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Application of Artificial Intelligence in Evaluating the Crossflow Microfiltration Process for Treating Effluent Generated in a Sewage Treatment System

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Abstract

This study explores the application of artificial neural networks (ANNs) to optimize the crossflow microfiltration process in wastewater treatment. This membrane filtration method is efficient in removing suspended particles, turbidity, and microorganisms, but faces challenges such as membrane clogging, which reduces efficiency and increases operating costs. The research aims to develop an artificial intelligence-based model capable of optimizing filtration conditions and improving overall system performance. The experimental data used include variables such as time, volume, flow rate and temperature to predict permeate flux. The ANN model was trained in MATLAB software using the Levenberg-Marquardt method, with data percentages distributed between training, validation, and testing. The analyses were performed using error histograms, linear regression plots, percentage errors, and mean squared error (MSE) metrics. Two models were developed: one for mixed liquor and one for water, demonstrating high accuracy in both cases. The results indicated that the models were able to predict data patterns with coefficients of determination (R^2) equal to 1, indicating a perfect linear relationship between actual and predicted values. The MSE graph showed a consistent reduction over the epochs, evidencing the efficiency of the training. Furthermore, low relative mean errors (0.064 for liquor and 0.0031 for water) reinforce the effectiveness of the model. The research validated the use of ANNs in optimizing effluent treatment processes, promoting operational efficiency and sustainability.

Keywords: Artificial neural networks; Crossflow microfiltration; Wastewater treatment; Sustainability

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1. Introduction

The growing interest in more sustainable practices has encouraged the search for effective solutions for treating effluents generated in sewage systems. In Brazil, although 82% of the population has access to water services, less favored regions still face challenges in this area.

In this context, crossflow microfiltration emerges as a promising alternative, especially when associated with biological reactors, such as the UASB (Upflow Anaerobic Sludge Blanket) reactor. This technique is effective in removing suspended solids, turbidity, and microorganisms, promoting significant improvements in effluent quality and contributing to environmental sustainability. However, clogging of filter membranes still presents challenges, increasing operating costs and requiring frequent maintenance.

Since its beginnings in the 1940s, artificial intelligence (AI) has proven to be essential for replicating human cognitive tasks. Artificial neural networks, with their interconnected layers of artificial neurons, are widely used in pattern recognition and prediction tasks, and are effective in effluent treatment, as demonstrated in studies that optimize biological processes and for the removal of contaminants. Crossflow microfiltration, in turn, uses porous membranes to purify effluents, ensuring high efficiency in the removal of particles and microorganisms, despite the challenges related to clogging. Its use has been explored in sewage treatment plants and even in industry, with promising results in the retention of suspended material and organic matter.

One of the main roles of neural networks in wastewater treatment is to model and predict the performance of water or waste treatment systems. There are some applications, such as one that demonstrated the use of artificial neural networks to optimize the integration of biological processes with the photo-Fenton method in the treatment of leachate. The photo-Fenton method uses a combination of iron, hydrogen peroxide (a strong oxidizing agent) and UV light to generate free radicals, which degrade organic contaminants. In this context, neural networks were effective in predicting and optimizing operating parameters, promoting efficient removal of COD (Chemical Oxygen Demand, a measure of the amount of oxygen needed to oxidize organic and inorganic compounds in a water sample) and other pollutants.

Therefore, the application of artificial intelligence to evaluate crossflow microfiltration processes represents a significant advance in wastewater treatment, combining technological innovation and environmental sustainability. By optimizing operational conditions and predicting failures, this approach not only improves system efficiency but also contributes to reducing costs and environmental impact. Thus, this study proposes an in-depth analysis of the transformative potential of artificial neural networks in this context, indicating new paths for the development of more sustainable practices in water resource management.

2. Materials and Methods

2.1 Database

The database used consisted of input values of time (min), volume (L), flow (L/h) and temperature (ºC). The input variables determined the output value of the permeate flux (L h^{-1} m^{-2}) (Vidal, 2006). An illustrative example of a data set was found in Table 1.

