International Journal of Scientific Research in Chemical Sciences
Vol.10, Issue.5, pp.09-15, October 2023
E-ISSN: 2455-3174
Available online at: www.isroset.org

Research Paper

Neural Network Modeling for The Microfiltration Process of Bacteria Harvesting From Fermentation Liquid

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Received: 26/May/2023; **Accepted**: 22/Aug/2023; **Published**: 31/Oct/2023

Abstract— Microfiltration is considered useful processes in the field of food industry separation. In the present study, neural network modeling for laboratory data was performed using a ceramic microfiltration membrane to isolate Kocuria rhizophila bacteria from the feed stream. The independent parameters of this process are the back pressure of the membrane, speed of the current entering the membrane, contact time, and the dependent parameter of the flux passing through the membrane. The neural network used was a multilayer perceptron (MLP) system. The data are divided into three main parts of education, validation, and evaluation with a distribution percentage of 15-15-70. The variable of the number of hidden layer neurons in this study was changed from 1 to 20, and the value of 17 neurons was selected as the optimal number according to the results. for verify the prediction performance of the data in the neural network, two basic parameters of the determination coefficient (R2, mean square error (MSE)) were used. The R2 values for the training data, validation, evaluation, and all data using the learning function and the optimal transfer function of Levenberg-Marquardt and Tansing were 0.9995, 0.99966, 0.999111, and 0.9994, respectively. In addition, an MSE value of 0.008 was obtained, indicating a very low error rate. The results show that the neural network used and the optimal function obtained had the least errors in the data calculations and predictions.

Keywords— neural network - microfiltration - bacteria - MLP

1. Introduction

Since the emergence of separation In the 19th century, microfiltration (MF) underwent significant advancements and transformed into a membrane-driven separation technique employed for treating different types of waste materials[1]. Fermented liquid bacteria can be used in various applications. Therefore, the development of efficient and low-cost liquid purification technologies for fermentation is necessary to ensure the safety of food processes [2]. These bacteria can be separated using microfiltration [3]. These bacteria sometimes have useful applications, and sometimes, due to their damage, they are separated from the stream. It is clear that, in microfiltration processes, some parameters such as pH, ambient temperature, and pollutant concentration are influential, and obtaining the best parameters requires a lot of money and various experiments. With the correct method of training neural networks, it is possible to obtain sufficient benefits in this field [4]. Artificial neural networks (ANN) utilized as a highly effective method to solve complex problems in Experimental data in a wide range of industry and enginering. Artificial neural networks are The lowest degree of resemblance allows for a smoother application in modeling various processes compared to alternative modeling techniques[5,6].

ANN models allow the investigation of the relationship between input variables and the objective(s) or output(s) of a process using a limited number of experimental data. ANN models can be easily constructed using an appropriate experimental design. In ANN methods, No need to have much additional information about the exact equations used, and this is one of the advantages of ANN. Artificial neural networks have been used in a wide range of membrane separation processes such as reverse osmosis (RO), nanofiltration (NF), ultrafiltration (UF), microfiltration (MF), gas separation (GS), membrane bioreactors (MBRs), and fuel cells[7].

Also, in various published researches, it is clear that the neural network has been used in membrane systems to separate different components such as proteins, colloids, etc.
The lowest level of likeness pertains to Artificial Neural Network (ANN) modeling, which serves as a valuable tool for resolving both multivariate linear and nonlinear regression challenges.The advantages of using artificial neural networks In contrast to other experimental or theoretical models, ANN has advantages that can be categorized into four distinct groups.

To begin with, artificial neural networks excel in addressing highly nonlinear and intricate problems involving mathematical equations. second, their structure can be more intricate, allowing for greater expressiveness compared to various other theoretical models. Furthermore, there is no strict requirement for explicitly expressing the problem's structure. Lastly, these models exhibit considerable flexibility [8]. It is important to note that the superiority of artificial neural networks is contingent solely upon the specific problem, and in certain cases, other methods may outperform ANN [9].

