, and nitrogen (CHN) were used to do the physicochemical characterization. The adsorption parameters, which included pH levels between 6 and 8, dosages between 0.5 and 5 mg/l, an initial concentration of 5 mg/l, particle sizes between 75 and 300 µm, and contact periods between 60 and 720 minutes, were examined in the batch experimental study (De *et al*. 2016).

The carbonization process was employed to utilize the peels of banana and lemon as adsorbents. The experiments demonstrated that lemon peels are superior to banana peels in their efficacy for removing contaminants from wastewater. The carbonization approach is determined to be more effective for both lemon and banana peels, with the lemon peel exhibiting the highest percentage of BOD elimination. The ideal pH range for both orange and banana peels is between 6 and 8 and the ideal duration for the carbonization process of lemon and banana peels is 100 minutes. The ideal amount of adsorbent needed for carbonizing lemon and banana peels is 0.32 g. Additionally, the optimal particle size for lemon and banana peels is 300 µm (Patil *et al*. 2016). To determine the factors influencing the adsorption of Ni (II), batch experiments were conducted at a temperature of 27 °C. Contact time, solution pH, adsorbent dosage, and initial concentration are some of the factors that affect the adsorption process. Using 2.0 g/50 ml of coconut leaves at a pH of 8.0 throughout the ideal 4-hour period, the maximum level of Ni (II) elimination attained was 93.18%. The Langmuir and Freundlich equations were used to analyze the experimental data.

The removal is anticipated to be rather inexpensive, given that the adsorbent is affordable and readily accessible in substantial amounts. The current investigation demonstrated the capability of coconut leaves to effectively eliminate Ni (II) from a liquid solution (Nagar *et al.* 2017).

The discharge of dye effluents is a significant concern in water pollution due to its ecotoxic properties. Significant quantities of pigmented dye waste are being released into aquatic ecosystems. Various techniques are employed for its treatment. Adsorption is a successful method for removing colors from water. The process of preparing activated carbon from *Nerium oleander* leaves involves chemical activation using sulphuric acid, followed by thermal activation. The testing results demonstrated that the highest level of dye removal (99.5%) was achieved at a concentration of 10 ppm, while a removal rate of 96.5% was seen at pH 9. The results of the study demonstrated that the data followed the Langmuir isotherm. The equilibrium kinetic investigations demonstrated that the adsorption process was governed by the pseudo-first-order and intra-particle diffusion, which acted as the rate-determining step (Gowda *et al.* 2012).

The effectiveness of using banana stem juice as a common coagulant to remediate spent coolant effluent was investigated. Three main metrics were the focus of the study: effluent turbidity, suspended solids (SS), and COD. Coagulation studies were performed to examine the effects of banana stem juice dosage and pH levels in spent coolant effluent on coagulation efficiency. With removal percentages of 80.1%, 88.6%, and 98.5% for COD, SS, and turbidity, respectively, the banana stem juice had the highest documented removal rates. These outcomes were obtained after using a 90 ml dosage and treating the effluent with a pH of 7. It was found that the banana stem contained 1.22016 mg/ml of inulin. The findings suggest that banana stem juice has significant potential as a natural coagulant for water treatment, namely in the pre-treatment phase of Malaysian-spent coolant effluent before undergoing secondary treatment (Sherin *et al.* 2017).

The peels of pomegranates were used to recover nickel, chromium, and zinc from industrial waste. Concerning environmental factors like pH, temperature, and contact time, three different types of these peels - fresh, dried minute pieces, and powder, were investigated. The findings showed that these peels could significantly reduce the amounts of zinc, chromium, and nickel ions. While the dried peels demonstrated the lowest capacity for all tested metals, the powdered peels were the most effective in bioremediating zinc, chromium, and nickel ions. However, a series of chromium, nickel, and zinc was shown to have the highest capacities.

