

Treatment of Textile Wastewater by Nanofiltration Membranes: A Neural Network Approach

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Abstract

Textile industries represent an important environmental problem due to their high water consumption. In order to economically water consumption, wastewater treatment is necessary for water reuse in the textile industries. Predicting the performance of nanofiltration membrane, as an effective separation process, is necessary for the design and depiction of process. Prediction of the rejection of degradable components is especially important. In this work, an Artificial Neural Network (ANN) is used to predict the rejection of Chemical Oxygen Demand (COD) in a cross-flow nanofiltration membrane at textile wastewater effluent stream. Rejections are predicted as a function of feed pressure and permeate flux with cross flow velocity. ANN predictions of the COD rejection are compared with experimental results obtained using two different nanofiltration membranes (NF-90 and DK-5). The results show a good agreement between experimental data and the output from the neural network simulation.

Keywords: Artificial neural network; Nanofiltration Membrane; Textile waste water; Rejection

Introduction

Textile wastewater treatment for industrial reuse remains as a complicated problem due to several reasons. Among them, Biological Oxygen Demand (BOD), Chemical Oxygen Demand (COD), Total Dissolved Solids (TDS) content of the wastewater and Non-biodegradable nature of organic dyestuffs present in the effluent are the main obstacles. Thus, any adopted treatment system, especially with respect to primary treatment, should be able to address these issues. To solve these problems, several technological advancements are made. Conventional water-treatment technologies are including filtration, ultraviolet radiation, chemical treatment and desalination, whereas the nano-enabled technologies include a variety of different types of membranes and filters. The study on the comparison between the conventional and the nano-enabled technologies for water treatment is explained in [1]. Nanofiltration membranes selectively reject substances, which enables the removal of harmful pollutants and retention of nutrients present in water that are required for the normal functioning of the body. The reverse osmosis membranes removed about 99% of all the solutes, but the concentrations of essential nutrients, such as calcium and magnesium ions, were reduced to the levels that are below the specifications of the standard water. Many literatures are considering the potential of nanoscience to solve technical challenges associated with the removal of water contaminants. Separation membranes with structure at the nanoscale based on carbon nanotubes, nanoporous ceramics, magnetic nanoparticles and the other nanomaterials can also be used in low-cost methods to produce potable water. Nanofiltration, a pressure-driven separation process, has various applications in many fields, especially in water treatments. In the last decade, this process have received a considerable attention because of its advantages such as low operating pressures, high fluxes, high retentions of multivalent salts, low investment and operation costs [1,2]. Nanofiltration membranes can achieve enough permeate quality for certain processes at a lower operating pressure than reverse osmosis. Nanofiltration has been applied for the treatment of colored effluents from the textile industry [3,4]. The use of membranes in combination with physico-chemicals processes is very interesting to produce water to be reused from the global effluent of the industry. A combination of adsorption and nanofiltration can be adopted for the treatment of

textile dye effluents. In addition, ultrafiltration and nanofiltration can be coupled in order to study the effect of ultrafiltration as pre-treatment in a nanofiltration system. The results showed that the permeate flux of the nanofiltration increased a lot and the COD concentration was reduced in the nanofiltration feed [5]. This pretreatment is required to avoid the fouling of the nanofiltration membranes and the damage of the equipment.

In order to reuse the water in the rinse processes, it is necessary to have a negligible amount of COD concentration in the permeate stream. Bes-Pia et al. [6] have shown that the physico-chemical treatment applied to the textile wastewater achieves COD removal efficiency around 50%. Also, the average removal color by use of biologically processes attained only 70%, which are recommended potential of using nanofiltration for postprocessing treatment. The quality of the treated wastewater can be improved if the advanced processes are combined with them. The use of ultrafiltration process can not significantly reduce the COD of the physicochemically treated water. However, using nanofiltration membranes, the COD concentration can significantly be reduced in such ways that permeate of the nanofiltration membrane can be reused in the industry. The combination of the physico-chemical treatment and the nanofiltration leads to a COD removal of almost 100%. Also, a comparison between the role of the activated sludge treated wastewater combined with nanofiltration and ozonation processes have been studied [7]. The results of the study showed that nanofiltration of the biologically treated wastewater of the textile industries produce permeates with insignificant amount of COD. The treatment of dyeing wastewater by