According to research published in this field, there are multitude of diverse structures exist for neural networks, each bearing a minimal degree of resemblance to the others.

In the process of microfiltration, many parameters have a linear or non-linear effect on the flow rate and microfiltration performance. Some of these relationships and related parameters cannot be provided by many simple mathematical relationships, but the neural network can make a proper prediction of these relationships.

ANN can be used in different ways, Among these methods, can be mentioned Multilayer Perceptron (MLP) and The Back Propagation (BP) feedforward neural network, commonly referred to as stands as the prevailing form of artificial neural network (ANN). Diversifying from this foundation, other ANN types, like the Radial Basis Function Neural Network (RBFNN), Recurrent Neural Network (RNN), Elman Neural Network (ENN), and Deep Neural Network (DNN), present variations by adjusting model parameters, structure, and training algorithms[10].

The accuracy criterion of many models is the coefficient of determination between the model results and experimental data. The R2 values were determined to be between 0 and 1, and the value of R2 that was closest to 1 indicated the highest accuracy. The coefficient of determination (R2) is calculated as follows [2]:

Numerous models adopt the coefficient of determination, which measures the correlation between model outcomes and experimental input data. R2 values range from 0 to 1, expresses the prediction accuracy of the ANN and other numerical methods. when R2 value closest to 1 signifying the highest level of accuracy. The calculation of the coefficient of determination (R2) is outlined as follows equation (1) [2].

$$R^2 = 1 - \frac{\sum_{i=1}^{n}\left[x_i^{sim} - x_i^{exp}\right]}{\sum_{i=1}^{n}\left[x_i^{sim} - x^m\right]} \,, x^m = \frac{\sum_{i1}^{n} x_i^{exp}}{n} \quad (1)$$

where xiexp is a value obtained by experiment, xisim is value of the model and n is the experimental data numbers.

Chelam[13] has used neural networks were employed to predict values of permeate flux By changing the input parameters such as initial pressure, initial permeate flux , suspensions and feed concentration.According to the results of this article, with a hidden layer number, you can usually get acceptable results for predicting the membrane passing through the membrane.

In a similar work Helal and Colleagues (2008) [11], An ANN was employed as model and with changing in process variables, such as encompassing system pressure, feed concentration and feed temperature to forecast the permeate flux frim membrane. also They investigated the stability of the passing flux with Backpropagation Neural Network (BPNN). The maximum error observed in flux prediction in this study was 5%. Their works, like other works, emphasized the characteristics of ANN.

Madaeni et al. (2012) [12] used ANN to chemically clean MF membranes contaminated with milk. The concentration of the cleaner, type of cleaning material, speed of the cross current,time and temperature, Is regarded as as inputs, and the recovery of the flux and Decrease of the resistance were the outputs. Multiple linear regression was also utilized to model this process. The results of their study demonstrated that an Artificial Neural Network (ANN) can accurately assess the impact of operational parameters on resistance removal and flux recovery in the microfiltration (MF) membrane cleaning process, achieving an R2 value greater than 0.99[12].

ANN has been used in the microfiltration process by Liu et al [13] that with the desired model, they predicted permeate flux of calcium carbonate suspensions. In this research, a turbulent flow generator has been used to improve the permeate flux. As obtained from previous research, the neural network can provide a reasonable prediction of the microfiltration performance. One of the most important parameters used in MLP systems Is the count of neurons within the concealed layer in this research, the most optimal value for these neurons was used, and a suitable function for accurate data prediction was obtained and presented [12].

2.Neural network modeling

In this research, the experimental data of an article published in 2021 was used [2] In the experimental study, a ceramic membrane with cylindrical shape was used at formed through extrusion, employing readily accessible clay materials like ball clay, white clay, quartz, calcium carbonate, and then subjected to calcination at a temperature of 1000 degrees.