The emphasis was placed on the positioning of electrodes used in processes such as Electro-coagulation (EC), Electro-flotation (EF), and Electro-oxidation (EO). More than 300 relevant publications were examined, out of which 221 were either cited or evaluated. Electrodeposition is a highly efficient method for extracting heavy metals from wastewater streams. It is widely regarded as a mature technology with the potential for additional advancements in enhancing space-time efficiency. Electrocoagulation (EC) has been utilized for water production or wastewater treatment; further uses are being discovered by employing either aluminum, iron, or hybrid aluminum/iron electrodes (Alwi *et al.* 2013). The Electrochemical Oxidation (EO) is distinguished by three unique qualities as an electrochemical technique. The first reason is that it is the most versatile process in the field of water treatment. It can be used for various purposes, including treating industrial effluents from industries such as distilleries, agrochemicals, pulp and paper, textile dyes, oil fields, and metal plating. It is also effective in treating hazardous effluents from hospitals. Additionally, it can remove pathogens, persistent pharmaceutical residues, and biological contaminants from municipal wastewater treatment plants. Water pollution reduction and recycling are important ways to manage water resource issues today. Sewage treatment plants are vital here. Sewage treatment prevents pollution and allows reuse such as irrigation (Shen *et al.* 2003).

Predictions are inaccurate and unreliable, violating scientific criteria. Sewage treatment plants need sophisticated management systems to meet effluent quality criteria due to the difficulty of anticipating it. It is common to use excessive dosage and air blowing to treat contaminants, regardless of the water quality. This wastes resources and raises running costs. High human resource costs emerge from the necessity for human skills to precisely assess effluent quality and allocate resources in the sewage treatment process. The water treatment facility finds it difficult to maintain a consistent level of operation and administration because of the unequal labor distribution and high personnel turnover (Dimitrijević *et al*. 2013). Poorly managed sewage treatment plants, intended as environmental protection facilities, can cause pollution and waste energy. High operational costs might also hurt business. The challenges prevent the sewage treatment industry from developing sustainably (Latha *et al*. 2023).

Fig. 1: Chopped cabbage

Fig. 2: Chopped betel leaves

A disinfection model uses real-time water quality data to predict Peracetic Acid (PAA) disinfection performance. The trained artificial neural networks and performed Principal Component Analysis (PCA) were applied pre- and post-disinfection using online and offline water quality data. The researchers agree that Membrane Bioreactor (MBR) technology has many advantages over activated sludge such as superior effluent quality, decreased space, less sludge, and simplified automatic control. The thorough validation of artificial intelligence-based models in sewage treatment operation and management is widely accepted (Ma *et al.* 2021). The researchers used an AI-based prediction model to study trace metals and COD (Sun *et al*. 2021). This study investigated treating wastewater utilizing affordable absorbents and EO to reduce the environmental impact. This wastewater treatment method removes 68.2% of pollutants. This study suggests mimicking the wastewater treatment system's electrochemical oxidation with a neural network for better control and adaptation. This study predicts COD in an electrochemical oxidation system effluent from paper and pulp-making wastewater using a neural network model.

2. MATERIALS AND METHODS

2.1 Cabbage

Cabbage, like other plants, may remediate wastewater through phytoremediation. Phytoremediation uses plants to clean up polluted soil and water. Cabbage is not the top choice for this reason, but it can help phytoremediation work. Cabbage roots filter wastewater naturally. The roots filter out particle matter and certain contaminants, clearing the water and lowering suspended solids. Cabbage absorbs heavy metals and organic pollutants from water like other plants. As they expand, plant roots can absorb these compounds. Fig. 1 shows the chopped cabbage used in this research.

2.2 Betel Leaves

A few wastewater treatment plants use betel leaves (Piper betel). Research and experience suggest that betel leaves may have limited phytoremediation capacity in small-scale or decentralized wastewater treatment systems. Filtering wastewater with betel leaf roots reduces suspended particles and improves clarity. Betel leaves absorb nitrogen and phosphorus from water like many plants. Eutrophication and water quality concerns can result from wastewater nutrients. Betel leaves grow by absorbing nutrients, lowering nutrient levels. Betel leaf roots support beneficial microorganisms. Organic materials and pollutants are broken down by these bacteria to purify wastewater. Fig. 2 shows chopped betel leaves used in this research.

2.3 Primary Process

Organic cabbage and betel leaves absorb the sample at an affordable cost. After treatment with betel leaves and cabbage, pebbles are employed in the first setup to remove organic contaminants and dust. Sand filters generate high-quality water without chemicals. A sand filter removes floc and particles from flocculated water, lowering germs and solids.

