An Artificial Neural Network (ANN) Modelling Approach for Evaluating Turbidity Properties of Paper Recycling Wastewater

Serkan Kardeş,[a,*] Uğur Özkan,[b] Okan Bayram,[c] and Halil Turgut Şahin [b]

A pre-treatment process was evaluated in this work for wastewater from paper recycling using microwave technology followed by rapid precipitation of contaminants through centrifugation. Artificial neural networks (ANNs) were used to analyze and optimize the turbidity values. Thirty experimental runs were utilized including microwave (MW) power, duration, centrifuge time, and centrifuge speed as input variables, generated by the Central Composite Full Design (CCFD) approach. The experimental turbidity ranged from 8.1 to 19.7 NTU, while predicted values ranged from 8.4 to 19.7 NTU by ANN. The ANN model showed a robust prediction performance with low mean squared error values during training and testing. Moreover, high R^2 values showed a remarkable agreement between the experimental observations and ANN predictions. The results obtained from the input values (A:150.00, B:60.00, C:15.00, D:30.00) of sample 2, which gave the lowest turbidity value, showed the most removal of pollution. The results obtained from the input values (A:250.00, B:60.00, C:7.00, D:20.00) of sample 30, which gave the highest turbidity value, showed the least removal of pollution. The results showed that increasing RPM and time of the centrifugation process significantly affected the removal of pollution in wastewater.

DOI: 10.15376/biores.19.3.5003-5018

Keywords: Paper recycling; Wastewater; Turbidity; Artificial neural network; Microwave technology

*Contact information: a: Department of Business Administration, Bursa Technical University, 16310, Bursa, Türkiye; b: Department of Forest Products Engineering, Isparta University of Applied Sciences, 32200, Isparta, Türkiye; c: Department of Chemistry, Süleyman Demirel University, 32000, Isparta, Türkiye; *Corresponding author: serkan.kardes@btu.edu.tr*

INTRODUCTION

The depletion of natural resources has prompted a worldwide surge in paper recycling as an environmentally sustainable option (Čabalová *et al*. 2011; Sahin 2013). Thus, paper recycling has become a pivotal focal point in the paper industry, encompassing the retrieval and processing of post-consumer paper into innovative products. Nevertheless, the use of recycled papers varies, with high-quality items such as printing and writing paper frequently requiring virgin pulp (Biermann 1996).

The recycling process includes stages such as re-pulping, screening, deinking, and papermaking. Re-pulping transforms waste paper into a dispersed form in water, facilitating subsequent stage preparation by segregating fibrous and non-fibrous particles. Screening eliminates large particles such as clips and staples, while de-inking processes (washing or flotation) are necessary for particles less than 25 µm in diameter, such as toners, which pose challenges during de-inking (Borchardt *et al*. 1998; Sui *et al*. 2009; Kamali and Khodaparast 2015).

Paper recycling introduces a diverse array of pollutants into the water stream, incorporating various chemicals and derivatives, including hydrogen peroxide, chlorinated compounds AOX (absorbable organic halides), starch, calcium ion (Ca^{2+}), sticky matter, and sulfate. These pollutants present environmental challenges, requiring the identification of effluents, effective treatment methods, and a reduction in water consumption for water system management (Pokhrel and Viraghavan 2004; Toczyłowska-Mamińska 2017; Han *et al*. 2021; Coskun 2022). Treating papermaking wastewater is costly, very difficult, and requiring a multi-step process. Therefore, wastewater treatment methodologies for the pulp and paper industry encompass primary, secondary, and tertiary treatments (Hubbe *et al*. 2016; Han *et al*. 2021).

Water, which can be regarded as the second most critical component in the structural composition of paper in the paper industry, following cellulosic matter (Biermann 1996; Hubbe *et al*. 2016), plays a pivotal role in various processes, including furnish preparation, pulp treatment, and paper web formation. The quantity of water utilized varies among mills, contingent upon the desired paper grade, with each ton of paper production requiring a significant amount of fresh water (Biermann 1996; Ozkan *et al*. 2023). Paper production encompasses multiple stages, where the primary contributors to pollution are organic substances, suspended solids, and chlorinated organics resulting from bleaching processes. To mitigate adverse effects, sustainable water management practices and advanced treatment technologies are implemented. Regulatory frameworks ensure compliance with environmental standards. Wastewater generated by paper mills can be classified as industrial wastewater, subject to specific regulations. The discharge of untreated or inadequately treated effluents poses a potential threat to aquatic ecosystems. Although paper mills employ wastewater treatment processes to alleviate adverse effects, challenges persist in developing more efficient and sustainable treatment technologies. Ongoing research is dedicated to addressing these challenges in the paper industry. The treatment of industrial wastewater encounters difficulties in adhering to strict environmental regulations due to its potential adverse impacts on the environment, such as toxicity and settling effects. Various technologies, including centrifugal action and coagulation, have been developed for water treatment to remove particles, monitoring turbidity, and natural organic matter (Chandegara and Varshney 2014; Majekodunmi 2015).

Conventional technologies, including heating processes widely adopted in engineering manufacturing, serve purposes such as drying or inducing chemical and physical changes. While industries have alternatively employed electro-heat technologies including induction, radio frequency (RF), direct resistance, and infrared, microwave (MW) heating has gained prominence in sectors such as textiles, rubber, and food processing. Its efficiency in volumetric heating has spurred interest in its potential application in other industrial processes, such as waste-stream treatment and mineral ore processing (Orsat *et al*. 2005; Remya and Lin 2011; Wang and Wang 2016; Wei *et al*. 2020).

Microwave (MW) radiation has higher energy levels than UV and infrared radiation because of its lower frequency. As a result, it can break down the chemical connections that allow electromagnetic energy to influence molecules. In general, the microwave system is made up of an applicator that distributes the microwaves to the application region and a generator, also known as a magnetron. With the use of a rotor, microwaves produced in a contained area are released into the material as beams, allowing the substances in the surrounding environment to absorb them (Ozkan *et al*. 2023; Özkan and Şahin 2023).

