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Study of Membrane Transport for Protein Filtration Using Artificial Neural Networks

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ABSTRACT: Artificial Neural Networks (ANNs) are nonlinear mapping structures which functions same as human brain. Modeling can be made stronger especially while the underlying data relationship is not known. ANNs may recognize and learn inter-related patterns between input data sets and related target values. After training, ANNs may be utilized to judge the output of new independent input data. Thus ANNs are used best for the modeling of membrane processes, like ultra filtration and microfiltration. This allows us to judge the permeate flux and membrane rejection as functions of process variables. The aim is modeling of membrane transport for protein filtration is to analyze membrane systems by means of ANNs. To analyze this different ANNs are developed with the help of Mat lab. [1a][9]

I. INTRODUCTION

1.1 Membrane Technology:-

The membrane technology is used in various engineering activities where separation of particular component is needed. Permeable membranes are used for this purpose. Membrane technology is a mechanical separation process which is used for separation of gaseous/liquid stream. The advantage of this processes is that it operates without requirement of heat and thus is economically feasible than conventional separation processes. Due to its gentle separation both fractions could be used. Two basic models may be differentiated for the mass transfer operation at the membrane; one is the solution diffusion model and the other is hydrodynamic model. [11] [13]

1.2 Ultra-filtration:-

Ultra-filtration process is widely used in the food, pharmaceutical, polymer, biotechnology industries and purification plants. It is the process of separation of multi component mixture into two streams of different concentration. This is accomplished using a porous membrane. The driving force is the hydrodynamic pressure difference. The separation is carried out according to the sizes. The flow of feed stream in the process is crossways and alongside the membrane. It does not need a high pressure or temperature and economical due to low energy consumption. Although the process is simple, different factors causes the process to be less well understood as compared to the other separation techniques. The efficiency and the cost of the process are highly dependent upon the factors such as 1) movements of permeate through the membrane 2) the total membrane resistances. This two also depend upon many other different factors. The type of the membrane, pressure, temperature, and the feed flow rate and physio-chemical properties of the fluid are the important factors. Generally, ultra filtration is used for separation of proteins. There is some major phenomenon in protein ultra filtration. Let’s take a look at one of them:

1.3 Membrane fouling:

Ultra filtration is widely used for protein bio separation. Fouling and change in concentration are the main issues in protein ultra-filtration. Ultra filtration happens at a constant pressure across the membrane and the impressions of fouling and change in concentration are observed with respect to permeate flux decline with time. This type of ultra filtration is difficult to model. Convective transport of protein towards the membrane is constantly changing, Due to this change in concentration and membrane fouling is mostly affected. Film theory of molecular diffusion was used to describe membrane transport. In this theory it is assumed that the concentration polarization plays a more important role than membrane fouling whiles the starting of filtration. Thus the rapid flux decrease that is seen initially is due to concentration polarization. But the experiments tell a different story altogether. It is revealed through experiments that the fouling plays an important role. Thus use of two film theory would be unsuitable. [12]

1.4 Artificial neural networks as a solution:

The ANNs are proven predictive model for the non-linear dynamic systems. Generally ANNs are used for ultra-filtration and microfiltration. This allows us to judge the permeate flux and membrane rejection with respect to process variables, i.e. solute concentration, flow velocity, pressure and temperature. The advantages are simple; require a lesser computing period in comparison with traditional way based on the analytical solution of mathematical model based on mass transfer theory, which are quite complicated. [1a]

II. ARTIFICIAL NEURAL NETWORKS

An Artificial Neural Networks is a computational structure. An ANNs have similar inspirations of working as that of by neurons in the brain. Human brains are the fastest natural processors. ANN is made up of simple computational units called neurons. These neurons are also connected to each other complexly. ANN has gained popularity as of its ability to solve different types of problems. They can treat complex problems with ease. ANN is parallel computational model which is comprised of densely interconnected processing units. ANNs can be used to model the processes where the relationship between the data is unknown. It identifies the co-relationship between input and output data. It can be utilized to judge the output of new input data. [1]