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nanofiltration represents one of the rare applications possible for the treatment of solutions with highly concentrated and complex solutions [8,9]. Nanofiltration membranes achieves higher rejection of dyes and other low molecular-weight organic compounds [10]. The performance of the nanofiltration membranes has improved by either changing the chemical composition of the membrane or modifying the membrane surface [11,12]. The performance of the nanofiltration membrane separation is important for the design and optimization of the filtration processes. In the nanofiltration membrane, the charge interaction between the membrane surface and the ions was resulting in Donnan repulsion and differences of diffusivity of the ionic components known as the sieving effect. The combination of these phenomenons or considering each ones separately, will affect the separation performance of the nanofiltration membrane. Many mathematical models were derived from physical descriptions and understanding of the nanofiltration process, but these models is complex and required a very detailed knowledge about the filtration process [13-15]. Moreover, experimental data in terms of permeation flux, solute rejection data, the properties of the solutes and solvent and operating pressure are necessary for the modeling. Due to the lack of experimental data and presence of nonlinearity effects and interactions, these models often could not accurately predict the process performance. On the other hand, ANNs are used to correlate the complex relationship between the input and output of complex process, irrespective of the physical meaning of the system.

Other articles [16-18], also, have considered the use of ANN in simulation of the wastewater treatment. Recently, some studies have considered the use of ANN in wastewater treatment processes by using nanofiltration membranes. Bowen et al. [19] studied the use of ANN for predicting the salts rejection and mixtures of these salts at a nanofiltration membrane. The results indicated that the ANN has superiority as compared with complex physical-based models. Darwish et al. [20] investigated the application of ANN to the modeling of crossflow nanofiltration of NaCl and MgCl₂. Dornier et al. [21] used the ANNs to predict the evolution of membrane fouling during cross flow microfiltration of cane sugar an gum streams. Many studies rely on the correlation between increased hydrophilic characters of the membrane surface with less fouling. Hence, efforts are made to modify the membrane surface into more hydrophilic one, with minimal change of the transport properties of the membrane. ANN has been harnessed to predict steady-state contaminant removal efficiency during nanofiltration in the drinking water treatment system [22]. Chen et al. [23] applied the radial basis function neural network to predict the permeate flux on crossflow membrane filtration as a function of trans membrane pressure, ionic strength, solution pH, particle size, and elapsed filtration time. ANN have been applied for predicting the permeate Total Dissolved Solid (TDS) in RO/NF plants for diffusion controlled membranes [24]. The results indicated that the ANN model predicted permeate TDS more accurately than any of the diffusion based models, and did not over or under predict permeate TDS at low and high permeate TDS. This paper compares the actual and predicted COD concentration in the permeate stream by using an ANN model. The developed ANN model as an adequate powerful tool is used to predict the solute rejection based on the available experimental data.

Neural network model design and implementation

Artificial neural network represents a complex configuration, which consists of many nodes, arranged in layers. In this study a three-layer feed forward or back propagation network was constructed. An ANN

acts as a black box and learns to predict the value of specific output variables given sufficient input information. The developed ANN model have an input layer, one hidden layer and an output layer, which include 2, 4 and 1 nodes, respectively. Figure 1 shows the schematic of a three layer neural network with a feed forward configuration. The selection of this topology was based on a large set of trials using different architectures by monitoring the performance of each candidate ANN against the validation error and the normality of the distribution of the residuals. The independent variables (inputs to the neural network) form the input layer of the ANN, which is multiplied by a weights matrix W^1 , which contains a set of weight factor W_{ji}^1 that j represents the j^{th} hidden node and i is the i^{th} input variable, between the input and the hidden layer. Each neuron in the hidden layer receives weighted inputs plus bias from each neuron in the previous layer, and the output from each node are given by

$$O_j^1 = f^1 \left(\sum_{i=1}^m x_i w_{ji}^1 + b_j^1 \right) \quad \text{for } j = 1, \dots, n \quad (1)$$

Where f denotes the non-linear transfer function for the first hidden layer, x_i is the i^{th} input variable, w_{ji} is the weight between the j^{th} hidden node and the i^{th} input node, b_j is the bias value of the j^{th} hidden node, and the superscript 1 represents the first hidden layer. The output of the hidden layer, weighted with the respective layer weight matrix W^2 enters the output layer, where the non-linear function f^2 is once more applied for obtaining the final model output, as in the following equation:

$$y_p = f^2 \left(\sum_{j=1}^n O_j^1 w_{pj}^2 + b_p^2 \right) \quad \text{for } p = 1, \dots, l \quad (2)$$