2.4 Electrochemical Oxidation

Electrochemical processes rely on the electrolytic cell. An electrolytic cell consists of an anode and a cathode submerged in an electrically conductive solution (the electrolyte) and connected outside of the solution by a current source and a control device. Oxidation and reduction occur between electrodes and electrolytes. Reduction occurs at the cathode and oxidation at the anode.

Fig. 3: Primary process using low-cost absorbents

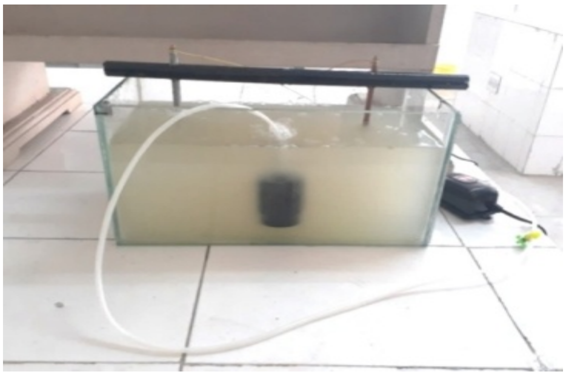

Fig. 4: Electrochemical oxidation

Current flows in electrochemical cells due to the electron flow generated by an electrical source. EO is performed on the partially treated sample using copper as the cathode and zinc as the anode. Electrochemical Oxidation is shown in Fig. 4.

2.5 Data Pre-processing

If the original data is fed into the neural network, elements with high values will significantly impact it and override other aspects. This will result in the internal connections between the components being indistinct, making the network model ineffective. When the sample data is normalized or allowed to fall within a uniform range, all the input factors are made uniform before being used. This model uses the following formula to standardize sample data.

$$x_i^* = \frac{x_i - x_{imin}}{x_{imax} - x_{imin}} \quad \ldots (1)$$

The formula incorporates the variables x_i, x_{imax}, and x_{imin}, which denote the initial input data, the maximum value, and the minimum value of an input component, respectively. Additionally, the variable E represents the normalized value of the i^{th} input data. Following the process of normalization, the values of each input element will be spread within the interval of (0, 1). Likewise, it is imperative that the output of the network consistently undergo normalization.

Table 1. Index range of electrochemical oxidation reactor inlet and outlet wastewater

Index	Wastewater inflow (lps)	COD inflow (mg/l)	COD outflow (mg/l)
Range	3.3 to 5.1	1107 to 1200	244-250

Table 2: Inlet and outlet wastewater data of electrochemical oxidation reactor

S. No.	Date	Wastewater inflow (lps)	COD inflow (mg/l)	COD outflow (mg/l)
1	01.03.2023	3.25	1120	235
2	02.03.2023	4.61	1065	239
3	03.03.2023	3.16	1116	245
4	04.03.2023	3.98	1105	248
5	05.03.2023	4.58	1124	250
6	06.03.2023	4.96	1109	225
7	07.03.2023	5.10	1150	230
8	08.03.2023	3.56	1174	229
9	09.03.2023	3.66	1165	247
10	10.03.2023	4.56	1134	246
11	11.03.2023	3.83	1155	230
12	12.03.2023	4.94	1148	239
13	13.03.2023	3.52	1139	245
14	14.03.2023	3.91	1122	250
15	15.03.2023	4.55	1109	243
16	16.03.2023	4.76	1121	245
17	17.03.2023	4.89	1124	235
18	18.03.2023	4.68	1129	240
19	19.03.2023	3.97	1150	244
20	20.03.2023	4.99	1151	250

2.6 Principal Component Analysis

Potential outliers can be identified in data collection by analyzing the level of influence exerted by each input variable. The Pareto diagram displaying the primary component analysis may be noticed (Newhar *et al.* 2021). Based on this study, we can deduce that the three primary components account for more than 90% of the total variance. Thus, by studying the two-dimensional principal component plot obtained from the analysis of the first three principal components, probable outliers in the sample can be identified. Data distribution can be visualized within a two-dimensional principal component framework using MATLAB code, making it easier to get the information when needed.