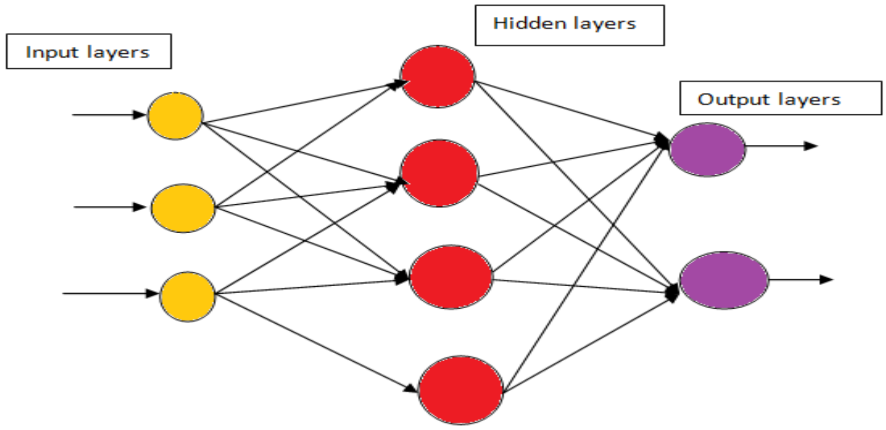


Fig 1: Multilayered Artificial Neural Network

Artificial Neural Networks can be utilized in applications where statistical methods are applied. Classical statistical methods, such as discriminant analysis, logistic regression, and Bayes analysis, multiple regression, etc. are less effective than ANNs in tackling problems. So it is recognized as strong tools for data analysis. [8] McCulloch and Pitts introduced the simplified neurons. Thereafter the interest in neural networks emerged. In our nervous system, synapses works as the connector between two neuron cells. 'Weights' are the analogy of the synapses in the artificial neural network. Weights modulate the effect of the input signals. An ANN is supposed to be a parameterized system as the weighs are adjustable parameters. Neurons exhibit nonlinear characteristic in a mathematical model. These characteristic is shown by transfer function. The total of the input signals, collected by the transfer function, is been computed by the neuron impulse. The basic architecture of ANN consists of three types of neuron layers: input, hidden and output layers. ANN is made up of layers of units, and so is termed multilayer ANNs. All the units in a single layer of ANN perform same functions. The first layer is called as input layer. Last one is called as output layer. Input layer is made up of independent variables and output layer is made up of response variables. All the other units are called as hidden units.

According to Mcculloch and Pitts, the output signals are shown by:

$y_i = f(\Sigma w_{ij} x_j + b_i)\, i,j = 1,2,\ldots\ldots.(1)$

where: y_i– the output signal;
x_j– the input signal;
w_{ij}– the weights between node i and node j;
b_i– the threshold value. [7a]
The activation function is shown by the function f(u) in equation. It starts the transmission of the information. A lot of dynamic processes can be modeled with the help of ANN since 1943. Non-linear and complex problems can be modeled with the help of ANN.

ANN is categorized into three ways :
• Recurrent Networks,
• Radial Basis Function Networks (RBF),
• feed forward multi-layer perceptrone (MLP) which is the most popular one.

In MLP, neurons form the layers (input, hidden and output layers). The neurons are connected to each other even from two nearby layers. The process of transmission is dependent on different activation functions. Artificial neural networks collects their information by detecting the patterns and relationships in data and learn (or are trained) through experience, not from programming. By two ways we can learn ANN :
• Supervised learning,
• Unsupervised learning.

Generally, the first method is better, as it converges the experimental and forecasted parameters. The network gains a specified level of accuracy only when inter unit connections are updated. Once the network is finalized it can be given new input information to predict the output.

III. CASE STUDY: FILTRATION OF PROTEINS

3.1:- Filtration of bovine serum albumin :-

BSA means bovine serum albumin, which is a protein. Many researchers have used this BSA as a sample protein to study the exact mechanism of protein ultra-filtration, which is a complicated process. Research on filtration of BSA was done by Stefano Curcio and Germana Scilingo (University of Calabria). [2]
In this work the Matlab Neural Network Toolbox, is used to develop different ANNs to model the ultra-filtration process of BSA by poly-ether-sulfone membranes in pulsating conditions. The researchers trained the neural network by using different sets of parameters. They also developed a feed-forward multilayer perceptrone model to predict permeate flux decline across the membrane due to concentration polarization. They found out that the model predicted nearly accurate results for those set of parameters that were not used for training the neural network. The error between the experimental value and that of the predicted value was found out to be less than 2.3%.