Where f denotes the non-linear transfer function applied to the output layer, w_{pj} is the weight associated with the p^{th} output node and the j^{th} hidden node, and b_p is the bias value for the p^{th} output node. The most commonly used transfer functions are the S-shaped log-sigmoid transfer function, the S-shaped tan-sigmoid transfer function and the pure linear transfer function. The log-sigmoid transfer function produces outputs in the range of 0 to 1 while the tan-sigmoid transfer function produces outputs in the range of -1 to 1 and the pure linear transfer function can produces outputs lies between $-\infty$ to $+\infty$. In the present study, a tan-sigmoid and a pure linear transfer function were used as the propagation functions in the hidden layer and in the output layer, respectively. The next step in neural network modeling is training the network. The training process is simply an optimization process, which aims at finding the set of weights and biases associated with each layer that will minimize the error performance function related to the

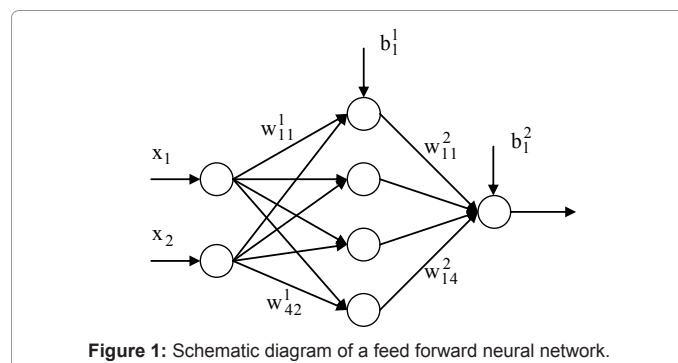


Figure 1: Schematic diagram of a feed forward neural network.

deviations of the neural network predictions from the actual values. The performance function is based on the mean square errors (mse) between actual systems output y_k and network prediction \bar{y}_k for N sample points. This is expressed as:

$$mse = \frac{1}{N} \sum_{k=1}^N \left((R_{SALT} \%)_k^{exp} - (R_{SALT} \%)_k^{cal} \right)^2 \quad (3)$$

In this work, the Levenberg-Marquardt back-propagation algorithm is chosen to train the network. Specific care was taken to avoid over-fitting by means of checking the generalization error. After several attempts, the neural network with four neurons in the hidden layer was found to be excellent in representing the nanofiltration process.

Results and Discussion

In this work, an ANN model has been used to predict the rejection percentage of COD in a cross-flow nanofiltration process. The membranes used for obtaining the experimental data were DK-5 and NF-90 [7]. In their work, at the steady state conditions, the permeate flux and rejection were determined by varying the applied feed pressure and the cross flow velocity at 25°C. The pressure and cross flow velocity were varied between 10-20 bars and 200-400 L/h, respectively. It is important to note that a system of four plane membranes with 30 cm² active surface area have been used in their experiments. The ANN developed in this work is explained with respect to 3 layers. The input data to the ANN are feed pressure, cross flow velocity and the permeate flux while the output is the COD rejection. The inputs and the output were normalized so that they have zero mean and unity standard deviation. This would make the neural network training more efficient. Approximately 70% of all the available data is used for training, and the remaining 30% is used for model performance verification. The feed-forward ANN has been used in this work with single hidden layer with tansig transfer function and a linear function is used as transfer function in output layer. The best network architecture is found to be four neurons in the hidden layer. The mse of the optimal neural network architecture is 0.000012. Prediction of COD rejection is depicted in (Figures 2-5). (Figures 2 and 3) shows the rejection versus permeate flux at different flow rates for NF-90 and DK-5 membranes, respectively.

As shown in (Figure 2), there is an excellent agreement between the ANN prediction results and the experimental values for the NF-90 membrane. This figure depicted the prediction performance of the ANN for the data that does not used in the training phase. The COD rejection percent increases with the increase of permeate flux and similarly the higher cross flow velocity will result the higher rejection. It is worth mentioning that NF-90 membrane have the acceptable performance in salt rejection even at low permeate flux as can be seen in (Figure 2). This is due to the fact that NF-90 has relatively small pore size as shown by atomic force microscopy [25].