2.7 Cluster Analysis of Data

Table 1 presents the index range of the inlet and exit wastewater for the electrochemical oxidation reactor. Table 2 presents the inflow and exit wastewater data of the electrochemical reactor. After that, many distance-based clustering techniques were used for the samples, including the shortest distance, longest distance, center of gravity, and average distance. The cophenetic correlation coefficient was also computed to evaluate the degree of similarity between the original data and the clustered set. The results of the calculations are depicted in Table 3. How well the data fits into the categories was measured by the cophenetic correlation coefficient. The closer to 1 the value is, the better the fit.

Table 3. Neural network learning sample cophenetic correlation

Correlation Coefficient	SDM	LDM	BDM	AVM
Euclidean Distance	0.5962	0.7105	0.7553	0.8161
Mahalanobis Distance	0.7853	0.6430	0.8462	0.8273
Absolute Distance	0.5844	0.6807	0.7415	0.7411

2.8. Prediction Techniques

There exist numerous variables that influence the chemical oxygen demand (COD) of effluent derived from the treatment of paper and pulp wastewater through EO reactors. Every electrochemical oxidation exhibits distinct features resulting from its unique structural design and the specific attributes of the treated wastewater (Asaithambi L *et al*. 2024; Calderón *et al*. 2021; Du *et al*. 2020; Dimitrijević *et al*. 2013). Nevertheless, the data necessary for conventional reactor modeling is intricate and challenging to quantify. Accurately representing the intricate multiple parameters and effectively predicting and controlling the operational outcomes of the reactor is deemed unattainable. The goal of this research is to create a Back Propagation neural network model for forecasting the operational performance of an EO process by utilizing the advantages of artificial neural networks. The fundamental principle underlying the prediction model for the operational impact of an EO, which is based on a Back Propagation neural network, involves utilizing multiple factors that influence the Electrochemical Oxidation operational impact as input parameters for training the network. The network's self-learning capability is then employed to iteratively adjust the network's weight and threshold values, thereby enabling the system's output to closely approximate the actual monitoring value (Newhart *et al*. 2021).

- ❖ The input layer comprises the variables that influence the functioning of the Electrochemical Oxidation. The input elements considered in this study include the influent flow rate and influent COD; consequently, the input layer of the neural network model consists of four nodes.
- ❖ The hidden layer is made up of just one layer, and P is the number of nodes in this layer. P is typically learned by trial and error or by experiential learning.
- ❖ The necessity to represent the electrochemical oxidation's measured effluent COD value determines the number of nodes in the output layer, resulting in a single node.

The processed data should be partitioned into two distinct groups. The first group, consisting of 60 sample pairs, will be utilized for training the BP network. The second group, including 20 sample pairs, will be employed for simulating and predicting the performance of the BP network.

3. RESULTS AND DISCUSSION

The water sample was first processed to determine the parameters. High quantities of oil and grease, dissolved and suspended particulates, COD, and BOD were found. The original oil and grease concentration in sewage was 142 mg/l. Table 4 presents the characteristics of raw samples.

Table 4. Characteristics of raw sample

S. No.	Parameters	Values	Units
1	pH	7.1	-
2	Oil & Grease	142	-
3	BOD	306	mg/l
4	COD	792	mg/l
5	TSS	1246	mg/l
6	TDS	2876	mg/l
7	Turbidity	183.4	NTU

After adding cabbage and betel leaves, the sample solution had significantly less particles, turbidity, oil, and grease. The secondary procedure eliminated turbidity and all other criteria are satisfactory. Table 5 shows the characteristics of Effluent after Primary and Secondary processes. Figures 5 and 6 represent pH, oil and grease, turbidity, BOD, COD, TDS, and TSS removal in the primary and secondary treatments, respectively.

3.1 Selection of Learning Parameters

Currently, there is a lack of comprehensive academic guidance about the collection of the influencing factors for the study. To optimize the predictive performance of the neural network, this study used a trial-and-error approach to discover the optimal parameters. The fundamental concept entails employing the fixed variable approach, wherein certain parameters are held constant while altering the value of another parameter. The configuration that produces the lowest average absolute error was then chosen as the ideal network.

