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Studying Rheology of Tannery Waste Liquor Using Artificial Neural Networks

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Abstract

Understanding the rheology of tannery waste is essential for efficient waste management and the design of required devices such as pumps and agitators. Experimental studies have shown that tannery waste exhibits shear-thinning, non-Newtonian behavior, where the increase in solid concentration and decrease in temperature lead to higher shear stress and viscosity. To verify these findings, an artificial neural network (ANN) model was developed to predict the rheological behavior of tannery waste. The model takes solid concentration, shear rate, and temperature as inputs and provides shear stress and viscosity as outputs. The ANN demonstrated exceptional accuracy, achieving mean squared error (MSE) values of 0.0003 and 0.0001 and determination coefficients (R^2) of 0.9999 and 0.9945 for shear stress and viscosity, respectively. These results confirm that the ANN can accurately replicate the experimental observations and outperform traditional curve-fitting techniques, offering a robust tool for analyzing the complex rheology of tannery waste. This approach underscores the potential of integrating machine learning into waste management systems, promoting sustainable industrial practices.

Keywords: Artificial neural network, flow properties, tannery waste, shear stress, viscosity.

1. Introduction

The leather tanning industry plays a vital role in Egypt's economy; however, it faces substantial environmental challenges, particularly in managing toxic waste containing sulfides and chromium salts. Consequently, numerous studies have been conducted to address these issues and develop sustainable solutions. [1-5] In response, the Egyptian government has modernized operations through initiatives like El-Robbiki City, which integrates advanced machinery and a planned central wastewater treatment facility. Effective waste management requires a thorough understanding of tannery waste rheology, essential for optimizing treatment processes. Previous research by the authors [6] experimentally analyzed tannery waste rheology, revealing its non-Newtonian, shear-thinning behavior. Varying solid concentrations (20%–30%) and temperature (10°C–40°C) demonstrated that increasing concentration raises shear stress and viscosity, while higher temperatures reduce both properties as revealed from Figure (1).

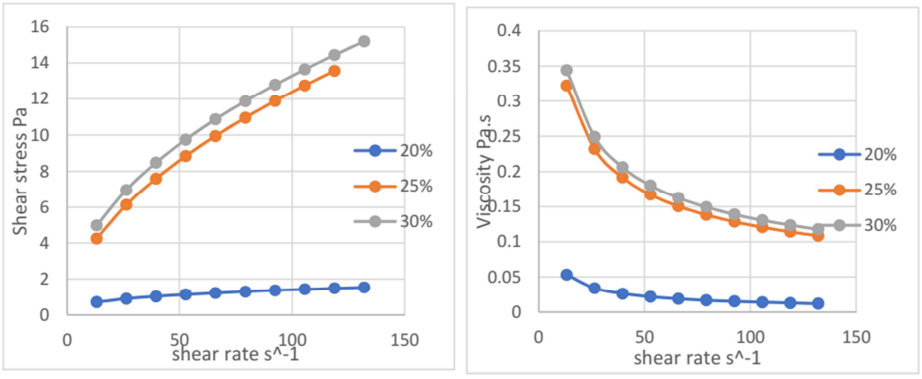

Figure 1: Experimental results showing effect of concentration at 30

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The primary objective of this study is to simulate these experimental findings through the development of an artificial neural network (ANN) model, providing a more predictive understanding of tannery waste rheology. This work is recent in its context since the study of flow behavior of tannery waste liquor is scarce and was previously studied experimentally by the authors. However, simulating these findings using artificial neural networks (ANNs) is novel and has not been covered in the literature before. While ANNs have been applied in rheology modeling, our study introduces an optimized ANN architecture specifically tailored for tannery waste liquor, a unique industrial waste stream with complex rheological properties.