The comparison between the ANN predictions of COD rejection as a function of cross flow velocity with the experimental values for DK-5 membrane is shown in (Figure 3). According to (Figure 3), it can be seen that the ANN successfully predicts the non-linear behavior of rejection versus permeate flux. It can be observed that DK-5 yielded permeate flux rates substantially higher than NF-90. The variation of salt rejection with permeate flow rate was similar for both membranes, reaching higher values for NF-90. The lowest COD rejection is

observed using DK-5 membrane, which was in the range of 35-60% as can be seen in (Figure 3). This could again be explained due to relatively large pore size of DK-5 membrane. If the NF-90 membrane is used, the treated wastewater stream is appropriate for its reuse because of the permissible level of the residual COD concentration in the stream. From (Figure 3), it can be also observed that the constructed neural network was good in predicting the salt rejection for the new operating conditions. For DK-5 membrane, the higher rejection can be achieved by the higher permeate flux at the high cross flow velocity, as shown in (Figure 3).

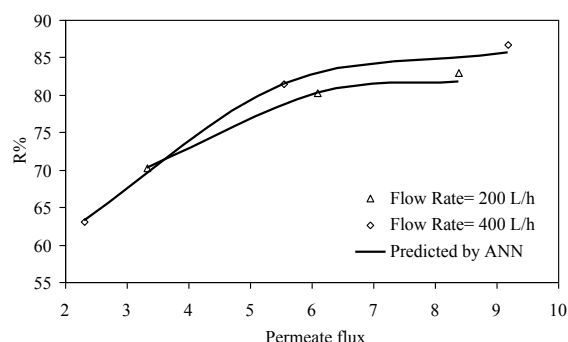


Figure 2: Comparison between the ANN predictions and experimental data in correlating rejection-permeate flux data using NF-90.

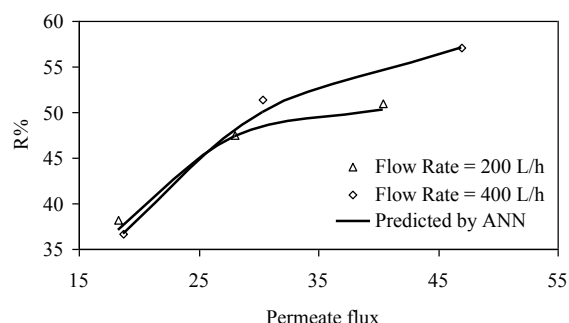


Figure 3: Comparison between the ANN predictions and experimental data in correlating rejection-permeate flux data using DK-5.

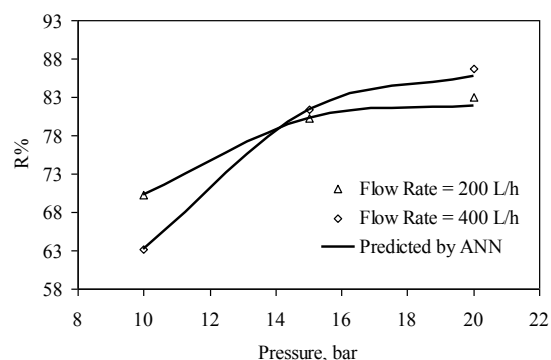


Figure 4: Comparison between the ANN predictions and experimental data in correlating rejection-pressure data using NF-90.

On the contrary, the molecular diffusion models such as the spiegler-kedem model was failed to predict accurately the rejections in the low flux region [25]. On the other hand, it can be seen that the ANN model successfully predicts the non-linear behavior of rejection-flux for the most cases. The ANN prediction results of COD rejection as a function of transmembrane pressure using the two investigated membranes NF-90 and DK-5 have shown in (Figures 4 and 5), respectively. The experimental data and the predicting results are shown in (Figure 4), which clearly shows the excellent predictability of the ANN for COD rejection by using NF-90 membrane. In this figure, pressure was varied between 10-20 bars while the rejection data was recorded at different cross flow velocities. It is again mentioned that these data are excluded from the training datasets to show the generalization ability of the constructed neural network. In (Figure 4), the ANN closely captures the non-linear behavior of rejection-pressure effects at two different cross flow velocities with NF-90. As expected, increasing transmembrane pressure improve the salt rejection at the higher cross flow velocity.

Moreover, the higher pressure significantly compresses the pre-built cake layer on the membrane surface so it becomes denser and additionally contributes to the rapid flux decline duo to the membrane fouling [23]. However, with pre-treatment techniques the membrane fouling can be reduced. Figure 5 show the experimental rejection data and the results of ANN prediction for DK-5 membrane. These data are excluded from the training datasets and they are used as the testing datasets to show the predicting ability of the developed neural network. It is evident from this figure that the ANN can accurately predict the non-linear characteristics of the interactions between ionic particles with membrane surface as reflected by rejection-pressure datasets.