Table 5. Characteristics of effluent after primary and secondary processes

S. No.	Parameters	Results			Limits	Units
		Raw Sample	After Primary Process	After Secondary Process		
1	pH	7.1	5.8	6.92	5.5-9	-
2	Oil and grease	142	37	6	-	-
3	Turbidity	183.4	15	-	-	NTU
4	BOD	306	364	30	30	mg/l
5	COD	792	1107	244	250	mg/l
6	Total Dissolved Solids	2876	2556	1490	2100	mg/l
7	Total Suspended Solids	1246	194	48	100	mg/l

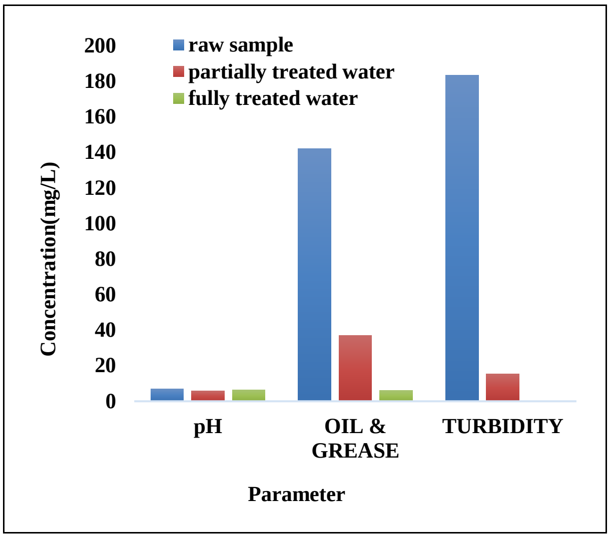

Fig. 5: Graph illustrating pH, oil and grease, and turbidity removal in primary and secondary treatments

The learning rate and learning error limit were further adjusted, with the starting estimate for the number of hidden layer nodes being 6. The experiment was conducted with a total of 20 iterations for each scenario, and the mean value of the five operation results with the lowest average absolute error was calculated (Du *et al.* 2020). Consequently, these values are chosen as the calculation parameters for the Back Propagation neural network (Matheri *et al.* 2021; Latha *et al.* 2024; Megido *et al.* 2021).

The ideal number of hidden layer nodes based on the operational factors was examined in the study. The best simulation prediction effect was obtained when the number of hidden layer nodes was set to six, as indicated by the data in Table 6. As a result, six hidden layer nodes in total, a learning rate of 0.05, and a learning error limit of 0.01 were selected as the model parameters.

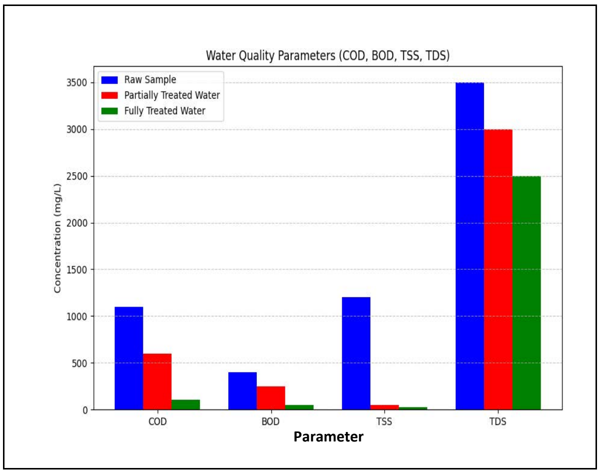

Fig. 6: Graph showing the changes in parameters such as COD, BOD, TSS and TDS of the sample after primary and secondary treatments

Table 6. Calculated average absolute error of different hidden layers

Learning Frequency	4	5	6	7	8	9
1st	0.0838	0.0784	0.0874	0.0797	0.0895	0.0897
2nd	0.0959	0.0852	0.0844	0.087	0.0885	0.0851
3rd	0.0831	0.0831	0.091	0.0854	0.082	0.0902
4th	0.0838	0.0951	0.0906	0.0782	0.0891	0.0893
5th	0.0858	0.0803	0.0868	0.0743	0.0882	0.091
Average value	0.0865	0.0844	0.088	0.0809	0.0875	0.0891

The constructed back propagation neural network was simulated and projected for a total of 20 iterations using the determined model parameters. Five calculation results were recorded and exhibited the most accurate prediction performance. Table 7 shows the learning frequency of the backpropagation network.