This membrane was used to isolate Kocuria rhizophila from a cake culture. The effect of cross-flow speed and pressure on the filtration has been investigated.Neural network modeling was performed on the laboratory events in the aforementioned article. Data analysis was done using MATLAB R2019a software. Artificial intelligence modules of MATLAB software were used for modeling. The architecture of the used neural network was changed to obtain the best answers. In this study, the number of 475 data for the transient flux output parameter (L/m2h) with three basic parameters of pressure behind the membrane (kPa), cross-flow speed (L/h), and time (min) have been investigated. In this study, all the data was divided into four main parts, which included training, validation, testing, and general data. The percentage of each of the available data is shown in table (1).

Table 1. Classification of available laboratory data for neural network modeling.

Data percentage (%)	Data type
70	Training
15	Validation (Walid)
15	Test
100	Total

After training, the analyzed data are entered into the second section or the same section where the evaluation data are separate from the training. In this section, the method of data communication is measured according to the education section; in other words, it is tested. In this study, a multilayer perceptron neural network (MLP) was used. This multilayered structure contains hidden layers with a specific number of neurons. To obtain or evaluate a suitable neural network with a specific and appropriate architecture, various parameters are used, one of which is the mean square error (MSE). Equation (2) provides the MSE formula:

$$E_{MSE} = \frac{\sqrt{\sum_{p=1}^{M}\sum_{i=1}^{N}(S_{ip} - T_{ip})^2}}{n_p \times n_0} \quad (2)$$

Where E_{MSE} is the mean square error in the training phase, S_p in the i neuron and P pattern is the output of the network, T_{ip} is the output and target, and the number of patterns, In this study, N represents the output neurons, and M indicates the quantity of training patterns. The precise architecture employed for this investigation is presented in Table (2).As is commonly understood, the count of input parameters and output layer neurons varies.

Table 2

The number of neurons used	Neuron type
3	Input layer
10	Output layer
2 to 20	hidden layer
100	Total

The inputs of the system included the pressure and cross-flow in the microfiltration, and the desired output was the flux parameter. The transfer or activation function is in charge of data processing, and its selection is the responsibility of the researcher. According to the error estimation method for different functions, The tansig function was chosen as the transfer function for the hidden layers, while the logsig function was utilized as the transfer function for the output section.In this research, the Levenberg-Marquardt function was employed as the training function, yielding the minimum error in the training phase.

3. Results and Discussion

3.1. Fine-tuning the count of neurons in the hidden layer

Selecting the appropriate number of neurons for the hidden layer The selection of this parameter is critical for utilizing an artificial neural network effectively.This is done by guess and error and by increasing the number of neurons and observing the changes in R^2 and MSE. As seen in figure (4), by increasing the number of hidden layer neurons from 1 to 14, R2 becomes closer to one, which indicates an increase in measurement accuracy and a decrease in error. Generally, increasing the number of neurons increases the time required to perform the calculations; however, the accuracy of the calculations also increases to an acceptable level.

As the count of hidden layer neurons rises beyond 19 onwards, the accuracy of calculations decreases again, which can be due to the increase in renum calculations. As shown in Figure (1), for 17 neurons in the hidden layer, the highest value of R^2 was obtained, which shows that for the desired transfer function and input data, The most optimal configuration attainable consists of 17 neurons in the hidden layer.