Table 1. Some input and output data sets

Time (min)	Volume (L)	Flow (L/h)	Temperature (ºC)	Permeate flux (L h^{-1} m^{-2})
30	15.0	30.0	25	833.3
60	16.7	33.4	25	927.8
90	17.5	35.0	26	972.2
120	18.0	36.0	26	1000.0
30	18.0	36.0	25	1000.0
60	18.5	37.0	25	1027.8
90	19.2	38.4	26	1066.7
120	19.9	39.4	26	1105.6

2.2 Artificial neural network

The organized data was loaded into the MATLAB software, which was used to run the artificial neural network models. During this process, the percentage distribution of the data set was established for the testing, validation and training stages, in order to ensure the accuracy of the model.

Artificial neural networks were made up of three main layers: the input layer, responsible for receiving the data and transferring it to the next

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processing stage; the hidden layers, which processed the information received and can vary in quantity, depending on the complexity of the model; and, finally, the output layer, which produced the final result, such as classifications or predictions. Each node in a layer connected to the nodes in the next layer through synaptic weights, adjusted during training to minimize errors and optimize the accuracy of the model.

The data was used to develop two neural network models: one for mixed liquor and the other for water. For the liquor, the input matrix had dimensions of 4x48, considering the parameters of time, volume, flow and temperature, while the output matrix was 1x48, representing the permeate flow, 48 representing the number of samples. For water, the input matrix has dimensions of 4x32, using the same parameters, and the output matrix was 1x32, also based on the permeate flow, with 32 being the number of samples.

2.3 Training algorithm

The Levenberg-Marquardt method arose from the need to improve optimization algorithms to solve nonlinear problems. The basic formulation of the Newton's method was Equation 1 below:

$$\Delta x = -[\nabla^2 V(x)]^{-1} \nabla V(x) \quad (1)$$

Where V(x) is a function to minimize with respect to the vector parameter x, $\nabla^2 V(x)$ is the Hessian matrix and $\nabla V(x)$ is the gradient. If we assume that V(x) is the sum of squares function we have the following Equation 2:

$$V(x) = \Sigma\, e^2_i(x) \quad (2)$$

Then is shown by Equations 3 and 4:

$$\nabla V(x) = J^T(x)\, e(x) \quad (3)$$

$$\nabla^2 V(x) = J^T(x)\, J(x) + S(x) \quad (4)$$

Where J(x) is the Jacobian matrix and S(x) is defined as (Equation 5):

$$S(x) = \Sigma\, e_i(x)\, \nabla^2 e_i(x) \quad (5)$$

For curve fitting and least squares problems, the Gauss-Newton method was an alternative to Newton's method. Replacing the Hessian with an approximation based on the Jacobian matrix in Equation 6:

$$\Delta x = [J^T(x)\, J(x)]^{-1}\, J^T(x)\, e(x) \quad (6)$$

To overcome these problems, Kenneth Levenberg (1944) and Donald Marquardt (1963) proposed incorporating a regularization term into the update equation, we have Equation 7:

$$\Delta x = [J^T(x)\, J(x) + \mu I]^{-1}\, J^T(x)\, e(x) \quad (7)$$

The parameter μ is dynamically adjusted during training, increasing if the interaction fails to reduce the error and decreasing if the interaction is successful.

Each neuron computes an output based on a linear combination of the inputs and weights, plus a bias term b, and applies an activation function f. The output of neuron j can be represented in Equation 8 below:

$$y_j = f(\Sigma\, W_{ij}\, x_i + b_j) \quad (8)$$

The goal of training a neural network was to adjust the weights W_{ij} and biases b_j to minimize the error between the output and the expected value.

Training a neural network involves presenting a set of training data, allowing the network to adjust its synaptic weights to identify patterns and relationships in the data. This adjustment is performed using optimization algorithms, such as the gradient descent method, which modifies the weights with the aim of minimizing an error function.

Next, the training parameters, such as the learning rate and the number of epochs, are defined. The training process is conducted using the previously separated data sets, while monitoring the error rate throughout the training.