Artificial neural networks (ANNs) are computational models inspired by biological neural systems, designed to learn from data and recognize patterns. They approximate nonlinear functions and are widely applied in artificial intelligence fields such as image recognition, natural language processing, and financial forecasting. ANNs consist of an input layer, one or more hidden layers where computations occur, and an output layer that generates predictions. Training involves adjusting neuron connections using algorithms like backpropagation to enhance performance. The multilayer perceptron (MLP), a commonly used feedforward ANN, is particularly effective for approximating multivariable functions. Determining the optimal number of neurons requires a balance as too few neurons lead to poor performance, while too many increase the computation time and the risk of overfitting that's why a systematic trial-and-error approach is necessary.

Recent studies highlight the growing role of artificial neural networks (ANNs) in rheology, particularly for predicting fluid viscosity. Esfe et al. developed an ANN model that accurately estimated the viscosity of Al_2O_3-MWCNT/5W50 hybrid nano-lubricant, outperforming traditional models with only a 0.07% deviation [7]. Heidari et al. achieved an R^2 value of 0.99998 for nanofluids, demonstrating ANN's precision in capturing complex fluid behavior [8]. Esfe further expanded ANN applications to other nano-lubricants and non-Newtonian fluids [9][10]. Skare et al. applied ANNs to model cement paste rheology, showcasing their versatility [11], while Zhou et al. incorporated additional parameters like temperature and pressure for biodiesel viscosity prediction [12].

In petroleum engineering, Alsabaa et al. used ANN models to estimate the rheological properties of synthetic oil-based mud, achieving R^2 values between 0.91 and 0.97 with errors below 9.66% [13]. Similarly, Gowida et al. developed ANN models for high-bentonite mud, achieving high accuracy and outperforming existing empirical correlations [14]. ANNs have also been successfully applied to predict the viscosity of nanofluids [15][16][17], biofuels [12], carbon nanotube suspensions [18][19], and nano-lubricants [20][21], demonstrating their broad applicability in fluid property analysis.

Artificial neural networks were also used for tannery waste liquor in different aspects. **Ongen et al.** evaluates the gasification of tannery sludge for syngas production using artificial neural network (ANN) modeling. [22] Durai et al. utilized an artificial neural network (ANN) with a radial basis function to model the performance of a sequential batch reactor (SBR) in treating tannery wastewater.[23] Priyaa et al. developed an artificial neural network (ANN) model using a Levenberg–Marquardt feed-forward back-propagation approach to predict the performance of a common effluent treatment plant (CETP) treating tannery wastewater. [24] Mahmoud et al. explored the application of bimetallic Fe/Cu nanoparticles (Fe/Cu NPs) for chrome (Cr) removal from tannery wastewater and utilized artificial neural networks (ANNs) to model the process. [25] Khan et al. investigated the combustion behavior of tannery sewage sludge using kinetic and thermodynamic analysis alongside artificial neural network (ANN) modeling.[26] However, no research is valid for the study of tannery waste rheology using artificial neural networks.

2. Methodology

In our research, MATLAB neural network toolbox (nntool) was utilized to construct a feedforward backpropagation artificial neural network specifically designed to model the rheology of tannery sludge. various neural network configurations were explored drawing upon 120 experimental data points. Of these, 70% were allocated for training the network, while the remaining data was split equally between validation and testing. with the training and testing data used for adjusting the network's weights and biases, and the validation data for assessing predictive capability on new data. The performance of different configurations was evaluated while modifying the number of hidden layers, adjusting the number of neurons within these layers, and experimenting with different activation functions for the hidden layer. Single and double hidden layer structures were experimented while maintaining an equal number of neurons in each hidden layer and the number of neurons was varied from 2 to 20 in increments of 2. The activation function of the hidden layer was varied between TANSIG and LOGSIG while the PURELIN function proved to be inadequate in our case.