Table 7. Calculated results of back propagation network

Learning Frequency	4	5	6	7	8
MAE (Mean Absolute Error)	0.7852	0.0775	0.0711	0.0725	0.0764
MRE (Maximum Relative Error)	0.2011	0.2671	0.1851	0.1685	0.2389

The third group exhibits the lowest average absolute error among the five prediction outcomes, while the fourth group demonstrates the smallest maximal relative error. Typically, in applied projects, the assessment of the model would mostly center on its mean predictive performance. Consequently, this study will examine the operational outcomes of the third cohort (Kang *et al*. 2020).

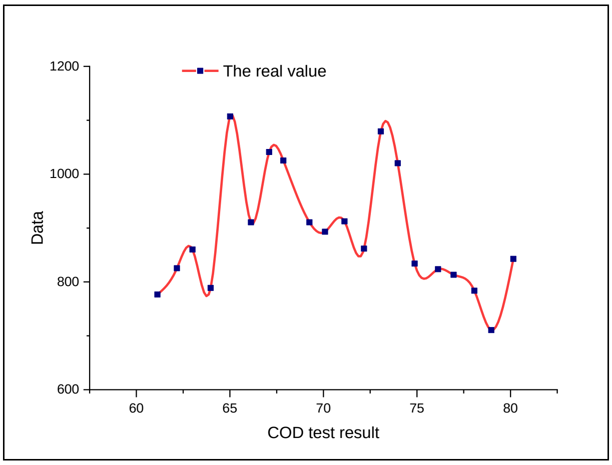

Fig. 7: Simulation of back propagation neural network

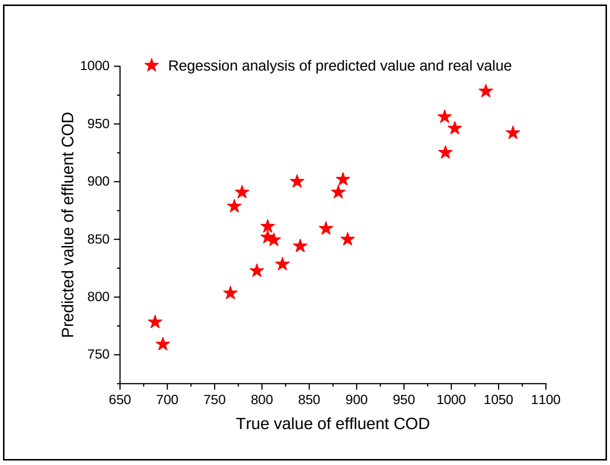

Fig. 8: The relative inaccuracy of back propagation neural network simulation prediction