To evaluate the performance of the trained model, error histograms, linear regressions, percentage errors, and performance graphs are used. The results obtained are compared with experimental data to analyze the accuracy of the neural network predictions. In addition, adjustments can be made to the model to improve its performance and reduce error.

In addition, an additional window will be created to predict output values with the insertion of input data by the user who wishes to predict a result, making it possible to choose which network the value will be predicted for. And with the predicted values, the best result of the data predicted by the user will be displayed graphically.

3. Results

The results of this study demonstrated the performance of the artificial neural network model applied to the crossflow microfiltration process for effluent treatment, using several approaches for validation and analysis of the results obtained. Two neural models were developed, one focused on the analysis using mixed liquor and the other with water, and trained using the Levenberg-Marquardt training method with 5 neurons in the hidden layers. For the liquor network, it used 300 epochs maximum and for the water network 200 epochs maximum.

3.1 Mixed liquor

Figure 1 shows three fundamental aspects for analyzing the performance of neural networks: residual errors, model accuracy, and training evolution.

The error histogram with 20 classes (Figure 1a) shows the distribution of errors, i.e. the difference between the real values and the outputs predicted by the network, for the training, validation and test sets. The greater concentration of errors close to zero indicates that the neural network performed well, with the majority of errors being minimal.

The comparison graph between the real data and the neural network predictions (Figure 1b) shows that the predictions follow the real data with high precision, indicating the network's ability to generalize the input data and accurately predict the expected values.

Finally, the best-performing validation graph shows how the mean square error (MSE) behaves over the 219 epochs analyzed (Figure 1c). The lowest MSE, corresponding to the network's best performance in validation, was found in epoch 213, reaching a value of 0.0018. This shows that the training of the neural network was efficient and achieved excellent results, both in minimizing errors and in the accuracy of predictions for the data set analyzed. These results reflect the successful training and robust capacity of the neural network in the context of the study carried out.

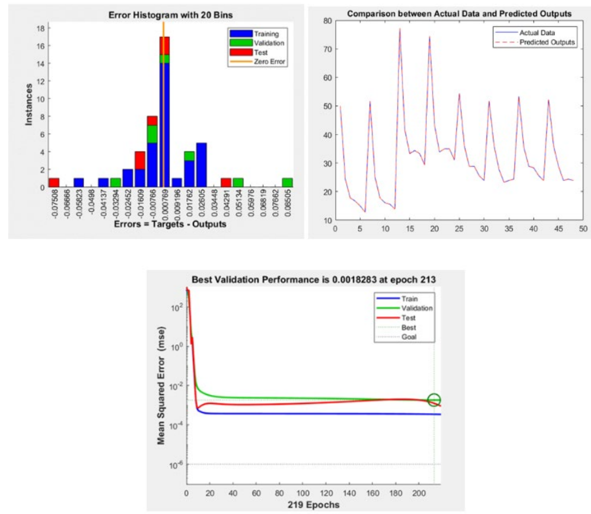

Figure 1. Liquor model with (a) error histogram, (b) comparison between actual data and predicted values and (c) mean squared error (MSE)

Figure 2 shows linear regression graphs that show the accuracy and consistency of the neural network model. The results show a good correlation between the predicted values and the real values in all the subsets analyzed, training, validation and testing, with coefficients of determination (R^2) equal to 1. This shows that the model was able to fully capture the patterns of the experimental data.

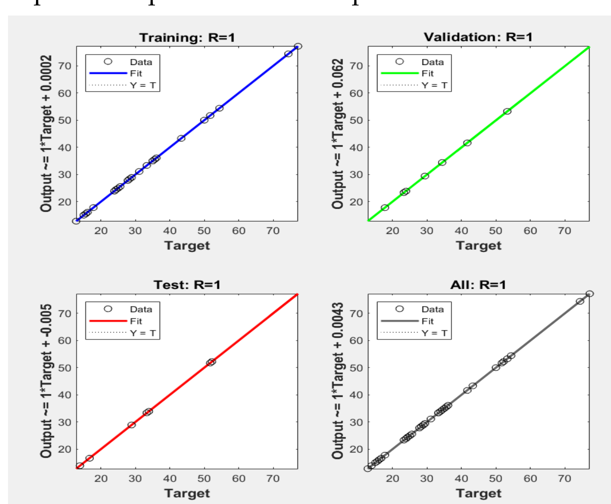

Figure 2. Linear regression graphs representing prediction by dataset for the liquor model