To determine the optimal architecture for studying rheology using neural networks, the process outlined in the workflow diagram (Figure 2) involves several key steps similar as the process used in most ANN research papers [10][27][28]. The inputs for the model include temperature, concentration, and shear rate, while the outputs are shear stress and viscosity. All input and output variables are normalized using the following equation:

$$X_{norm} = \frac{X - X_{min}}{X_{max} - X_{min}} \qquad (1)$$

Following normalization, the architecture, including the number of hidden layers, neurons per layer, and activation functions, is refined through a trial-and-error process. The objective is to minimize the mean squared error (MSE) and to maximize the coefficient of determination.

$$MSE = \sum_{i=1}^{n} \frac{(y_{exp} - y_{predicted})^2}{n} \qquad (2)$$

$$R^2 = \frac{\sum_i^n (y_{exp} - \overline{y_{exp}})(y_{pred.})}{\sqrt{\sum_{i=1}^n (y_{exp} - \overline{y_{exp}})^2} \sqrt{\sum_{i=1}^n (y_{pred.} - \overline{y_{pred.}})^2}} \quad (3)$$

The Levenberg-Marquardt (LM) backpropagation algorithm is utilized for training, effectively combining the Gauss-Newton method and gradient descent to facilitate faster convergence in small to medium-sized networks. It is particularly beneficial for regression tasks. The model is tested with different activation functions focusing on two primary functions: the LOGSIG and TANSIG activation functions.

$$\text{LOGSIG: } f(x) = \frac{1}{1+e^{-x}} \quad (4)$$

$$\text{TANSIG: } f(x) = \frac{1-e^{-2x}}{1+e^{-2x}} \quad (5)$$

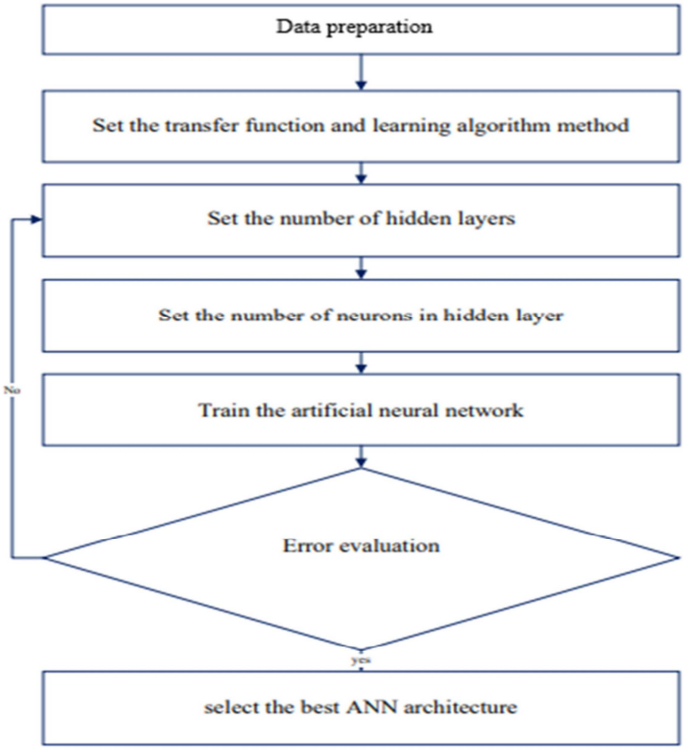

Figure 2: Flow diagram shows the steps of determining the optimum ANN architecture

3. Results and discussion

The findings reported in Table (1) revealed that the most effective configuration consisted of a neural network with a single hidden layer comprising ten neurons as depicted in Figure (3), while employing the LOGSIG activation function for the hidden layer. This configuration achieved optimal performance by maximizing R^2 and minimizing MSE for predicting both shear stress and viscosity outcomes with values of R^2 equal 0.9997, 0.9904 and values for MSE equal 0.015, 0.00018 for shear stress and viscosity respectively. Observations indicate that the R^2 values for all data sets (training, testing, and validation) exceed 0.9999, as shown in the comparison between the actual outputs and the target outputs Figure (4). The training process of the neural network over 76 epochs is depicted, showing the Mean Squared Error (MSE) for the training, validation, and testing datasets as shown in Figure (5). Initially, the MSE is high as the model starts learning. As training progresses, the MSE for the training (blue), validation (green), and test (red) datasets decreases, reflecting improved accuracy. The optimal validation performance, with an MSE of 0.0022448, is achieved at epoch 70, marked by the dotted green line. This suggests that the model is well-optimized at this stage, effectively learning from the data and generalizing well, as evidenced by the consistent decrease in validation and test errors.