Typically, microwave (MW) irradiation, characterized by electromagnetic ultrahigh-frequency radiation ranging from 0.3 to 300 GHz, has attracted attention for its molecular-level heating capabilities in various processes. Researchers have extensively explored microwave technology for wastewater treatment, reporting successful applications in the oxidation of ammonia, phosphorous compounds, phenols, pesticides, medical preparations, and other elements (Lin *et al*. 2009; Jung 2011; Cheng *et al*. 2015; Wei *et al*. 2020; Vialkova *et al*. 2021; Wang *et al*. 2021; Ozkan *et al*. 2023).

This study aimed to perform a pre-treatment process on wastewater obtained from paper recycling using microwave irradiation, followed by the rapid sedimentation of pollutants in the wastewater through centrifugation. This integrated and efficient process represents a significant step in the quest for sustainable and environmentally friendly solutions in wastewater management. In the subsequent stages of the study, artificial neural networks (ANNs) were employed to analyze further and optimize the obtained purified water data. ANNs are known for their ability to model and predict complex water quality parameters. This technology includes learning algorithms that can be utilized to enhance the efficiency and effectiveness of wastewater treatment processes. Based on the data acquired, training the ANN enhances the understanding of its impact on water quality and improves its ability to make future predictions. This modeling approach could contribute to the predictability and optimization of processes in wastewater treatment. Therefore, this study may explore the powerful potential of artificial neural networks to assess the obtained purified water data and enhance future water treatment processes.

EXPERIMENTAL

Materials

The study involved the use of wastewater resulting from the repurposing of old newspapers in a controlled laboratory setting. Initially, a conventional 1.0-L laboratory blender/defiberizer was utilized to convert sheets into pulp within a water medium. The recycling consistency was measured at 15 to 20% in terms of weight/volume (w/v). After a disintegration phase lasting 5 to 10 min, all sheets had been transformed into a secondary pulp state. Subsequently, this mixture underwent filtration through a 200-mesh sieve, and the resulting wastewater was subjected to irradiation using a household microwave oven (Beko brand with a 20-L capacity, operating at 2.4 GHz), to degrade impurities. A specimen of the wastewater, consisting of 25 mL in a glass vial, was placed at the center of the microwave oven and continuously irradiated for a specified duration.

Following irradiation, the wastewater was exposed to atmospheric conditions and then subjected to centrifugation processes using a laboratory centrifuge device (Medwelt 800 D, China) equipped with a 20 mL tube capacity (Özkan and Şahin 2023). Then, the turbidity characteristics of the water were determined. For measuring the turbidity of water samples, a turbidity meter compliant with the ISO 7027 International Standard (Hanna HI 93703, East Drive Woonsocket, RI, USA) was utilized. Turbidity removal efficiency was calculated using Equation (1) (Choy *et al*. 2016),

$$\boldsymbol{Turbidity\ removal}\ (\%) = \frac{\tau_i - \tau_f}{\tau_i} \times \mathbf{100} \tag{1}$$

where τ_i is the initial turbidity and τ_f is the final turbidity.

Methods

The low and high values of factors in artificial neural networks (ANN) are given in Table 1. For each factor, the ranges between low and high values are specified. These values represent different conditions in the experiment or process. In ANN modeling, MW power represents the irradiation of wastewater in a microwave oven at selected powers (Watts). MW time indicates that the wastewater inside the microwave oven is irradiated for a specified duration. Centrifuge time shows the duration of wastewater subjected to irradiation in the microwave oven in the centrifuge device. Centrifuge RPM specifies the rotation speed of the centrifuge in the centrifugation process. MW power (Watts), MW time (seconds), Centrifuge time (min), and Centrifuge revolutions per minute (RPM) were used as input variables in the ANN modeling. These variables are defined as factors A, B, C, and D within the model. The output variable is the turbidity (τ) values of wastewater, and the modeling aims to capture both experimental and predictive values of turbidity data.

Table 1. The Low and High Values of Factors in ANN

Factor	Name	Low	High
A	MW power (Watts)	100	300
B	MW time (Second)	7.5	77.5
C	Centrifuge time (Min)	3	19
D	Centrifuge (RPM)	15	35

In the context of this study, the identified factors A, B, C, and D play crucial roles in shaping the ANN model. These factors contribute to understanding and predicting the turbidity values. It is noteworthy that the ANN model aims to bridge the gap between experimental observations and predictive simulations. The model takes into account the complex relationships between input variables (factors A, B, C, and D) and the output variable (turbidity: τ). By incorporating both experimental data and predicted values, the model aims to provide a comprehensive understanding of the intricate dynamics in wastewater treatment processes.

The significance of this modeling lies in highlighting the potential to optimize and enhance wastewater treatment efficiency. Accurate predictions of turbidity values based on experimental conditions are considered to contribute to more effective and sustainable wastewater management practices.

Table 2 shows that the thirty experimental runs generated by Central Composite Full Design (CCFD) approach. The MW power was in the range 100 to 300 Watts, MW time was 7.5 to 77.5 seconds, centrifuge time was 3 to 19 min, and centrifuge rotational speed was 15 to 35 RPM. Meanwhile, the turbidity ranged from 8.1 to 19.7 NTU, based on measurements during this work. As a result of the prediction with ANN, turbidity data ranged from 8.4 to 19.7 NTU. Table 1 shows that were given four independent variables were determined as A, B, C, and D for ANN.

Artificial Neural Network Modelling

The Artificial Neural Network (ANN) approach serves as a computational modeling tool for articulating input-output connections in processes or systems where deriving mathematical models poses challenges. Modeled after neural networks observed in biological entities, artificial neural networks (ANNs) employ artificial neurons, with feedforward multilayer perceptron networks being a prominent example. Backward propagation algorithms, such as gradient descent, Levenberg-Marquardt, or genetic algorithms, are employed for learning in these networks (Russell and Norvig 2003; Haupt and Haupt 2004; Diamantopoulou *et al*. 2023). Consisting of nodes representing neurons, the input nodes depict independent variables, while the output nodes represent dependent variables.