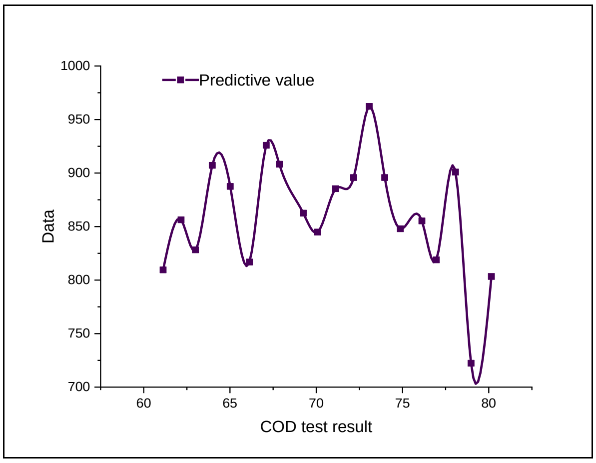

Fig. 9: Prediction results of back propagation neural network

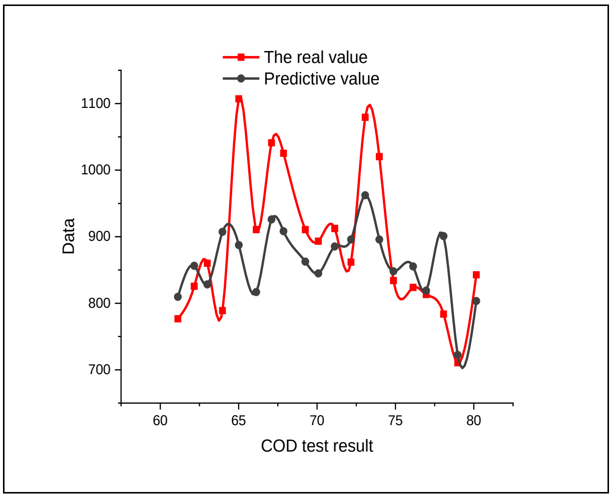

Fig. 10: Comparison analysis of back propagation neural network

Table 8. Relative error values

No.	Relative Error value	No.	Relative Error value
1	0.0471	11	−0.0067
2	0.0565	12	0.0622
3	−0.0218	13	−0.0817
4	0.1576	14	−0.1062
5	−0.1851	15	0.0328
6	−0.0912	16	0.0515
7	−0.0834	17	0.0171
8	−0.1017	18	0.1711
9	−0.0253	19	0.0218
10	−0.0531	20	−0.0245

Nine of the twenty sets of sample data pairings used for simulation prediction had predicted relative error levels below 5%. This indicated that around 45% of the data pairings in the sample have prediction errors that fall within the 5% criterion. The relative error for a collection of 15 sample data pairs was calculated to be under 10%. This suggested that the prediction error for about 75% of the sample's data pairings was less than 10%. 18.6% was the largest relative inaccuracy that had been measured. In summary, even when the relationship between the input variables and the output is nonlinear, the backpropagation (BP) neural network can learn and comprehend it (Wu *et al*. 2021). Furthermore, Wang *et al*. (2021) have shown that the Back Propagation neural network is capable of accurately predicting the effects of electrochemical oxidation on effluent.

4. CONCLUSION

This study highlights the effectiveness of using inexpensive absorbents and electrochemical oxidation to treat industrial wastewater, particularly for lowering COD levels. The addition of an artificial neural network model enhances process management and prediction accuracy, demonstrating its ability to improve wastewater treatment systems. The BP neural network is able to predict changes in COD within a reasonable margin of error, but it might be made more accurate with further adjustments. The findings highlight the feasibility of combining sophisticated oxidation techniques with artificial intelligence-based modeling for effective and sustainable wastewater management, which will contribute to the preservation of the environment and the sustainability of water resources.

FUNDING

This research received no specific grant from any funding agency in the public, commercial, or not-for-profit sectors.

CONFLICTS OF INTEREST

The authors declare that there is no conflict of interest.

REFERENCES

Abiola, O. K. and James, A. O., The effects of Aloe vera extract on corrosion and kinetics of corrosion process of zinc in HCl solution, *Corros. Sci.*, 52(2), 661–664(2010). https://doi.org/10.1016/j.corsci.2009.10.026

Alwi, H., Idris, J., Musa, M. and Ku, H. K. H., A Preliminary Study of Banana Stem Juice as a Plant-Based Coagulant for Treatment of Spent Coolant Wastewater, *J. Chem.*, 2013(1), 165057(2013). https://doi.org/10.1155/2013/165057

Asaithambi, L., Govindaraj, V., Ramachandran, G. and Barmavatu, P., Removal of turbidity from lake water using novel Chrysopogon zizanioides and Hemidesmus indicus, *Desalin. Water. Treat.*, 317100245(2024). https://doi.org/10.1016/j.dwt.2024.100245

Calderón, F. D., Apoorva, S., Medema, G., Van, L. M. C. M. and Weissbrodt, D. G., Upgrading residues from wastewater and drinking water treatment plants as low-cost adsorbents to remove extracellular DNA and microorganisms carrying antibiotic resistance genes from treated effluents, *Sci. Total. Environ.*, 778, 146364(2021). https://doi.org/10.1016/j.scitotenv.2021.146364

Du, X., Shi, Y., Jegatheesan, V. and Haq, I. U., A Review on the Mechanism, Impacts and Control Methods of Membrane Fouling in MBR System, *Membr.*, 10(2), 24(2020). https://doi.org/10.3390/membranes10020024

Dimitrijević, S. B., Dimitrijević, S. P. and Vuković, M. D. Modern water treatment by electrochemical oxidation-a review. *Int. Res. Expert. Confe., vol* 10-11(2013).