Table 1: Performance of ANN in determining both shear stress and viscosity

Number of hidden layers		Shear Stress				Viscosity			
		TANSIG		LOGSIG		TANSIG		LOGSIG	
	n		MSE		MSE		MSE		MSE
	2	0.9919	0.52986	0.99212	0.51175	0.44702	0.01931	0.49391	0.00717
1	4	0.9964	0.24242	0.99681	0.2252	0.83382	0.00297	0.94113	0.00114
1	6	0.9979	0.14366	0.99695	0.20145	0.69253	0.00562	0.94061	0.0105
1	8	0.9996	0.02551	0.9984	0.10573	0.98353	0.00033	0.9531	0.00103
1	10	0.999	0.06538	0.99979	0.01508	0.86483	0.00244	0.99046	0.00018
1	12	0.9989	0.08097	0.99967	0.02154	0.97068	0.00054	0.87047	0.0023
1	14	0.9941	0.38832	0.99781	0.16074	0.9416	0.02348	0.86644	0.00242
1	16	0.9995	0.02669	0.99928	0.04761	0.91324	0.00161	0.921	0.00147
1	18	0.9997	0.01515	0.99883	0.0764	0.97999	0.00038	0.71028	0.00523
1	20	0.9989	0.06897	0.99673	0.46565	0.92764	0.00132	0.98812	0.00022
2	2	0.886694	6.983872	0.817599	10.90393	0.776103	0.004017	0.797873	0.003878
2	4	0.997451	0.166136	0.998573	0.093136	0.397674	0.009644	0.519473	0.007519
2	6	0.170586	86.74383	0.999377	0.043291	0.801424	0.003929	0.920231	0.001481
2	8	0.729554	29.72028	0.999966	0.002332	0.63362	0.025471	0.989903	0.000193
2	10	0.843737	15.57084	0.999839	0.010587	0.024337	0.045326	0.967739	0.000611
2	12	0.999756	0.016081	0.999086	0.059694	0.98643	0.00026	0.916734	0.001503
2	14	0.883714	17.85945	0.999117	0.058806	0.269006	0.018563	0.663764	0.005332
2	16	0.999725	0.017976	0.998924	0.071889	0.996147	7.31E-05	0.880707	0.002133
2	18	0.992141	0.646992	0.998371	0.108892	0.872984	0.003308	0.804437	0.003362
2	20	0.996493	0.228393	0.998963	0.069832	0.992549	0.000157	0.974011	0.000511