In this work, a neural black-box model has been developed and trained to predict the ultra-filtration performances under pulsating conditions. This, in order to answer two different questions that were not fully analyzed:
1) Is neural networks technology suitable to model the membrane processes behavior even if the operating conditions are periodically changed during the experiments?
2) May artificial neural network be used to design an advanced control system that indicates the best trend of pulse frequency that has to be chosen to maximize the permeate flux?
MLP networks makes use of the generalized delta rule (GDR). In this method descending gradients used so that the connections weights change proportionally to the derivative of the deviation between the network output and the target (error).

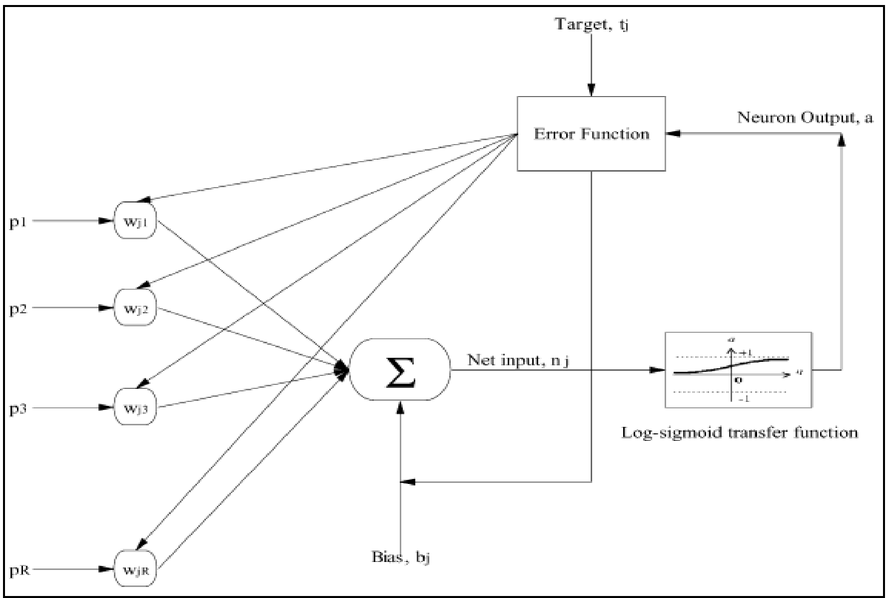


Fig 2: Schematic adjustment process for generic jth neuron

The input signal is fed, and then the output value of the transfer function is compared with that of the target value. An error is generated, which is back propagated to the neurons. The error is divided into parts. With the help of error signals the weights and the differences (biases) of the connections are changed to decrease the global error signal. The adjusting process is drawn in schematic manner for a generic jth neuron in Fig 2. The sum of every single weighed i^{th} input and of a threshold value, b_j, called bias or polarizing unit, gives the so-called net input, n_j

$n_j = \Sigma\ (p_j * w_{ji} + b_j)$ …………(2)

The bias is used to make an adjustment in the weights so that they converge to an Optimum value. The output is the argument of the transfer function. In this case study, the logistic sigmoid transfer function has been used. The log-sigmoid transfer function is majorly used in ANN. It is comparable (important for gradient descent learning), it increases monotonically and can take any input in the range of values between $-\infty$ and $+\infty$, always giving an output in the range 0–1, thus preventing the exponential growth of values through the network. The obtained output, a_j, is compared to the corresponding target, tj, by calculating the average squared error (e_j) between a_j and t_j:

This allows to update both the set of input weights, w_{ji}(i= 1,2,……N), and the bias, bj, relative to the generic *jth* unity, according to the following relationships:

$w_{ji} = w_{ji}(old) + n\delta_j p_i$…………………..(3)

$b_j = b_j(old) + n\delta_j$………………………(4)

where $w_{ji}(old)$ and $b_j(old)$ are, respectively, the previous (old)values of the i^{th} input weight and of the bias, n the learning rate, i.e. a parameter that acts as a gain on the weights and on the bias changes during the training, δj the derivative of the error e_j, and p_i the input. The training is repeated until the sum of the squared errors of the network, reaches a minimum absolute value.

All the experiments were performed changing, during each trial, the applied TMP that was increased stepwise by increments of 0.5 bars, from 0.5 to 2.0 bars. Operating temperature is maintained at 45 ◦C. Due to this applied technique, the concentration polarization layer which would have been built-up in normal case, is disrupted. Such ANN have been prepared just to individuate the non-linear relationships existing between the permeate flow rate, i.e. the ANN output, and the operating variables, i.e. the ANN inputs.