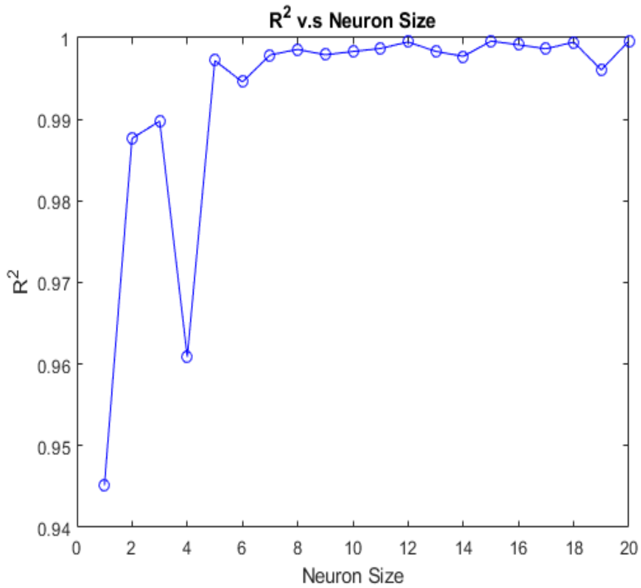

Figure (1): Changes of the graph of R^2 with increasing the count of neurons

The next criterion for checking the most suitable count of neurons in the hidden layer is the mean squared error (MSE), which means that the reduction in this value the calculation errors are reduced, and accordingly, the accuracy of the calculations increases. Figure (2) shows the changes in the MSE value by increasing count of neurons, which bears resemblance to the results of the changes in the R^2 value by increasing the number of layers to 19. However, as the number of neurons increased from 1 to 17, the MSE value decreased, indicating that 17 neurons was the optimal number for the highest R^2 value and the lowest MSE value, that is, the highest computational accuracy. As it is known, for any number of neurons in the hidden layer, the calculation is repeated to get the best answer.The results have shown that after the number of 6 neurons, a good performance of the desired prediction has been observed.

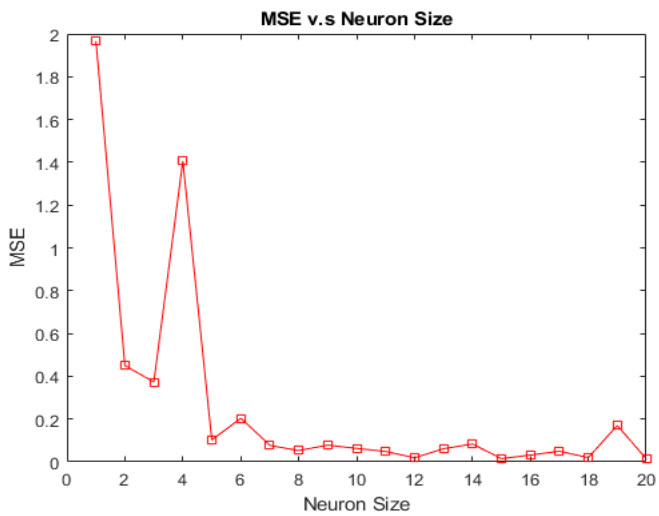

Figure (2): Changes of MSE changes with increasing the count of neurons within the hiden layer of the ANN

To check the effectiveness of the artificial neural network in the optimal number of hidden layer neurons, some other answers were checked. For example, in figure (3) for the count of optimal neurons,The number of iterations conducted to attain a reduced MSE is verified. As shown in the figure, in the number of repetitions of 25, the MSE reached its lowest value, and with an increase in the number of repetitions to more than 25, the trend of MSE changes increased. These MSE changes were performed for all data groups, such as training, evaluation, and test data, and the best chart was drawn from these data. The best evaluated value was calculated to be 0.12349.

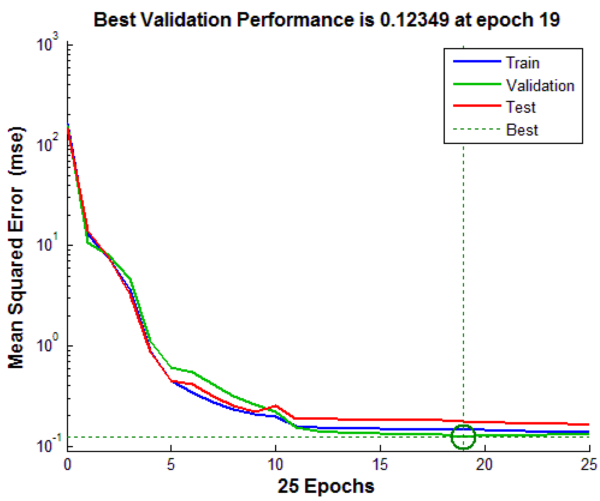

Figure (3): Changes of MSE with increasing the number of repetitions for the four categories of functions train, validation, test, and best functions with the number of 17 neurons.