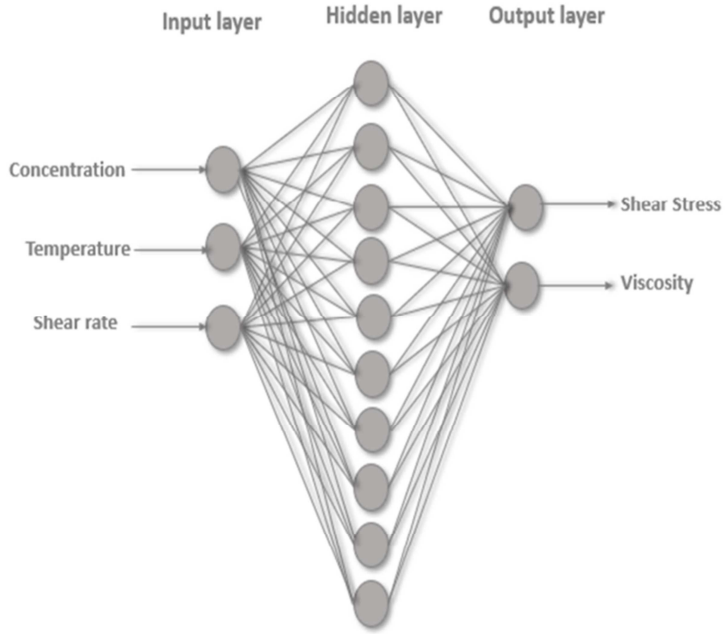

Figure 3: Optimum ANN architecture

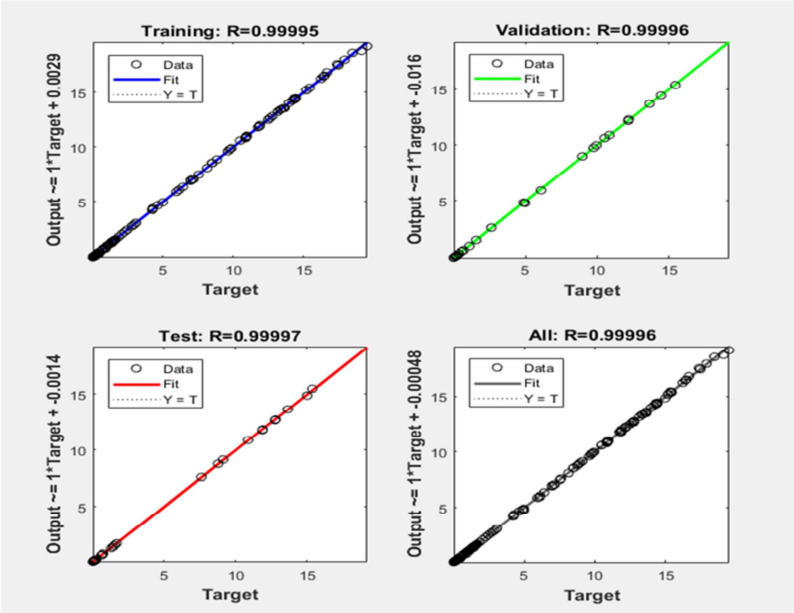

Figure 4: Comparison between the ANN output and target for all data sets (training, testing, validation) using Logsig Transfer function for hidden layer

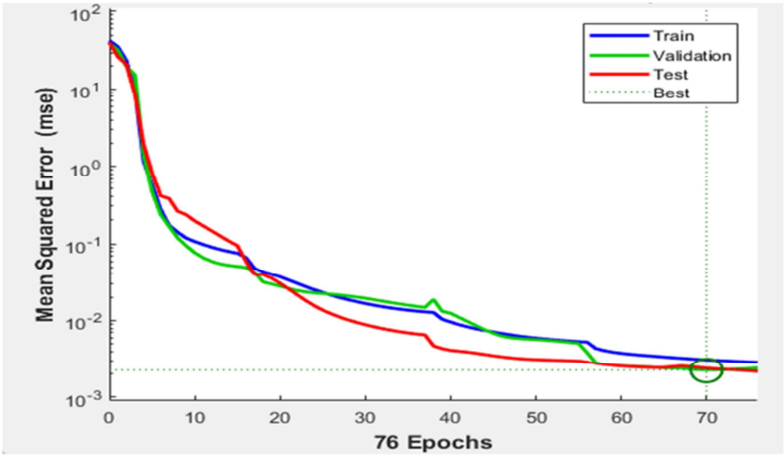

Figure 5: Mean square error change with number of epochs

Figures (6) and (7) present a comparison between experimental and predicted values for shear stress and viscosity, derived from the proposed neural network model. In both charts, the x-axis displays the experimental values (Yexp), while the y-axis shows the predicted values (Ypred). It should be noted that line represents the line of perfect agreement, where the predicted values would match the experimental ones exactly.

In the shear stress graph on the left, the data points are closely aligned along line , suggesting a strong correlation between the experimental and predicted values. This indicates that the neural network model has effectively captured the relationship between input variables and shear stress, with high accuracy in its predictions.