Again, the rejection percentage is lower for DK-5 than NF-90 for the entire range of transmembrane pressure. It is important to note that for two investigated membranes lower rejection have reported at lower pressure region. Figure 6 shows the plot of experimental rejection data versus R%, predicted by ANN for the two investigated membrane for the range of operating variables reported in the literature [7]. From (Figure 6), it can be observed that the ANN was successful in predicting the COD rejection in the wastewater treatment by using nanofiltration process. From this figure, it can be seen that the ANN performs well in both training and testing phases where a good predictions are obtained for the entire range of operating conditions that are studied in this work. The results showed that the prediction of the COD rejection are very close to the experimental ones as they

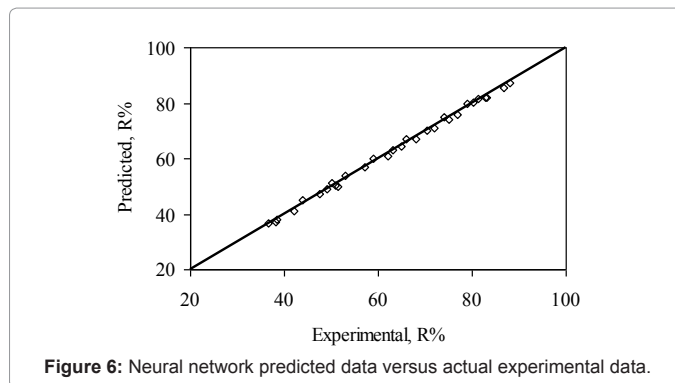


Figure 6: Neural network predicted data versus actual experimental data.

lie close to the diagonal line with a regression coefficient $R^2=0.995$ for the whole range of the available experimental data, which are used in this work. This training accuracy offers a good foundation for confidently using the trained neural network as a representation of a nanofiltration process. In order to obtain the qualified treated water with lower cost in the textile industries, i.e., because of its high water consumption as well as its effect on the environmental biology, it is necessary to use the membrane technology in the wastewater treatment plants; in particular nanofiltration processes. This can be achieved by proper operation of these processes, which are needed to be having the knowledge about the effect of the operating conditions on the quality of the effluent stream. One of the major of these variables is the salt concentration in the effluent stream that can be predicted through hydrodynamic conditions, membrane properties and ambient conditions; e.g., solution pH, temperature, ionic strength...etc. Thus, accurate prediction of salt rejection using the aforementioned variables will optimize the operation of nanofiltration process due to the proper design of the process as well as the operating conditions.

Conclusions

An ANN modeling approach was implemented to predict the membrane rejection versus permeate flux and pressure at different cross flow velocity and pressures using NF-90 and DK-5 membranes. We obtained the optimized network architecture based on the least mean squared error. It was found that a network with one hidden layer comprise four neurons is the optimized network architecture. The results show excellent agreement between experimental literature data and the ANN predicted results. The uses of the ANN for the prediction purposes have been investigated and the capability of the constructed network for rejection prediction is recommended due to its accuracy and efficacy. This study shows that feed forward ANN model could predict rejection percentage very well.

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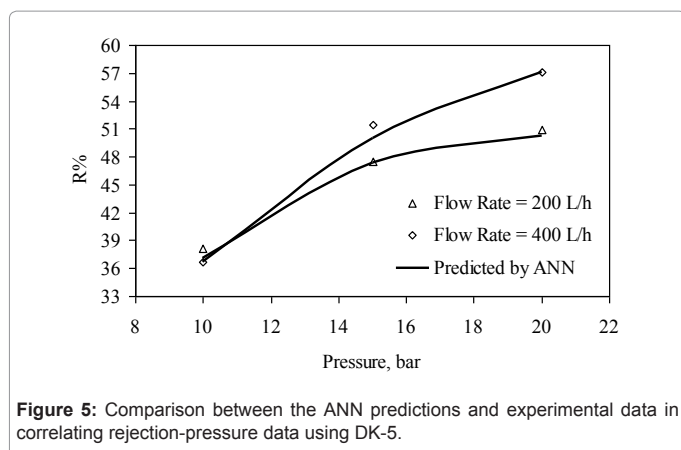


Figure 5: Comparison between the ANN predictions and experimental data in correlating rejection-pressure data using DK-5.

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