3.2. Curve fitting

As mentioned in the previous sections, all data were separated into three fundamental segments: training part, validation, and evaluation. For each of these intended data and available general data, the regression results were calculated in the artificial neural network, as shown in Figure (4) the primary parameter for checking the regression results is the R^2 value, which is very appropriate and close to 1 for all the available data divided into different parts. The regression results for the tansig transfer function and 17 neurons in the hidden layer were obtained, which shows that this transfer function and the number of neurons present excellent performance in regression. As it is clear from the figure, most of the data are close to linear and a good fit of the used experimental data has been observed.

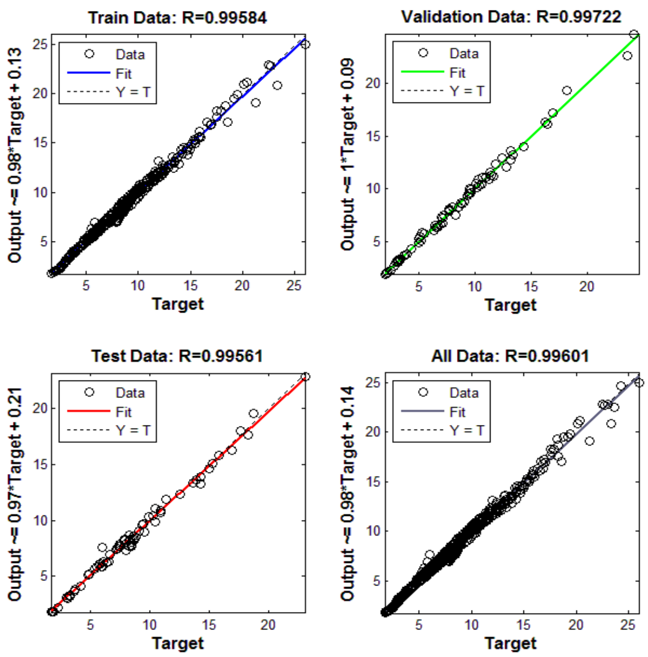

Figure (4): Regression results and R2 values for four types of training data, validation, evaluation, and overall data in the number of 17 neurons.

In addition, the errors between the available laboratory data from the reference article and The data forecasted by the artificial neural network are displayed in Figure (5).As is clear from the figure, the maximum error calculated in the three datasets of the study was 5 percent, which was only observed at some points. These values show that the data and fitted functions have an acceptable correlation with a very low difference.

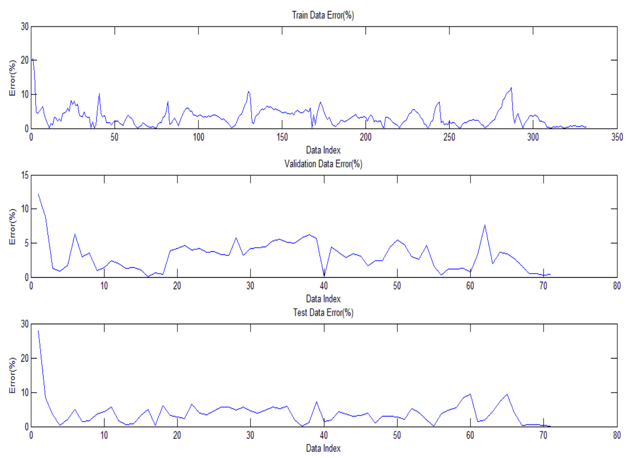

Figure (5): Diagram of error values for different experimental input data for three groups of test, validation, and evaluation data for 17 neurons.

3.3. Function modeling

In the final stage of the work, an optimal parametric function for better prediction of the existing data input and output processes was obtained. MATLAB software was used to obtain the function. At first, 11 function models were tested for this purpose, and the best function with the highest Confidence factor R^2 and the least mean error of the sum of squares (RMSE) was selected. Table (3) shows the fixed parameters of the predicted models.