The conducted studies indicate the effectiveness of turbidity removal in modeling with ANN. The ANN technique has been used to predict the efficacy of turbidity removal and is well known for its capacity to represent complex linear and nonlinear input-output correlations (Ezemagu *et al.* 2021). An input layer, a hidden layer, and an output layer are all included in the used ANN model. One output neuron represents turbidity, whereas four input neurons represent various parameters. To maximize the model, the network's architecture includes identifying hidden neurons, and choosing transfer functions was improved. The Levenberg-Marquardt method was used to implement a feedforward backpropagation neural network to learn with the goal of minimizing the difference between experimental and predicted values (Abu Musa *et al*. 2024). Scatter plots were used to compare standardized anticipated data with experimental data in order to assess accuracy.

Table 2. Values of Input and Output Variable

Sample No	A (Watts)	B (Second)	C (Min)	D(RPM)	T (Experimental)	T (Predicted)	Residual
1	150.000	25.000	7.000	30.000	9.780	10.143	-0.363
2	150.000	60.000	15.000	30.000	8.130	8.358	-0.228
3	200.000	42.500	11.000	25.000	9.020	8.938	0.082
4	150.000	60.000	7.000	20.000	8.860	8.882	-0.022
5	250.000	60.000	15.000	20.000	12.170	12.189	-0.019
6	150.000	25.000	15.000	20.000	11.890	11.866	0.024
7	200.000	42.500	11.000	25.000	9.020	8.938	0.082
8	250.000	25.000	15.000	30.000	10.620	10.534	0.086
9	250.000	25.000	7.000	20.000	13.350	13.854	-0.504
10	250.000	60.000	7.000	30.000	9.990	10.314	-0.324
11	200.000	42.500	11.000	25.000	9.020	8.938	0.082
12	100.000	42.500	11.000	25.000	10.710	10.555	0.155
13	200.000	42.500	11.000	15.000	13.770	14.582	-0.812
14	200.000	42.500	19.000	25.000	9.560	9.816	-0.256
15	200.000	7.500	11.000	25.000	16.220	15.990	0.230
16	200.000	42.500	11.000	25.000	9.020	8.938	0.082
17	200.000	42.500	11.000	35.000	9.250	9.218	0.032
18	200.000	77.500	11.000	25.000	11.000	10.893	0.107
19	300.000	42.500	11.000	25.000	16.670	16.232	0.438
20	200.000	42.500	3.000	25.000	15.850	15.240	0.610
21	200.000	42.500	11.000	25.000	9.020	8.938	0.082
22	150.000	25.000	7.000	20.000	8.730	8.831	-0.101
23	200.000	42.500	11.000	25.000	9.020	8.938	0.082
24	150.000	60.000	15.000	20.000	14.740	14.650	0.090
25	250.000	60.000	15.000	30.000	15.140	15.102	0.038
26	150.000	60.000	7.000	30.000	9.410	9.420	-0.010
27	250.000	25.000	7.000	30.000	12.220	12.241	-0.021
28	250.000	25.000	15.000	20.000	15.890	15.920	-0.030
29	150.000	25.000	15.000	30.000	10.980	10.573	0.407
30	250.000	60.000	7.000	20.000	19.730	19.698	0.032

Since the purpose of the application was prediction, a feed-forward backward propagation neural network was employed. R software was used to analysis with ANN model in removal turbidity. As can be seen in Fig. 1, there were four hidden layers (H1 − H4) that provided the best performance. The Levenberg-Marquardt algorithm was used for training. The ideal architecture of an artificial neural network (ANN) was created using the data produced by the experimental design that was prepared using Central Composite Full Design (CCFD), as indicated in Table 2. In order to make the units of measurement between variables independent, the data had to be standardized first. There were thirty data points in the original data set. Next, 22 data points were used for 75% of the training set and 8 data points for 25% of the testing set. Randomly splitting data was done for testing and training. According to Venkatesh *et al*. (2016), the implication is to measure the network's performance, which in turn helped with "unseen" data prediction that wasn't used for training. In this study, four input units microwave power, microwave time, centrifuge time, and centrifuge rpm four (4) hidden layers, and one output unit turbidity made up the network architecture (Fig. 1). Compared to other examined setups, this structure worked better.

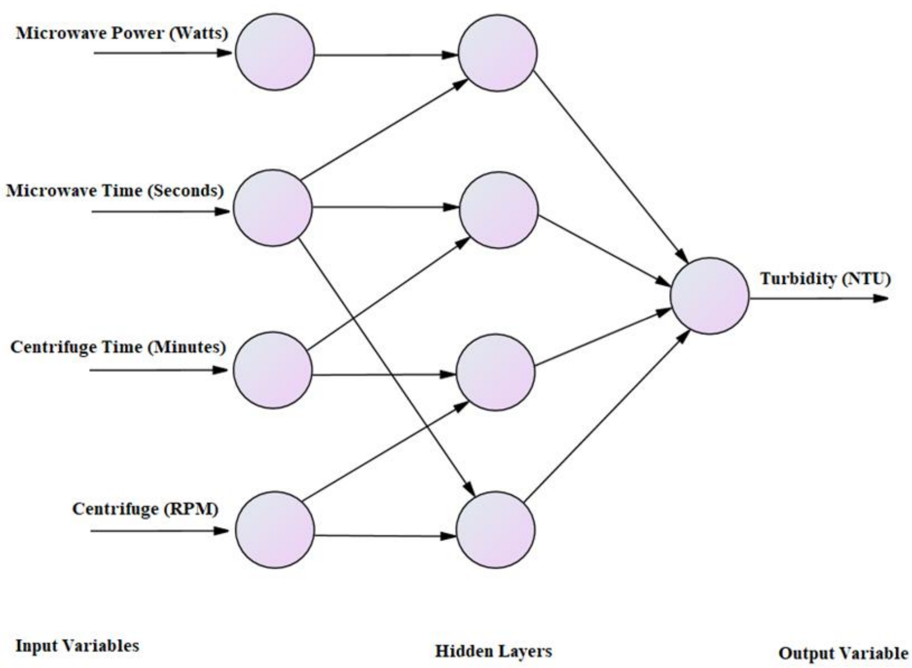

Fig. 1. Architecture of neural networks for input and output variables for the turbidity

The least mean squared error (MSE) and maximum R^2 values were used to select the topologies. The developed ANN architecture can be seen in Fig. 1, with the output neuron displaying turbidity reduction and the input neuron housing all independent variables. With a focus on comprehending the elimination of turbidity, the analysis sought to evaluate the relative significance of different input variables on the output variable. For the study, sigmoid function was adopted. The input factor consisted of MW power (x_1), MW time (x_2), centrifuge time (x_3), and centrifuge rpm (x_4), while the output was turbidity removal (Y). Equation 2 is the functional relationship between the input and output that the ANN estimated.

$$Y = f(x_1, x_2, x_3, x_4) \tag{2}$$

To calculate a neuron's output, Eq. 3 (Shokri *et al*. 2011) was used.

$$O_i = f\left(\sum_{j=1}^{n} w_{ij} I_j + b_i\right) \tag{3}$$

In this case, O_i, f, b_i, w_{ij}, n, and I_j stand for the neurons' outputs.