The single neural network can be obtained by performing following four steps:

(1) Analysis and elaboration of the experimental data: In this step the network is being trained by the use of experimental data which is available at that operating conditions

(2) Building of the neural model: In this step, the number of layers and the neurons are decided. But this step is strictly dependent on the two successive steps. This has to be decided by the trial and error method. The number of hidden levels and the number of neurons belonging to every single layer have been determined. (fig3)

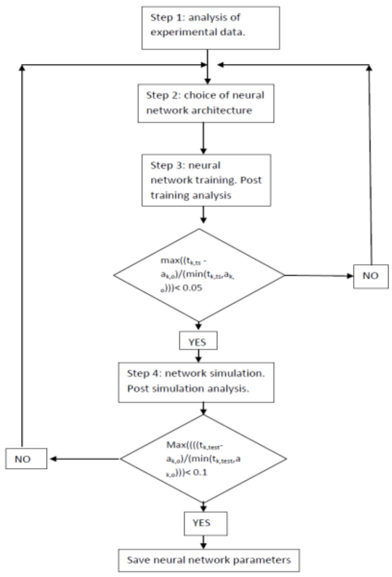


Fig 3:Trial-and-error for neural network identification

(3) Training of the network and post-training analysis: The training process is initiated with the help of a learning algorithm that updates the network weights, initially set to unity, until the convergence is gained. If the maximum relative error, defined as:

ε_{max}= (t_k,t_s– ak,0) / (min(t_k,t_s, a_k,0)) < 0.5 …………(5)

where t_k,t_s and a_k,o are, respectively, the target of the training set and the corresponding network output, then the iteration stops.

(4) Post-simulation analysis: reason of post-simulation analysis, is to find the agreement between network outputs and experimental data never presented for learning and, therefore, ignored by the network. Now the iterations are performed until the required conditions are satisfied. Then after achieving correct parameters, they are saved. In particular, the Neural Network training has been given feeding the model with 120 experimental points obtained in the following conditions:

(a) Q = 2 lit/min, top =60 s, t_k sampled between 0 and202 min.

(b) Q = 2 lit/min, top = 120 s, t_k sampled between 0 and202 min.

(c) Q = 6 lit/min, top =90 s, t_k sampled between 0 and202 min

Now for testing the neural networks, we have to input the parameters that have been never fed to the neural network during training. This will test the capacity of the model to accurately predict the permeate flux. The maximum relative error is equal to1.8%. It was found that, within the sampling time range chosen for network training, ' Net pulse ' can offer very accurate predictions of actual system behavior, with very small relative errors between the experimental data points and the related results of simulation. [1a]

3.2:- Extraction Of Proteins From Colloidal Suspension:-

In an another study, which included extraction of proteins from colloidal suspension, Albert S. Kim and Huaiqun Chen(University of Hawaii)used an Artificial Neural Network as the alternative approach to mathematical modeling. The aim of the study was to predict the long term flux decrease due to colloidal cake formation. Relation between flux and trans-membrane pressure, particle size, solution pH, ionic strength, and elapsed operation time during cross-flow MF/UF membrane filtration is studied. [3] Different conditions such as temperature, feed concentration, and axial velocity are kept constant for the experiments and also for ANN simulations. The emphasis of the work was, first, to reduce the amount of training data sets with a small network configuration in terms of the number of hidden layers and the number of neurons in each layer, and second, to predict new data sets that might not be available by giving the operation conditions belonging to the training data sets. To obtain the optimal network structure for prediction, various ANN network structures were , and the developed performance of the ANNs are calculated by estimating the difference between the predicted output and the target output in terms of root mean square error (RMSE).