Table (3): Calculated equation constants for 10 evaluated models

No	A1	A2	A3	A4	A5	A6	A7	A8	A9	A10	A11	A12
1	**-0.17**	0.94	0.039	0.019	-	-	-	-	-	-	-	-
2	51.38	-0.096	0.024	0.006	-36.41							
3	1.59e12	8.39e10	0.025	0.006								
4	25.69	0.17	1.30	0.024	0.006	-3.46						
5	-0.08	2.67	0.024	0.006	-1.13							
6	2.5e7	3.3e4	1.2e6	8.68e8	-3.1e6	2.62e8	1.3e8	1.86e7	1.9e9			
7	11.11	0.01	0.55	-3.00	0.0048	-0.24	-0.013					
8	0.001	2e-8	9.18e-6	6.50e-5	4.16e12	1.08e7	-8.2e9	2.08e12	4.16e10	-4.6e6	9.14e6	-6.2e1
9	-6.3	0.326	2.49	6.54e-1	2.18e12	1.63e-10	1.86e-3	-8.53e-3	1.95			
10	50.61	-0.09	0.001	1.44	-177.62	-0.002	141.93					
11	-72.71	0.056	0.048	-3.96e29	-13.90	0.018	4.61e14	-8.48	0.017	87.66		

Table (4) shows the results of the R^2 and RMSE parameters for the examined models. As shown in the table, models 2, 8, and 11 show more appropriate values; among these three models, we consider model 11 the best predictive function for the system in question because it shows the least error and the most agreement with the laboratory data.

Table (4): R^2 and RMSE values for different reported models

RMSE	R^2	Model
2.26102	0.844815	1
0.688222	0.984718	2
2.07828	0.85056	3
0.7087	0.983782	4
0.84183	0.977052	5
1.18934	0.954224	6
1.27482	0.947391	7
0.623425	0.987241	8
0.743092	0.982162	9
0.711142	0.983795	10
0.558142	0.998549	11

As is clear from Table (4), model number 11 is selected as the optimal model or, in other words, the optimal function. To check the performance of the created optimal function, we should examine the difference between the input laboratory data and the functions. Therefore, in the first step, the target parameter (transient flux) for two laboratory and calculated values have been examined by the function. As shown in figure (5), the amount of transient flux in two different calculations of laboratory data and the intended optimized function are very close to each other. Therefore, this function can have an appropriate prediction of data that is not among the laboratory data. Therefore, to obtain unknown data that has been subjected to a laboratory process, this function has provided an acceptable prediction. The exact values of these errors in different data domains are shown in Figure (6). According to figure (6), The highest deviation between the experimental data and the predicted function was noticed in the initial dataset.Except for very specific values, this error is less than 10% in most data, which indicates that the error between the existing laboratory data and the existing fitted function is very small and has shown an acceptable prediction.

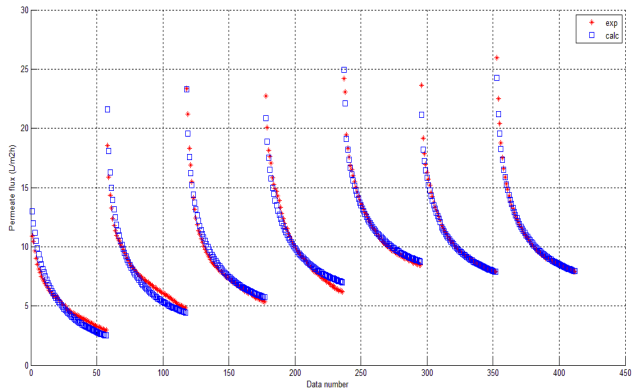

Figure (5): Difference between the values of the flux passing through the membrane (target function) in the laboratory and calculated by the function.