In the viscosity graph on the right, although the data points also generally follow line , there is more noticeable scatter compared to the shear stress graph. This suggests that the model's predictions for viscosity are less precise, with greater deviation from the experimental values. However, the overall trend still aligns well with the line of perfect agreement, indicating that the model is reasonably accurate in predicting viscosity but may require further refinement to improve precision.

Overall, the neural network model demonstrates strong predictive capabilities for shear stress and reasonable accuracy for viscosity, as evidenced by the close alignment of the data points with the line of perfect agreement in both figures.

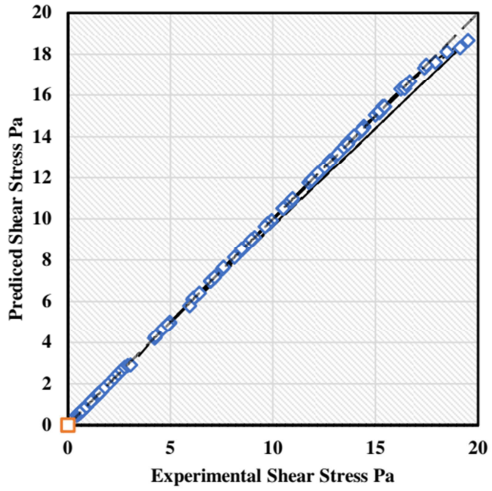

Figure 6: Comparison of neural network predictions and experimental data for shear stress

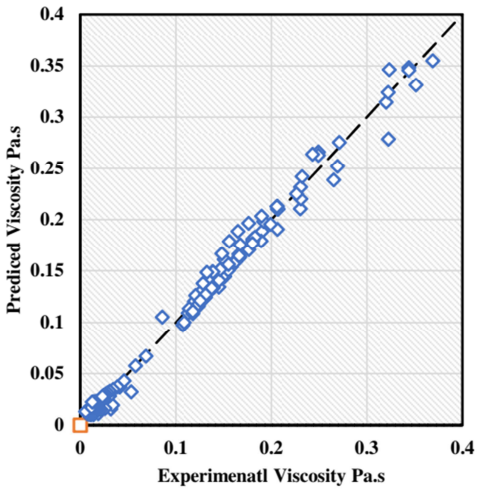

Figure 7: Comparison of neural network predictions and experimental data for viscosity

Additionally, figures (8) to (11) illustrate that the proposed model could be used in the predictions of unseen data such as the data for 5%,10%,15% and it gave very reasonable results for concentrations below 30%. However, its accuracy diminishes when concentrations exceed 30%.

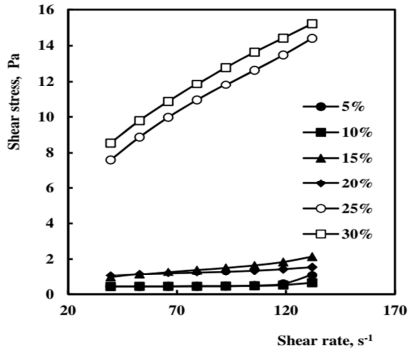

Figure 8: Simulated results of shear stress at different concentrations

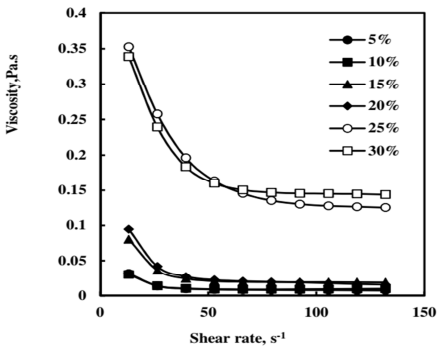

Figure 9: Simulated results of viscosity at different concentration

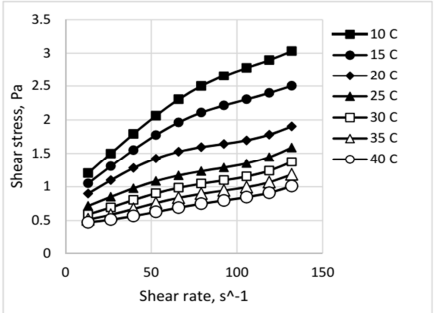

Figure 10: Simulated results of shear stress at different temperatures at 20% solid concentration