A number of statistics have been created to compare the predicted success of estimated models with one another. The predictive success of the estimated model is standardized using formulas based on the discrepancies between the projected values in the estimated model and the actual values in order to evaluate the accuracy of forecasts. It can be concluded that the model with the lowest error has excellent predictive capability. The Mean Absolute Error (MAE) and the Root Mean Square Error (RMSE) were the error statistics used in this study to gauge how well the model predicts the future.

The discrepancy between expected and actual values is indicated by the Mean Absolute Error (MAE). The absolute mean of the variations between the actual and anticipated values was used to calculate it. Regression loss functions such as the Root Mean Square Error (RMSE) are frequently employed. The square root of the sum of squared losses, which is derived by adding up the squared deviations between actual and predicted values for each case in the dataset, is then divided by the total number of examples (Chai and Draxler 2014).

The coefficient of determination is another metric used to evaluate the model's prediction performance (R^2). Based on the explanatory factors included in the model, the coefficient of determination shows how well the model explains the variability in the dependent variable. Stated differently, it represents a statistical indicator of how close the data is to the regression line. A decrease in the discrepancy between observed and anticipated values is implied by an increase in the coefficient of determination. This coefficient is represented as a percentage and takes values in the range of ($0 \le R^2 \le 1$). Using Eqs. 4 to 6, the coefficient of determination (R^2), root means square error (RMSE), and mean average error (MAE) were used to measure the prediction performance of the ANN (Dil *et al*. 2016; Asma *et al*. 2017; Jun *et al*. 2020; Yu *et al*. 2021; Wang *et al*. 2022).

$$R^2 = 1 - \frac{\sum_{i=1}^{N} (P_i - E_i)^2}{\sum_{i=1}^{N} (P_i - E_{mean})^2} \tag{4}$$

$$RMSE = \sqrt{\sum_{i=1}^{N} \frac{(P_i - E_i)^2}{n}} \tag{5}$$

$$MAE = \frac{1}{n} \sum_{i=1}^{N} P_i - E_i \tag{6}$$

where E_i is the experimental values, E_{mean} is the mean values and P_i is the predicted values from ANN (Dil *et al*. 2016; Asma *et al*. 2017; Jun *et al*. 2020; Yu *et al*. 2021; Wang *et al*. 2022).

RESULTS AND DISCUSSION

In this investigation, the application of a multi-layered genetic algorithm (GA) was integrated with a proficiently trained artificial neural network (ANN) to refine the optimization process for turbidity. The GA, characterized by diverse parameters such as population size, threshold, iteration count, and learning rate, was configured with specific values of 30, 0.04, 268, and 0.05, respectively. The dataset was split into testing and training sets, with 75% and 25% of the dataset in each set.

Outlines of the weight are shown associated with both the input-hidden layer and hidden-output layer of the ANN model in Table 3. Different combinations were tested to determine the best artificial neural network architecture. The structure that produced the minimum values in error statistics (MSE, RMSE, MAE) provided optimal results. In this context, extensive experimentation with various layers, node configurations, and activation functions was undertaken to refine the model's accuracy and predictive capabilities. Thus, optimal configurations were achieved for 4-4-1 topology in the ANN system. The mean squared error (MSE), serving as a metric for evaluating performance, was quantified for the network's training, testing, and the overall dataset, resulting in respective values of 0.0068, 0.0079, and 0.0065. These outcomes signify the average squared error between the model's outputs and the desired targets during both the training and testing phases of the study.

Table 3. Model Parameter Weights

Parameters	Values	Parameters	Values
error	0.221	Reached threshold	0.038
steps	268.000	Intercept to hidden layer 1	1.567
Microwave to hidden layer 1	-8.318	Time to hidden layer 1	2.626
Centrifuge min to hidden layer 1	3.486	Centrifuge rpm to hidden layer 1	-0.825
Intercept to hidden layer 2	-2.166	Microwave to hidden layer 2	5.177
Time to hidden layer 2	-1.179	Centrifuge min to hidden layer 2	3.583
Centrifuge rpm to hidden layer 2	-1.918	Intercept to hidden layer 3	3.551
Microwave to hidden layer 3	-3.696	Time to hidden layer 3	-4.736
Centrifuge min to hidden layer 3	-5.469	Centrifuge rpm to hidden layer 3	5.885
Intercept to hidden layer 4	-1.245	Microwave to hidden layer 4	-1.260
Time to hidden layer 4	-0.380	Centrifuge min to hidden layer 4	0.175
Centrifuge rpm to hidden layer 4	0.631	Intercept to turbidity	2.975
hidden layer 1 to turbidity	- 2.419	hidden layer 2 to turbidity	-1.575
hidden layer 3 to turbidity	-2.066	hidden layer 4 to turbidity	1.417

The error statistics used as indicators of the model's predictive performance are presented in Table 4. The obtained RMSE values for the training, testing, and overall dataset were 0.0547, 0.0891, and 0.0808, respectively. Similarly, the MAE values were calculated as 0.0388, 0.0577, and 0.0476 for the training, testing, and overall dataset, respectively.