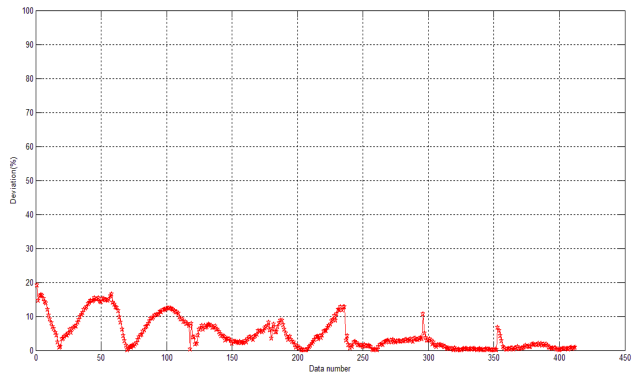

Figure (6): The amount of error between the laboratory data and the optimized function according to the number of available data checked

One of the other methods of checking the performance and efficiency of the intended optimized function, checking the regression chart and observing the values of R^2 and RMSE, for model number 11, these values are 0.9900 and 0.55, respectively, which indicates a high accuracy of this function. Also, the regression diagram for this function according to the available laboratory data is shown in figure (7).

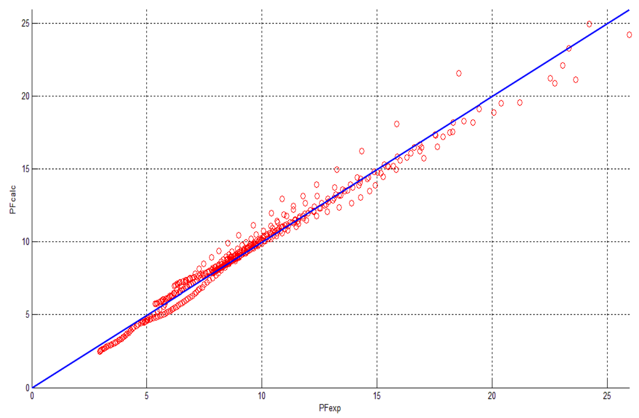

Figure (7): Regression results of existing optimal function and laboratory data**.**

The formula of the relationships obtained for this series of data is shown in equation (3).

$$Flux = A_1 \times T^{A_2} + A_3 \times T + A_4 \times P^{A_5} + A_6 \times P + A_7 \times V^{A_8} + A_9 \times V \qquad (3)$$

where T, P, and V are the time, pressure, and flow rate entering the membrane, respectively, and the values of A are the constants of the equation, which were given in the previous sections and are shown in Table (3).

4. Conclusion and Future Scope

In this study on MLP perception multilayer artificial neural network used for performance prediction of the laboratory data, a reference article was used, in which the flux changes through the membrane in relation to three independent variables, pressure, velocity, and time were investigated and reported. To check the data prediction performance of the neural network, two basic parameters, R^2 and MSE, were used. The ideal count of neurons in the hidden layer is 17.In addition, to better predict laboratory data about which no report has been made and there is no data, an optimal function has been reported to check the performance of this function from two very basic parameters, R^2 and RMSE.

Conflict of Interest
All authors are requested to disclose any actual or potential conflict of interest including any financial, personal or other relationships with other people or organizations that could inappropriately influence, or be perceived to influence, their work. Otherwise, Authors declare that they do not have any conflict of interest.

Funding Source
Provide funding source, supporting grants with grant number. The name of funding agencies should be written in full. for example: “This work was supported by the ISROSET Research laboratory [grant numbers xxxx, yyyy]; the National Science laboratory [grant number zzzz”. If no funding source exists, write, none

Authors’ Contributions
Authors are required to include a statement of responsibility in the manuscript that specifies the contribution of every author. The level of detail varies; some disciplines produce manuscripts that comprise discrete efforts readily articulated in detail, whereas other fields operate as group efforts at all stages.

For Example- Author-1 researched literature and conceived the study. Author-2 involved in protocol development, gaining ethical approval, patient recruitment, and data analysis. Author-3 wrote the first draft of the manuscript. All authors reviewed and edited the manuscript and approved the final version of the manuscript.

Acknowledgements
All acknowledgments (if any) should be included at the very end of the manuscript before the references. Anyone who made a contribution to the research or manuscript, but who is not a listed author, should be acknowledged (with their permission).

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