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Table 2 provides a detailed comparison between the estimated and actual values, based on the 48 samples analyzed, as well as the respective relative errors calculated for each one. The data show that the values estimated by the model are considerably close to the measured values, indicating high accuracy. Most of the relative errors are low, often close to zero, which highlights the model's ability to make accurate predictions. The average relative error is 0.0639, which reinforces the positive performance of the model across all samples.

Table 2. Comparison of estimated values, real values and relative errors for the liquor model.

Sample	Estimated	Real	Relative error
1	49.9989	50.0000	0.0022
2	24.4246	24.4000	0.1008
3	17.8003	17.8000	0.0017
4	16.6587	16.7000	0.2473
5	15.0146	15.0000	0.0973
6	12.8067	12.8000	0.0523
7	51.7032	51.7000	0.0062
8	24.9755	25.0000	0.0980
9	17.8003	17.8000	0.0017
10	16.1041	16.1000	0.0255
11	15.5701	15.6000	0.1917
12	13.9200	13.9000	0.1439
13	77.1997	77.2000	0.0004
14	41.6107	41.7000	0.2141
15	33.3793	33.3000	0.2381
16	34.4067	34.4000	0.0195
17	33.3176	33.3000	0.0529
18	29.4109	29.4000	0.0371
19	74.4000	74.4000	0.0000
20	43.3002	43.3000	0.0005
21	33.9082	33.9000	0.0242
22	34.9986	35.0000	0.0040
23	34.9896	35.0000	0.0297
24	31.0987	31.1000	0.0042
25	54.3983	54.4000	0.0031
26	36.1049	36.1000	0.0136
27	28.8994	28.9000	0.0021
28	28.8777	28.9000	0.0772
29	25.5717	25.6000	0.1105
30	23.8792	23.9000	0.0870
31	51.7032	51.7000	0.0062
32	36.1049	36.1000	0.0136
33	27.8016	27.8000	0.0058
34	23.3362	23.3000	0.1554
35	23.8980	23.9000	0.0084
36	24.4423	24.4000	0.1734
37	53.2460	53.3000	0.1013
38	35.5852	35.6000	0.0416
39	28.8994	28.9000	0.0021
40	28.3277	28.3000	0.0979
41	25.5717	25.6000	0.1105
42	23.8792	23.9000	0.0870
43	52.2171	52.2000	0.0328
44	36.1049	36.1000	0.0136
45	28.8994	28.9000	0.0021
46	23.8973	23.9000	0.0113
47	24.4566	24.4000	0.2320
48	23.8792	23.9000	0.0870
Average			0.0639

3.2 Water

Figure 3 shows three fundamental aspects for analyzing the performance of neural networks: residual errors, model accuracy and training evolution.

The error histogram (Figure 3a) shows the difference between the real targets and the network outputs, divided into 20 classes. The error values vary approximately from -0.0169 to 0.03913, with a higher concentration close to zero, which suggests that the network is reasonably accurate. This graph is segmented by training, validation and test sets, colored blue, green and red respectively. The presence of a large number of small errors indicates that the model has learned the patterns in the data set well.

The graph comparing the real data with the outputs predicted by the neural network (Figure 3b) shows that the predictions follow the real values very closely, with a range from 800 to 1150 over 32 data points. The actual data is indicated by a dashed red line, while the predictions appear as a solid blue line, showing the model's ability to generate consistent predictions.

The third graph illustrates the validation performance (Figure 3c), measured by the mean squared error (MSE), over 19 epochs. The best validation performance occurred in epoch 13, with an MSE of 0.0009. This low value reflects the network's ability to achieve good generalization for new data. The graph also clearly shows how the errors decrease over the course of training, suggesting that the model was trained efficiently.

The results presented indicate that the neural network was able to learn the data patterns

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accurately and efficiently, showing good suitability for the problem under investigation.