Table 4. Evaluation of Model Performance

Model	R^2	MSE	RMSE	MAE
Train	99.84%	0.0068	0.0547	0.0388
Test	99.08%	0.0079	0.0891	0.0577
Total	99.63%	0.0065	0.0808	0.0476

The experimental and ANN predicted results for turbidity are visually represented separately in Figs. 2 through 4, capturing the dynamics in both the training and testing phases. Table 4 demonstrates a notable alignment with the 45-degree line characterized by R^2 values of 0.9984 (training), 0.9908 (testing), and 0.9963 (overall data). This alignment underscores a significant consistency between the experimental observations and the outcomes predicted by the ANN model. In the evaluation of the trained neural network, experimental data was utilized, resulting in an R^2 value of 0.9908, as detailed in Table 4. Evaluation parameters collectively highlight the satisfactory performance of the developed ANN model in predicting turbidity. The model provided a comprehensive understanding and application in the field of turbidity optimization by taking into account influential input factors such as microwave power, microwave time, centrifuge time, and centrifuge rpm.

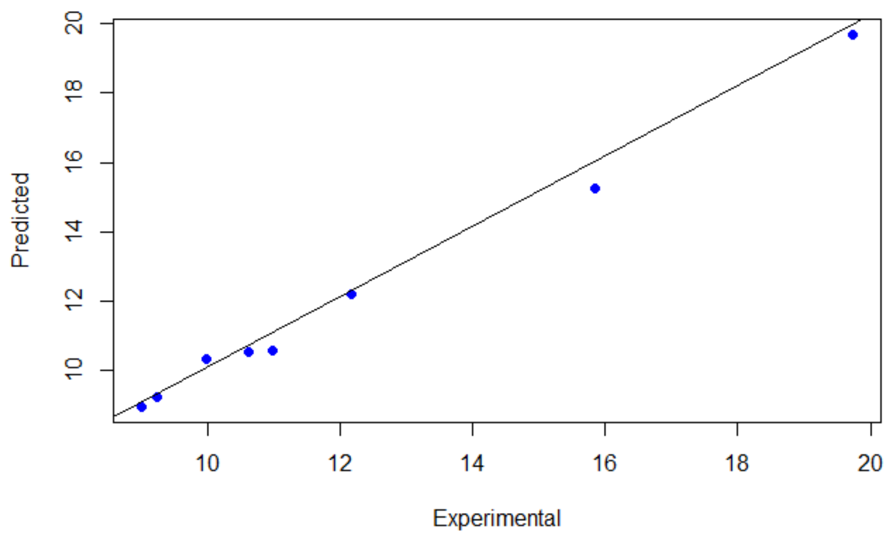

Fig. 2. Relationship between predicted and experimental data in test set

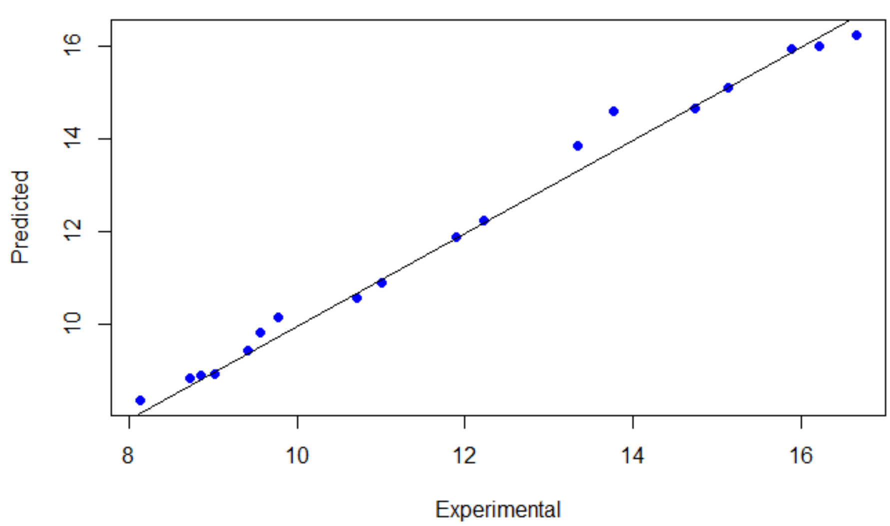

Fig. 3. Relationship between predicted and experimental data in train set

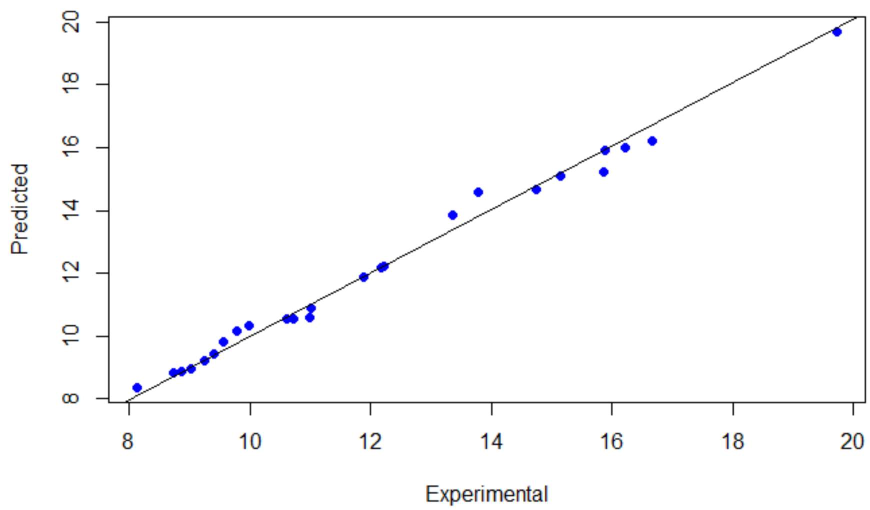

Fig. 4. Relationship between predicted and experimental data in total set

The experimental and predicted values of turbidity with ANN are given in Fig. 5. The assessment parameters demonstrated that, while taking into account the inputs of centrifuge rpm, centrifuge power, and microwave duration, the constructed artificial neural network (ANN) model was suitable in predicting the turbidity.