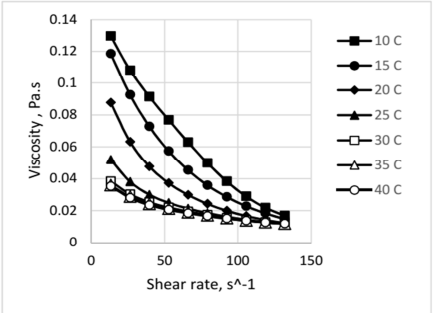

Figure 11: Simulated results of viscosity at different temperatures at 20% solid concentration

Once the optimal architecture for an Artificial Neural Network (ANN) has been established, including the selection of the number of hidden layers, the number of neurons per layer, and the activation functions used in the hidden layers, further refinements can be made to enhance performance. One such refinement involves experimenting with different activation functions for the output layer. According to existing literature, the PURELIN activation function is the widely used activation function for the output layer in most regression problems [29-33], therefore the effect of changing the output layer activation function into PURELIN will be tested in our study while the LOGSIG function proved to be inadequate in our case with strong deviations. It was observed that the use of PURELIN activation function has increased the overall coefficient of determination (R^2) close to 1 as shown in Figure (12) with values of R^2 equal to 0.9999, 0.9945 for shear stress and viscosity respectively and decreased the mean square error (MSE) to 0.0003, 0.0001 for shear stress and viscosity respectively which means better performance. Figures (13) and (14) present a comparison between experimental and predicted values for shear stress and viscosity, derived from the modified neural network after using "PURELIN" activation function for the output layer. The alignment of the data points along the line of best fit (line) demonstrates a strong correlation between the experimental and predicted values, suggesting that the modified neural network accurately predicts shear stress and viscosity values with narrower scattering around line. The close proximity of most data points to the line implies that the model's predictions are highly reliable, with minimal deviation from the actual experimental values.

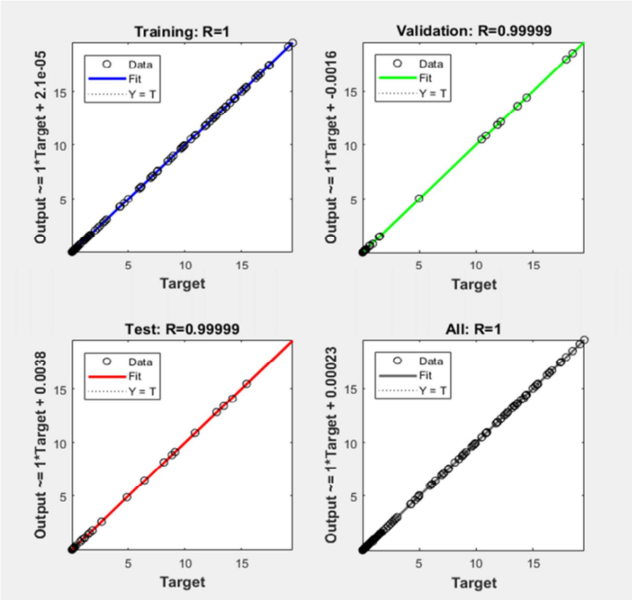

Figure 12: Comparison between the ANN output and target for all data sets (training, testing, validation) using LOGSIG Transfer function for hidden layer and PURELIN function for output layer