Kang, J. H., Song, J., Yoo, S. S., Lee, B. J. and Ji, H. W., Prediction of Odor Concentration Emitted from Wastewater Treatment Plant Using an Artificial Neural Network (ANN), *Atmos.*, 11(8), 784(2020). https://doi.org/10.3390/atmos11080784

Latha, A., Ganesan, R., Sai, B. A. V. S. L. and Barmavatu, P., An experimental investigation of textile dyeing wastewater using modified electro Fenton process with optimization by response surface methodology, *Environ. Qual. Mgmt.*, 33(3), 421–432(2024). https://doi.org/10.1002/tqem.22135

Latha, A., Ganesan, R., Venkatesan, G. and Baraneedharan, P., Removal of toxic heavy metal ion from tannery effluent by using Fusarium subglutinans and Hylocereus undatus, *Desalin. Water. Treat.*, 31270–78(2023). https://doi.org/10.5004/dwt.2023.29952

Ma, Y., Li, L., Yin, Z., Chai, A., Li, M. and Bi, Z., Research and application of network status prediction based on BP neural network for intelligent production line, *Procedia. Comput. Sci.*, 183, 189–196(2021). https://doi.org/10.1016/j.procs.2021.02.049

Matheri, A. N., Ntuli, F., Ngila, J. C., Seodigeng, T. and Zvinowanda, C., Performance prediction of trace metals and cod in wastewater treatment using artificial neural network, *Comput. Chem. Eng.*, 149, 107308(2021). https://doi.org/10.1016/j.compchemeng.2021.107308

Megido, L., Negral, L., Fernández-Nava, Y., Suárez, P. B., Ormaechea, P., Díaz-Caneja, P., Castrillón, L. and Marañón, E., Impact of organic loading rate and reactor design on thermophilic anaerobic digestion of mixed supermarket waste, *Waste. Manage.*, 12352–59(2021). https://doi.org/10.1016/j.wasman.2021.01.012

Nagar, H., Anusha, G. and Sridhar, S., Sulfonated Polyethersulfone/Torlon Blend Membrane Incorporated with Multiwalled Carbon Nanotubes for Energy Production from Kitchen Wastewater Using Microbial Fuel Cell, Energy Engineering, *Springer Singapore, Singapore*, 163–167 (2017)., https://doi.org/10.1007/978-981-10-3102-1_18

Newhart, K. B., Goldman-Torres, J. E., Freedman, D. E., Wisdom, K. B., Hering, A. S. and Cath, T. Y., Prediction of Peracetic Acid Disinfection Performance for Secondary Municipal Wastewater Treatment Using Artificial Neural Networks, *ACS. EST. Water.*, 1(2), 328–338(2021). https://doi.org/10.1021/acsestwater.0c00095

Shen, F., Chen, X., Gao, P., and Chen, G., Electrochemical removal of fluoride ions from industrial wastewater, *Chem. Eng. Sci.*, 58(3–6), 987–993(2003). https://doi.org/10.1016/S0009-2509(02)00639-5

Sherin, S., Sheeja, S., Sudha Devi, R., Balachandran, S., Soumya, R. S. and Abraham, A., In vitro and in vivo pharmacokinetics and toxicity evaluation of curcumin incorporated titanium dioxide nanoparticles for biomedical applications, *Chem. Biol. Interact.*, 27, 535–546(2017). https://doi.org/10.1016/j.cbi.2017.07.022

Sun, C., Sheng, T., Li, L. and Yang, L., Biohydrogen production from traditional Chinese medicine wastewater in anaerobic packed bed reactor system, *RSC. Adv.*, 11(10), 5601–5608(2021). https://doi.org/10.1039/D0RA09290H

Wang, G., Jia, Q.-S., Qiao, J., Bi, J., and Zhou, M., Deep Learning-Based Model Predictive Control for Continuous Stirred-Tank Reactor System, *IEEE. Trans. Neural. Netw. Learn. Syst.*, 32(8), 3643–3652(2021). https://doi.org/10.1109/TNNLS.2020.3015869

Wu, X., Han, H., and Qiao, J., Data-Driven Intelligent Warning Method for Membrane Fouling, *IEEE Trans. Neural. Netw. Learn. Syst.*, 32(8), 3318–3329(2021). https://doi.org/10.1109/TNNLS.2020.3041293