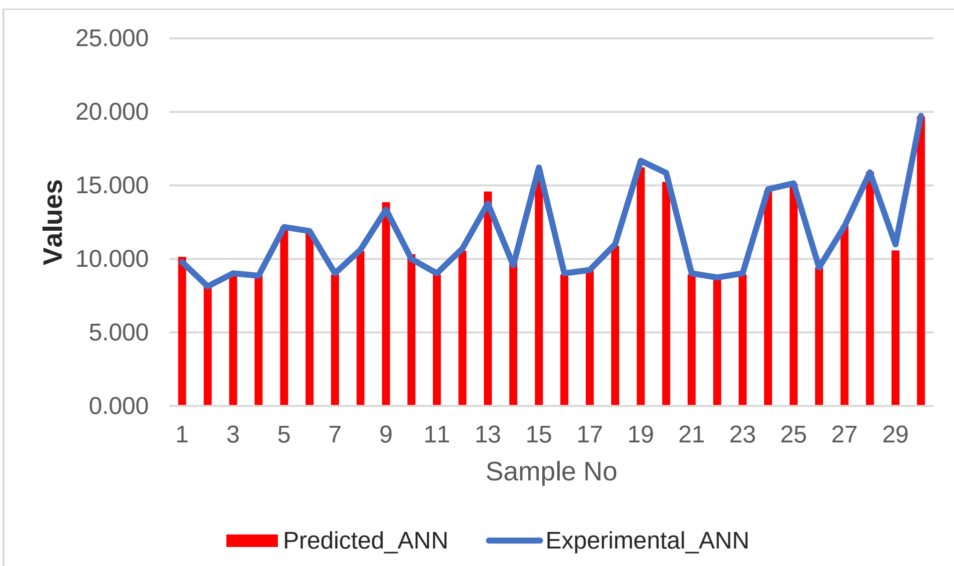

Fig. 5. Comparison of predicted and experimental values

A high turbidity value indicates that the pollution in the wastewater is high, while a low turbidity value indicates that the pollution is low. Figure 5 reveals that the sample with the highest turbidity value was number 30 (19.7 NTU), and the sample with the lowest turbidity value was number 2 (8.4 NTU). These outcomes not only align in both experimental and predictive outputs but also substantiate the accuracy of the model. In this context, the consistency between turbidity values obtained from experimental data and predictions strengthens the reliability of the model.

In the final part of this study, traditional statistical methods, specifically multiple linear regression, were compared with the artificial neural network models to provide researchers with insights into the direction and magnitude of the effects of input variables on wastewater turbidity removal. The purpose of this comparison is to evaluate the consistency of prediction outcomes between both methods. A detailed examination of the multiple linear regression analysis revealed that the R^2 value was 84.58%, with an MSE of 0.0119, RMSE of 0.1094, and MAE of 0.0956. Furthermore, the optimal model derived using multiple linear regression identified regression coefficients of 1.66 for microwave power, -0.28 for microwave duration, -0.79 for centrifugation time, and -0.88 for centrifugation speed. These coefficients indicate that microwave power had a positive effect on turbidity, *i.e.*, it increased turbidity; whereas microwave duration, centrifugation time, and centrifugation speed had negative effects, thus reducing turbidity. In other words, increases in microwave duration, centrifugation time, and centrifugation speed were understood to lower the turbidity levels of wastewaters. However, it was determined that microwave power did not have a significant reductive effect on turbidity. These findings are consistent with the expected outcomes. In conclusion, when comparing the predictions obtained from multiple linear regression and artificial neural networks, it has been determined that the results from artificial neural networks demonstrate superior performance.

Suggested Future Research

The optimization and control of wastewater treatment systems require monitoring and analysis of various parameters. While turbidity provides important information about the content of suspended solids in water, other variables should also be considered to fully evaluate and optimize system performance. In this context, below are some output variables that should be considered for future studies in wastewater treatment systems (Lee and Lin 2000; Spellman 2008; Tchobanoglous *et al*. 2014):

Chemical Oxygen Demand (COD): This parameter measures the amount of organic matter in water. COD indicates the amount of oxygen consumed by the chemical oxidation of organic matter, providing significant information about the degree of water pollution.

Total Suspended Solids (TSS): Similar to turbidity, TSS provides information about suspended solids, but it determines the mass density of suspended solids. This is important when evaluating the effectiveness of the treatment process.

Nitrogen and Phosphorus: The concentrations of nitrogen and phosphorus in wastewater are important, especially to comply with discharge standards and prevent ecological issues such as algal blooms. Specific nitrogen compounds such as nitrate, nitrite, and ammonia, along with total phosphorus and dissolved phosphorus levels, should be examined.

pH: The acidity or alkalinity level of wastewater can affect biological treatment processes and should therefore be regularly monitored.

Temperature: The temperature of wastewater has a significant impact on microbial activity and can affect the efficiency of treatment processes.

Dissolved Oxygen (DO): The level of dissolved oxygen in treatment tanks and effluent waters indicates the sufficiency of oxygen required for aerobic processes.

CONCLUSIONS

1. The wastewater of the paper industry contains a high concentration of suspended solids due to the raw materials and chemicals used in the production process. This makes the management of turbidity levels, which indicate the concentration of these particles in the wastewater, critical. The density of suspended solids can directly affect the efficiency of the treatment process, and turbidity is a key indicator used to monitor how efficiently these particles are removed from the treatment system. It is known that the increase or decrease in pollution in wastewater is directly proportional to turbidity. Therefore, turbidity has been considered as the sole output variable to examine the physical dimensions of pollution in wastewater.
2. In this study, employed microwave technology coupled with centrifugation as an innovative pre-treatment process for wastewater derived during paper recycling. The integration of these methods represents a significant stride towards sustainable and environmentally friendly solutions in wastewater management. The subsequent application of artificial neural networks (ANNs) in the analysis and optimization of purified water data show promising results.
3. The ANN model, configured with a 4-4-1 topology, demonstrated robust predictive performance, as indicated by low mean squared error (MSE) values during training (0.0068) and testing (0.0079). Evaluation metrics such as root mean squared error (RMSE) and mean absolute error (MAE) further underscored the reliability of the ANN model, with values of 0.0547, 0.0891, and 0.0388, 0.0577 for training, testing, and overall datasets, respectively. The high R^2 values (0.9984 for training, 0.9908 for testing, and 0.9963 for overall data) demonstrated a remarkable alignment between experimental observations and ANN predictions.
4. The visual representation of experimental and ANN-predicted turbidity values revealed the accuracy and applicability of the developed model. Notably, the model’s ability to predict turbidity based on input variables such as microwave power, microwave time, centrifuge time, and centrifuge RPM enhances its utility in optimizing wastewater treatment processes.
5. As a result, it was found that one of the input values, the microwave duration, did not have a significant effect on the model, but when the rpm and duration of the centrifugation process were increased, it was found to have a significant effect on the removal of pollution in the wastewater.
6. The successful application of microwave technology, centrifugation, and artificial neural networks in tandem offers a promising avenue for advancing wastewater treatment methodologies. This research contributes valuable insights towards the goal of achieving sustainable and efficient water treatment processes in the context of paper recycling.
7. Coping with the variability in the composition and behavior of daily wastewater poses a significant challenge for the effectiveness of wastewater treatment plants. Wastewaters from sources that constantly change, such as those from a paper factory, can hinder consistent performance in treatment systems. Artificial Neural Networks (ANN) analysis emerges as a potential technique to monitor daily changing wastewater conditions and optimize process parameters. Conducting ANN analysis on a daily or