Modeling results generated by the developed network showed an excellent agreement with experimental data. The effects of the solution pH, ionic strength, and trans-membrane pressure on the permeate flux are accurately demonstrated by the ANN simulations. It was found that the initial permeate flux decreased is given by the intrinsic membrane hydraulic permeability, and as filtration proceeds, the effect of the particle deposition becomes more significant. As the ionic strength increases, the ANN produces decreasing permeate flux which stems from formation of a dense cake layer comprised of less repulsive particles due to reduction of the electrostatic double layer. [4a] In this study, the capability of a radial basis function neural network (RBFNN) to predict long-term permeate flux decline in cross-flow membrane filtration was investigated. Operating conditions of trans-membrane pressure and filtration time along with feed water parameters such as particle radius, solution pH, and ionic strength were used as inputs to predict the permeate flux. Simulation results indicated that one single RBFNN accurately predicted the permeate flux decline under various experimental conditions of colloidal membrane filtrations and eventually produced better predictability compared to those of the regular multi-layer feed-forward back propagation neural network (BPNN) and the multiple regression (MR) method. We trust more development of the ANNs approach will enable us to design and analyze full scale processes from results of lab and/or pilot scale experiments. We finally conclude that the ANN approach can be effectively applied for optimal and management of membrane filtration systems by well predicting the system performance after a proper training process is completed. [4a]

3.3 Application of electric field for protein ultra filtration :-

With the fast development in the field of biotechnology, the enhanced membrane separation efficiency during protein separation has significant industrial interest. It has been found that application of D.C. electric field improves the permeate flux by a factor of 2–10 compared to conventional cross flow ultra-filtration. During electric field enhanced ultra-filtration, it is observed that permeate flux is a strong function of electric field, feed concentration, trans-membrane pressure, cross flow velocity, etc. Such processes would be very complex to model for prediction. Because of the complexity of the prediction of permeate flux of such processes, application of neural networks can be helpful. A research was conducted by (Indian Institute of

Technology, Kharagpur), in which electric field enhanced cross flow ultra-filtration of aqueous solution of bovine serum albumin (BSA) was carried out in a thin rectangular channel using 30,000 molecular weight cut-off membrane over a wide range of operating conditions. Much detailed study of every parameter has been performed to observe the effect of feed concentration, electric field, cross flow velocity and pressure on the permeate flux. An ANN approach with single hidden layer has been chosen for training. It was systematically trained to predict permeate flux using some of the experimental data. The objective of this study was to develop a neural network based model to accurately predict the permeate flux during cross flow which includes electric field enhanced ultra-filtration of bovine serum albumin. [5a]

Protein solutions were prepared by adding a sufficient amount of powdered bovine serum albumin of molecular weight 67,000. The iso-electric pH of BSA is found to 4.7.The continuous cross flow electro-ultra-filtration unit constructed in polypropylene was used. External electric field from a regulated D.C. power supply was applied across the membrane surface. Electro-ultra-filtration experiments were conducted by taking into account the effect of the four major conditions, namely, pressure, cross-flow velocity, electric field and feed concentration. The output of the network is permeating flux. Experiments were carried for different runs. Results showed consistencywithin±3% in terms of flux value. All of these variables were varied. This technique was used to converge the output values to the optimum so that the relative error between the experimental values and predicted values would reach to their minimum. The adopted network structure consisting of single hidden layer with 11 neurons and input layer with 4neurons results in excellent agreement. Results were obtained with maximum errors less than 1%. Experimental observations indicate that permeate flux increases with increase in electric field, cross flow velocity, trans-membrane pressure and decreases with increase in feed concentration. [4]

3.4 Effect of pH and ionic strength on protein ultra filtration:-

The research was carried out by W. Richard Bowen and Meirion G. Jones to predict the rate of ultra-filtration of bovine serum albumin with respect to pH and ionic strength. The previous studies that were carried out were based on the theory of the protein-protein interaction at the surface of the membrane during ultra filtration. It was observed that such kind of processes mainly depend on physical and chemical properties of the solution. Especially, the pH and ionic strength of the solution had a great deal of effect on the rate of permeate flow. Manipulation of these conditions provides substantial scope for process optimization. Such processes are very complex, so that the neural network used for prediction should be thoroughly trained. The experiments were performed in two groups. For group 1, solution pH was varied and ionic strength (I) was kept constant. For group 2, solution pH was constant and I was varied. Experimental results were presented as filtration time over filtrate volume (t/V) versus filtrate volume (V) graphs. The variation of solution pH and I resulted in substantial changes in the dynamic filtration behavior. The ANN approach to the problem was kept into three parts with each part being more general than the one before.