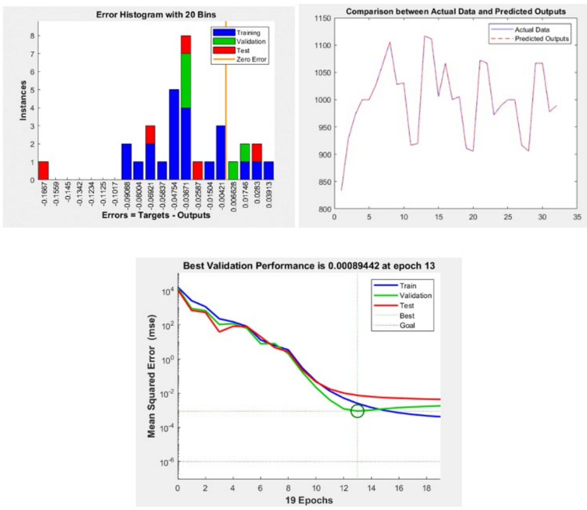

Figure 3. Water model with (a) error histogram, (b) comparison between actual data and predicted values and (c) mean squared error (MSE)

Figure 4 shows four linear regression graphs that provide a detailed assessment of the accuracy and consistency of the model. Each graph represents a different subset of the data, all of which have correlation coefficients equal to 1, indicating a perfect linear relationship between the actual and predicted values, demonstrating that the model was able to fully capture the patterns in the data analyzed.

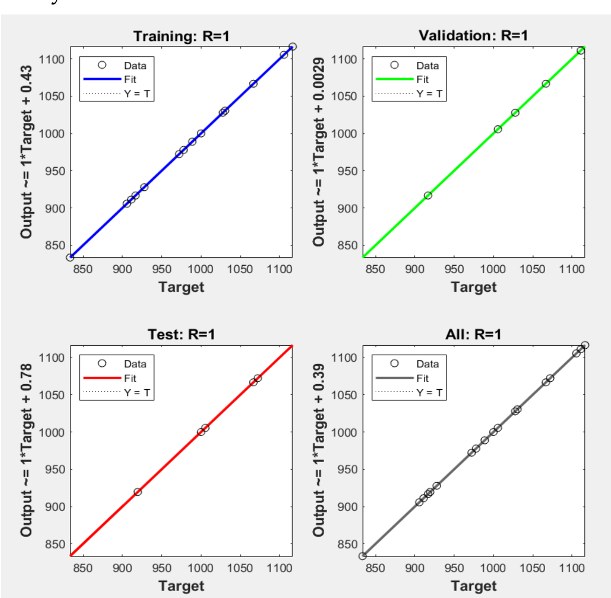

Figure 4. Linear regression of training, validation and test sets for the water model

Table 3 presents a comparison between the values estimated by the neural network and the real values, accompanied by the relative errors for each sample and an average. The values estimated by the model are close to the real values, indicating accuracy in the prediction. The average error calculated is 0.0031, indicating that the model has a good overall performance, demonstrating that it is capable of generalizing data patterns well and minimizing divergences in its predictions.

Table 3. Comparison of estimated values, real values and relative errors for water model

Sample	Estimated	Real	Relative error
1	833.3780	833.3000	0.0094
2	927.8343	927.8000	0.0037
3	972.2913	972.2000	0.0094
4	1000.0000	1000.0000	0.0000
5	1000.0000	1000.0000	0.0000
6	1027.8000	1027.8000	0.0000
7	1066.7000	1066.7000	0.0000
8	1105.6000	1105.6000	0.0000
9	1027.8000	1027.8000	0.0000
10	1030.6000	1030.6000	0.0000
11	916.7393	916.7000	0.0043
12	919.5721	919.4000	0.0187
13	1116.7000	1116.7000	0.0000
14	1111.1000	1111.1000	0.0000
15	1005.6000	1005.6000	0.0000
16	1066.7000	1066.7000	0.0000
17	1000.0000	1000.0000	0.0000
18	1005.6000	1005.6000	0.0000
19	911.1688	911.1000	0.0076
20	905.6587	905.6000	0.0065
21	1072.3000	1072.2000	0.0093
22	1066.7000	1066.7000	0.0000
23	972.2913	972.2000	0.0094
24	988.9106	988.9000	0.0011
25	1000.0000	1000.0000	0.0000
26	1000.0000	1000.0000	0.0000
27	916.7393	916.7000	0.0043
28	905.6727	905.6000	0.0080
29	1066.7000	1066.7000	0.0000
30	1066.7000	1066.7000	0.0000
31	977.8388	977.8000	0.0040
32	988.9491	988.9000	0.0050
Average			0.0031