more frequent basis may provide an opportunity to adapt to continuously changing wastewater conditions more dynamically. However, the cost and complexity of continuous ANN analysis should be taken into consideration. Additionally, the optimum settings generated by ANN may need to be 'calibrated' by focusing on specific conditions over a certain period. For this, it is important to establish reliable reference points, such as the initial turbidity of untreated wastewater. As a result, while techniques like ANN can enhance the performance of traditional systems, their applicability and effectiveness should be carefully evaluated depending on specific requirements.

ACKNOWLEDGMENTS

The authors declares that there are no funds and no conflict of interest.

REFERENCES CITED

Asma, N., Bhat, A. H., Mohamed, H. I., Mohammed, D., Abdul, N., Nawshad, M., and Taimur, K. (2017). "Efficient removal of methylene blue dye using mangosteen peel waste: kinetics, isotherms and artificial neural network (ANN) modeling,'' *Desalination and Water Treatment* 86, 191-202. DOI: 10.5004/dwt.2017.21295

Biermann, C. J. (1996). *Handbook of Pulping and Papermaking*, Elsevier.

Borchardt, J. K., Miller, J. D., and Azevedo, M. A. D. (1998). "Office paper de-inking," *Current Opinion in Colloid & Interface Science* 3(4), 360-367.

Čabalová, I., Kačík, F., Geffert, A., and Kačíková, D. (2011). "The effects of paper recycling and its environmental impact," *Environmental Management in Practice* 17, 329-350.

Chai, T., and Draxler, R. R. (2014). "Root mean square error (RMSE) or mean absolute error (MAE)," *Geoscientific Model Development Discussions* 7(1), 1525-1534. DOI: 10.5194/gmdd-7-1525-2014.

Chandegara, V. K., and Varshney, A .K. (2014). "Effect of centrifuge speed on gel extraction from *Aloe vera* leaves," *Journal of Food Processing & Technology* 5, 1-6. DOI: 10.4172/2157-7110.1000295

Cheng, G., Lin, J., Lu, J., Zhao, X., Cai, Z., and Fu, J. (2015). "Advanced treatment of pesticide-containing wastewater using Fenton reagent enhanced by microwave electrodeless ultraviolet," *BioMed Research International* Int. 1–8. DOI: 10.1155/2015/205903

Choy, S. Y., Prasad, K. N., Wu, T. Y., Raghunandan, M. E., and Ramanan, R. N. (2016). "Performance of conventional starches as natural coagulants for turbidity removal," *Ecological Engineering* 94, 352-364.

Coskun, S. (2022). "Zero waste management behavior: Conceptualization, scale development and validation—A case study in Turkey," *Sustainability* 14(19), article 12654. DOI: 10.3390/su141912654

Diamantopoulou, M. J., Özçelik, R., Koparan, B., and Alkan, O. (2023). "Artificial intelligence as an alternative modelling strategy for reliable height-diameter predictions of mixed-oaks species," *Turkish Journal of Agriculture and Forestry* 47(2), 228-241. DOI: 10.55730/1300-011X.3081

Dil, E. A., Ghaedi, M., Ghaedi, A., Asfaram, A., Jamshidi, M., and Purkait, M. K. (2016). "Application of artificial neural network and response surface methodology for the removal of crystal violet by zinc oxide nanorods loaded on activate carbon: Kinetics and equilibrium study," *Journal of the Taiwan Institute of Chemical Engineers* 59, 210-220. DOI: 10.1016/j.jtice.2015.07.023

Ezemagu, I. G., Ejimofor, M. I., Menkiti, M. C., and Nwobi-Okoye, C. C. (2021). "Modeling and optimization of turbidity removal from produced water using response surface methodology and artificial neural network," *South African Journal of Chemical Engineering* 35, 78-88. DOI: 10.1016/j.sajce.2020.11.007

Han, N., Zhang, J., Hoang, M., Gray, S., and Xie, Z. (2021). "A review of process and wastewater reuse in the recycled paper industry," *Environmental Technology & Innovation* 24, article 101860. DOI: 10.1016/j.eti.2021.101860

Haupt, R. L., and Haupt, S. E. (2004). *Practical Genetic Algorithms*, John Wiley & Sons, Inc., Hoboken, New Jersey, USA.

Hubbe, M. A., Metts, J. R., Hermosilla, D., Blanco, M.A., Yerushalmi, L., Haghighat, F., Lindholm-Lehto, P., Khodaparast, Z., Kamali, M., and Elliot, A. (2016). "Wastewater treatment and reclamation: A review of pulp and paper industry practices and opportunities," *BioResources* 11(3), 7953-8091.

Jun, L. Y., Karri, R. R., Yon, L. S., Mubarak, N. M., Bing, C. H., Mohammad, K., Jagadish, P., and Abdullah, E. C. (2020). "Modeling and optimization by particle swarm embedded neural network for adsorption of methylene blue by jicama peroxidase immobilized on buckypaper/polyvinyl alcohol membrane," *Environmental Research* 183, article 109158. DOI: 10.1016/j.envres.2020.109158

Jung, S. C. (2011). "The microwave-assisted photo-catalytic degradation of organic dyes," *Water Science and Technology* 63(7), 1491-1498. DOI: 10.2166/wst.2011.393

Kamali, M., and Khodaparast, Z. (2015). "Review on recent developments on pulp and paper mill wastewater treatment," *Ecotoxicology and Environmental Safety* 114, 326-342. DOI: 10.1016/j.ecoenv.2014.05.005

Lee, C. C., and Lin, S. D. (2000). *Handbook of Environmental Engineering Calculations*, McGraw-Hill, New York, pp. 1223-1261.