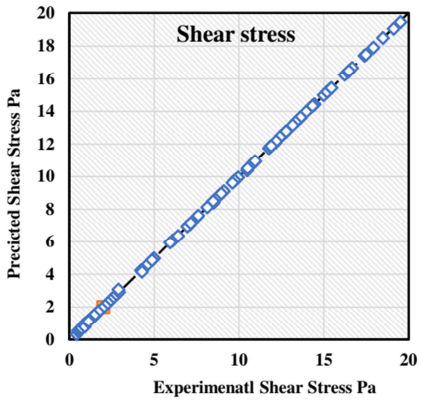

Figure 13: Comparison of neural network predictions and experimental data for shear stress using PURELIN output activation function

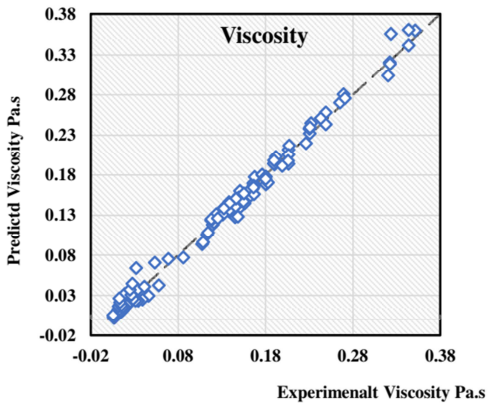

Figure 14: Comparison of neural network predictions and experimental data for viscosity using PURELIN output activation function

3.1 Linear regression vs artificial neural network regression

linear regression on EXCEL was introduced to relate between shear stress and viscosity as the dependent variables (outputs) to concentration, temperature, and shear rate as the independent variables (inputs). However, the R^2 values from these equations (6) and (7) indicate that the derived regression equations do not sufficiently fit the data. This highlights the necessity for a more robust modeling technique to accurately capture the complex interactions between the inputs (concentration, %solid), (temperature, T), and (shear rate) and the outputs (viscosity,) and (shear stress,). Therefore, the artificial neural network (ANN) was introduced.

τ= -19.4784 + 0.986722 %solid - 0.07613 T + 0.065851 γ· , (R^2 = 0.710903) (6)

μ = -0.15051 + 0.016013 %solid - 0.00125T - 0.00116 γ· , ($R^2 = 0.681769$) (7)

Generally, in the artificial neural network, the relation between the output value from each neuron (neurons in both the hidden layer and output layer) and input value can be described as follows:

$$y = f(\sum_{i=1}^{n} w_i x_i + b)$$

Where are the weights of connections from the neuron in the previous layer to that neuron, is the bias and *f* is the activation function.

4. Conclusion

This research aimed to study and model the rheological behavior of tannery waste liquor using an artificial neural network (ANN) approach. The experimental results served as the foundation for developing the ANN model, which was optimized to achieve high accuracy and reliability. After testing multiple configurations, the optimal architecture for the ANN was identified as a feed-forward backpropagation model. This architecture featured a single hidden layer containing 10 neurons, with the hidden layer employing the LOGSIG transfer function and the output layer utilizing the PURELIN transfer function. The model was trained using the Levenberg-Marquardt algorithm (TRAINLM), and the training process was terminated after reaching the defined epoch limit of 196 iterations.

The ANN model demonstrated exceptional performance in simulating the rheological parameters, including shear stress and viscosity. For shear stress, the correlation coefficient (R^2) was found to be 0.9999, indicating a nearly perfect agreement between the predicted and experimental values, while for viscosity, the R^2 value was 0.9945. Additionally, the mean squared error (MSE) values were remarkably low, measured at 0.0003 for shear stress and 0.0001 for viscosity. These metrics underline the precision and robustness of the developed ANN model in capturing the nonlinear and complex rheological behavior of the tannery waste liquor.

The findings of this study highlight the capability of artificial neural networks as an effective tool for modeling complex rheological properties of industrial waste streams. The proposed ANN model not only offers a reliable and accurate method for analyzing such behaviors but also provides a foundation for integrating machine learning into waste management and treatment processes. Future research can build on this work by exploring additional neural network architectures, expanding the range of rheological conditions studied, or integrating other machine learning techniques for enhanced predictive capabilities.

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