Group	pH	I(M)	ς (mV) (zeta potential)
1	5	0.03	-2.62
	5.5	0.03	-12.63
	6	0.03	-18.64
	7	0.03	-26.71
	9	0.03	-39.02
2	8	0.007	-42.78
	8	0.07	-28.23
	8	0.15	-23.86

Table1: - The two experimental groups used in this study

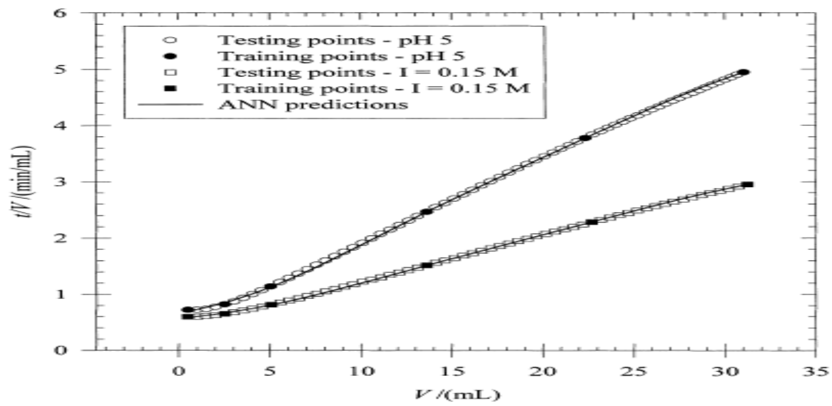


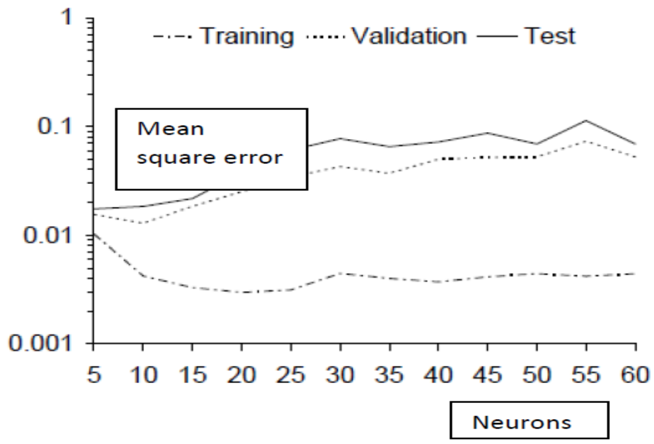
Fig 4:- filtration time over filtrate volume (t/V) versus filtrate volume (V)

The aim of using Artificial Neural Network is to predict the dynamic rate of BSA ultra-filtration by predicting t/V as a function of system conditions. Predictions from part one will be helpful in deciding on how to choose training points. Part two predictions will be helpful in the appropriate selection of network inputs. The experience achieved from the first two parts will be utilized in the proper selection of data points and inputs to the network that will ultimately represent the entire data set. Manipulation of such solution conditions gives substantial scope for process optimization. Because of complexity of the rate controlling phenomena, such manipulation also provides a demanding test of the application of ANNs to membrane processes. [3a]

The best agreement between prediction and experiment has been gained using small numbers of training points and simple networks. An intelligent selection of training points encourages such agreement. The variation of the dynamic rate of filtration with pH could be well-predicted using V and either pH or ζ as the input parameters. However, the variation of dynamic rate of filtration with I was best predicted using V and either log10(I) or ζ as input parameters rather than V and I or V, I and ζ. The variation of the dynamic rate of filtration with pH and I was best predicted using V and ζ as inputs parameters rather than V, I and ζ. From a practical point of view, pH and I may be readily determined using simple equipment. Determination of ζ requires specialized instrumentation, but using ζ as input allows a description of all the solution conditions studied. The dynamic rates of ultra-filtration of protein solutions have previously been predicted using sophisticated descriptions of the protein-protein interactions in the region close to the membrane surface. Such calculations have great generality, but require a detailed knowledge of the physicochemical properties of the protein solutions and the ability to generate complex computer code. The ANN approach may be applied directly to little sets of process data and requires simple inputs. However, ANNs have less generality than these calculations. [3a]