Lin, L., Chen, J., Xu, Z., Yuan, S., Cao, M., Liu, H., and Lu, X. (2009). "Removal of ammonia nitrogen in wastewater by microwave radiation: A pilot-scale study," *Journal of Hazardous Materials* 168(2-3), 862-867. DOI: 10.1016/j.jhazmat.2009.02.113

Majekodunmi, S. O. (2015). "A review on centrifugation in the pharmaceutical industry," *American Journal of Biomedical Engineering* 5(2), 67-78. DOI: 10.5923/j.ajbe.20150502.03

Musa, M. A., Chowdhury, S., Biswas, S., Alam, S. N., Parvin, S., and Sattar, M. A. (2024). "Removal of aqueous methylene blue dye over Vallisneria Natans biosorbent using artificial neural network and statistical response surface methodology analysis," *Journal of Molecular Liquids* 393, article 123624. DOI: 10.1016/j.molliq.2023.123624.

Orsat, V., Raghavan, V., and Meda, V. (2005). "Microwave technology for food processing: An overview," *The Microwave Processing of Foods* 105-118.

Ozkan, U., Bayram, O., Göde, F., Coskun, S., and Sahin, H.T. (2023). "Application of response surface methodology (RSM) for optimizing turbidity of paper recycling wastewater using microwave technology," *Asian Journal of Applied Chemistry Research* 13(1), 13-22. DOI: 10.9734/ajacr/2023/v13i1233

Özkan, U., and Şahin, H.T. (2023). "Treatment of paper recycling wastewater using microwave technology," *Turkish Journal of Forestry* 24(2), 134-138. DOI: 10.18182/tjf.1268140

Pokhrel, D., and Viraraghavan, T. (2004). "Treatment of pulp and paper mill wastewater a review," *Science of The Total Environment* 333(1-3), 37-58. DOI: 10.1016/j.scitotenv.2004.05.017

Remya, N., and Lin, J. G. (2011). "Current status of microwave application in wastewater treatment - A review," *Chemical Engineering Journal* 166(3), 797-813. DOI: 10.1016/j.cej.2010.11.100

Russell, S. J., and Norvig, P. (2003). *Artificial Intelligence: A Modern Approach*, Pearson Educational Inc, Upper Saddle River, New Jersey, USA.

Sahin, H. (2013). "A study on paper recycling effects on cellulose properties," *Turkish Journal of Forestry* 14(1), article 7480.

Shokri, A., Hatami, T., and Khamforoush, M. (2011). "Near critical carbon dioxide extraction of Anise (Pimpinella Anisum L.) seed: Mathematical and artificial neural network modeling," *The Journal of Supercritical Fluids* 58(1), 49-57. DOI: 10.1016/j.supflu.2011.04.011.

Spellman, F. R. (2008). Handbook of water and wastewater treatment plant operations. CRC press.

Sui, Z.-Y., Dong, S.-J., Cui, X.-J., Gao, Y., Li, L.-F., Wang, H.-Y., and Zhang, S. X. (2009). "Combined de inking technology applied on laser printed paper," *Chemical Engineering and Processing: Process Intensification* 48(2), 587-591. DOI: 10.1016/j.cep.2008.06.014

Tchobanoglous, G., Stensel, H., Tsuchihashi, R., and Burton, F. (2014). *Wastewater Engineering: Treatment and Resource Recovery*, Metcalf & Eddy, AECOM, McGraw Hill Education.

Toczyłowska-Mamińska, R. (2017). "Limits and perspectives of pulp and paper industry wastewater treatment- A review," *Renewable and Sustainable Energy Reviews* 78, 764-772. DOI: 10.1016/j.rser.2017.05.021

Venkatesh Prabhu, M., Karthikeyan, R., and Shanmugaprakash, M. (2016). "Modeling and optimization by response surface methodology and neural network–genetic algorithm for decolorization of real textile dye effluent using *Pleurotus ostreatus*: A comparison study," *Desalination and Water Treatment* 57(28), 13005-13019. DOI: 10.1080/19443994.2015.1059372

Vialkova, E., Obukhova, M., and Belova, L. (2021). "Microwave irradiation in technologies of wastewater and wastewater sludge treatment: A review," *Water* 13(13), article 1784. DOI: 10.3390/w13131784

Wang, W., Wu, X., and Long, S. (2022). "Optimizing the methylene blue removal from aqueous solution using pomelo peel based biochar assisted by RSM and ANN-PSO," *Polish Journal of Environmental Studies* 31(1), 329-346. DOI: 10.15244/pjoes/137947

Wang, N., Sun, X., Zhao, Q., and Wang, P. (2021). "Treatment of polymer-flooding wastewater by a modified coal fly ash catalysed Fenton-like process with microwave pre-enhancement: System parameters, kinetics, and proposed mechanism," *Chemical Engineering Journal* 406, article 126734. DOI: 10.1016/j.cej.2020.126734

Wang, N., and Wang, P. (2016). "Study and application status of microwave in organic wastewater treatment - A review," *Chemical Engineering Journal* 283, 193-214. DOI: 10.1016/j.cej.2015.07.046

Wei, R., Wang, P., Zhang, G., Wang, N., and Zheng, T. (2020). "Microwave-responsive catalysts for wastewater treatment: A review," *Chemical Engineering Journal* 382, article 122781. DOI: 10.1016/j.cej.2019.122781

Yu, A., Liu, Y., Li, X., Yang, Y., Zhou, Z., and Liu, H. (2021). "Modeling and optimizing of NH^{4+} removal from stormwater by coal-based granular activated carbon using RSM and ANN coupled with GA," *Water* 13(5), article 608. DOI: 10.3390/w13050608

Article submitted: February 2, 2024; Peer review completed: April 2, 2024; Revised version received: May 3, 2024; Accepted: May 24, 2024; Published: June 6, 2024.
DOI: 10.15376/biores.19.3.5003-5018