3.3 Flow forecast

With linear regressions and small errors, an additional window was developed, as shown in

Figure 5 below, where it is possible to select the network that will be used to predict the result, facilitating the application of neural network models.

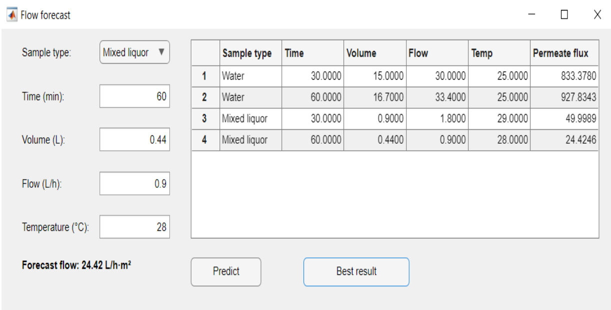

Figure 5. Additional flow forecast window

After selecting the network, only four numerical inputs are required for the system to perform the calculation and display, in real time, the estimated permeated flow value with an accuracy of up to four decimal places when the "Predict" command is activated. Each prediction is automatically recorded in a history table, which stores the sample identifier, the model used, the input values, the predicted result, and the date and time stamp. This feature supports both simulation traceability and comparative analysis of different operating scenarios without the need for manual data export.

With the results stored, the interface also offers an interactive graph (Figure 6) that displays all recent estimates, highlighting the sample that presented the highest predicted permeate flow at the moment. The visual representation allows trends and comparisons between the two network architectures to be identified, helping the operator to quickly understand which set of parameters maximizes the performance of the tangential microfiltration process. In this way, the tool not only validates the accuracy of the models, but also translates the robustness of neural networks into a practical solution for real-time operation and optimization decisions.

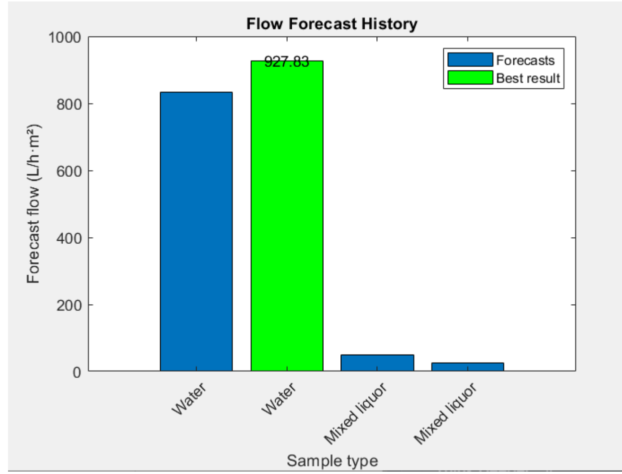

Figure 6. Graph showing the best results from the samples

4. Conclusion

The study demonstrated the effectiveness of using artificial neural networks (ANNs) in the crossflow microfiltration process for wastewater treatment. The ANN-based approach proved to be a robust and accurate tool, providing reliable predictions for the permeate flux and significantly reducing errors across different data sets. The application of ANNs enables the optimization of operational conditions of the microfiltration process and the prediction of failures, promoting greater efficiency and sustainability in wastewater treatment.

The results validate the potential of this technology as an innovative solution to environmental and operational challenges, integrating technological advances with sustainable water resource management. This study paves the way for future research that can explore additional improvements to the model and expand its applications in other water and wastewater treatment contexts.

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