3.5 Ultra filtration of β-lacto-globulin:-

In this research work, done by R. Ibáñez, A. Guadix, experimental data were gathered by carrying out the ultra filtration of β-lactoglobulin through a 300 kDa tubular ceramic membrane at different values of pH and ionic strength. PH was adjusted adding HCl or NaOH in the range3-12.Ionic strength was adjusted adding NaCl in the range 0-20 mM. The cross flow ultra filtration experiments were performed at 30 ºC. The implementation of the artificial neural network modeling was done by employing the Matlab 6.5 Neural Network Toolbox. The system studied comprised 3 input variables (pH, ionic strength and filtration time) and 2 outputs (observed transmission and filtrate flow). Feed forward networks with a single hidden layer including a number of neurons between 5 and 60 were tested. The sigmoid function was selected as transfer function in the hidden layer, while a saturated symmetric linear function was utilized for the output layer. To minimize the mean squared error (MSE) between experimental and predicted values, the networks were trained with the Levenberg-Marquardt algorithm, allowing a maximum of 10000iterations. The available dataset was randomly divided into three subsets: training (70 %), validation (15 %) and test set (15 %). In spite of the deterministic nature of the Levenberg-Marquardt algorithm, the initial values of weights and biases are assigned randomly which suggests that a network has to be trained a number of times high enough to obtain a representative population.



Graph2: Mean square error vs. no. of neurons

Fig 5:- Mean Square Error Vs. No. Of Neurons

Related to the validation and test error, their minimum values are obtained at 10 and 5 neurons, respectively. As observed from graph the best values lie between 10 and 25 neurons. A least value of the weighted error equal to 0.0076 resulted for a network with 10neurons. [6a] Let us now expand the topic to more generalized form. Now we will take a look at the rejection of components during milk ultra filtration and the effect of fouling.

3.6:- Extraction Of Proteins From Milk:-

The ultimate purpose of this study by Mohammad A. Razavi and Ali Mortazavi, is to create a neural network model in order to dynamically predict the permeate flux, total hydraulic resistance and components rejection during cross flow ultra-filtration of skim milk. The membrane was made up of poly-sulfone amide, MWCO 20 u (20 kDa), with external diameter 0.52 m, membrane length 0.47m providing membrane area of 0.33m2. Experiments were carried under different trans-membrane pressure levels, but few conditions such as temperature, flow rate and feed concentration were kept constant during each run. It is very important to know the changes of concentration of each component during membrane processing of milk. For example, high lactose and mineral concentrations in the retentate can result in poor cheese quality; furthermore, it is not clear which component has a more important role in flux decline and development of fouling. Thus, one of the main purposes of this research has been the possibility of components rejection prediction such as proteins, fat, lactose, ash and total solids rejection in order to provide a better understanding of the process. [2a] [6] Previous studies have the purpose to determine protein transmission, while all components of milk have an important role on flux decline, fouling behaviour and final product quality. The membrane transport phenomenon is of nonlinear type. So the feed forward back propogation algorithm was used. Also logistic sigmoid function was used as transfer function to cope up with the non linearity. [2a]

In this study, 675 experimental data were divided into three sets for developing ANNs model, 84 data(12.5%) for training, 321 data (47.5%) for validation and 270 data (40%) for querying. The training data was utilized for learning the ANN and the validation data was utilized to check the ANN predictability, whereas the querying data was utilized to check the neural networks predictability utilizing data not used in the training and validation process. There was an strong emphasis on three points in this research work, firstly, the use of small amounts of data for training, secondly, the sensible selection of training data, and thirdly, the use of small networks. The training data was divided into two training sets. The first training set contained 54 data for modeling of flux and total hydraulic resistance. The second training set contained 30 data for modeling of rejection of each component. Each of the data consists of two inputs: trans-membrane pressure (TMP) and time (*t*), but the network in the first training set had two outputs: permeate flux (*J*) and total hydraulic resistance (*R*T) and in the second training set had five outputs: the rejections of protein (*R*P), fat (*R*F), lactose (*R*L), ash (*R*A) and total solids (*R*TS). [2a] [6]

TMP (kPa)	Training Set 1	Training Set 2	Validation Set 1	Validation Set 2	Querying Set 1	Querying Set 2
50	18	10	102	5		
100					120	15
150	18	10	102	5		
200					120	15
250	18	10	102	5		
Total	54	30	306	15	240	30
Percent	9	40	51	20	40	40

Table 2:- Number of data used for training, validation and querying in the ANN analysis

The experimental data and the results of modeling using ANNs for the permeate flux (Jp) and total hydraulic resistance (RT) at five trans-membrane pressures (TMP) are shown in Fig. respectively.

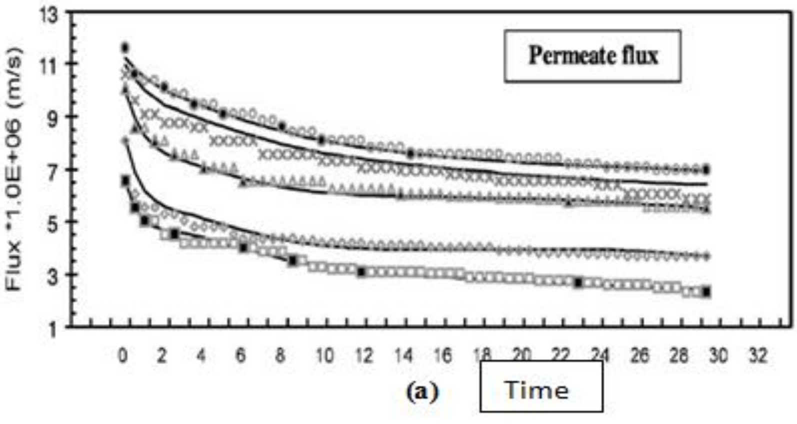
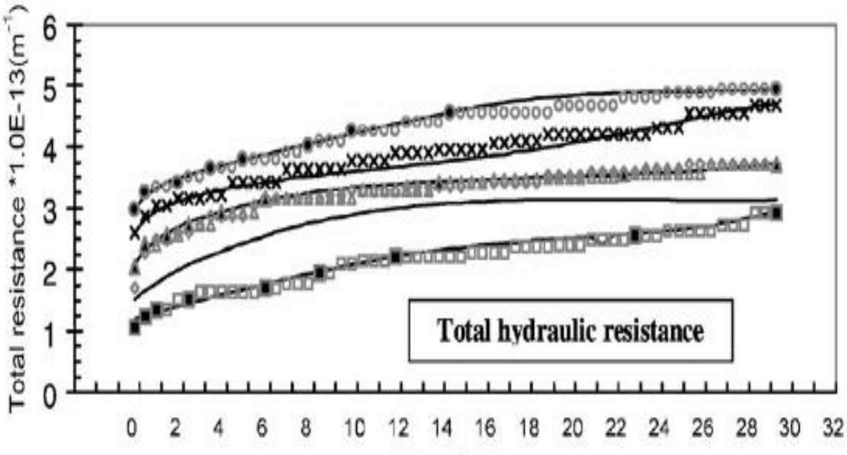


Fig 6: (a) permeate flux vs. time



(b)

Fig 6: (b) total hydraulic resistance vs. time.

The figures also show that the complex behavior (non-linearity) of Jp or RT—time profile is well reproduced by the ANNs. The ability to predict Jp and RT at intermediate TMP (100 and 200 kPa) could significantly reduce the computation time and the amount of practical work required before designing a new membrane process. The amount of all errors is less than 3.35%, Furthermore, most previous researches aim at predicting only the steady-state flux or total resistance, not the full-time profile. [2a] Totally, these results suggest that:(a) the total resistance was not constant with time at each TMP;(b) the flux was controlled by total hydraulic resistance(fouling) at each TMP; (c) the Jp and RT were probably very close to their steady-state values after 10 min processing. The protein rejection (Rp) at each value of TMP is almost constant with time, but the rejection of other components (such as RF, RL, RA and RTS) has increased significantly with time at each TMP. Thus, it can be concluded that flux decline and increasing total resistance with time is probably due to decreasing transmission of small soluble compounds(such as lactose, salts) and fat through the membrane and then adsorption of them onto the membrane surface. The experimental results also proved that the permeate flux at each TMP reduced significantly with time, while total resistance increased significantly with time at each TMP. As TMP increased, both flux and total resistance increased significantly. The rejection of each component increased greatly with time at each TMP, except for protein that was almost constant with time. Meanwhile the increasing of TMP led to a small increase of rejection of each component. [2a]

IV. CONCLUSION

We have seen from the above mentioned research papers that the artificial neural networks could handle the complexity and non-linearity of the system very efficiently. Thus, they could be used extensively to model various types of membrane separation processes. The ANN overcomes the disadvantages of the mathematical models; such as expensive and specialized equipments, complexity, lack of analytical solutions, assumptions of steady or pseudo steady state. Also none of the mathematical models show complete picture of the mechanism of fouling, etc. Also mathematical models many a times are concerned with a particular system. Thus ANN provides the general ability in the modeling, which is of great help.

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