A Neuro-Fuzzy Model for a Dynamic Prediction of Milk Ultrafiltration Flux and Resistance

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ABSTRACT: *A neuro-fuzzy modeling tool (ANFIS) has been used to dynamically model cross flow ultrafiltration of milk. It aims to predict permeate flux and total hydraulic resistance as a function of transmembrane pressure, pH, temperature, fat, molecular weight cut off, and processing time. Dynamic modeling of ultrafiltration performance of colloidal systems (such as milk) is very important for designing of a new process and better understanding of the present process. Such processes show complex non-linear behavior due to unknown interactions between compounds of a colloidal system. In this paper, ANFIS, Multilayer Perceptron (MLP) and FIS were applied to compare results. The ANFIS approximation gave some advantage over the other methods. The results reveal that there is an excellent agreement between the tested (not used in training) and modeled data, with a good degree of accuracy. Furthermore, the trained ANFIS are capable of accurately capture the non-linear dynamics of milk ultrafiltration even for a new condition that has not been used in the training process (tested data). In addition, ANFIS and Multilayer Perceptron (MLP) are compared and the Matlab software was adopted to implement the method.*

KEY WORDS: *Neuro-fuzzy inference system, Milk ultrafiltration, Permeate flux, Total hydraulic resistance, Multilayer perceptron, Fuzzy inference system.*

INTRODUCTION

Over the last few decades, neural networks and fuzzy systems have established their reputation as alternative approaches to information processing. Both have certain advantages over classical methods, especially when vague data or prior knowledge is involved. However, their applicability suffered from several weaknesses of the individual models. Therefore, combinations of neural networks with fuzzy systems have been proposed, where both models complement each other. These so-called neural fuzzy or adoptive neuro-fuzzy inference systems

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(ANFIS) allow overcoming limitations in parameter optimization which offers appealing features [1].

Numerical analysis approach of fuzzy system was first presented by *Takagi* and *Sugeno* and then a lot of studies have been made [2]. Since the systems using fuzzy theory can express rules or knowledge as "If-Then" form, they have advantages such as they do not need mathematical analysis for modeling. However, they need the appropriate model construction and parameter selection [2-8]. This kind of fuzzy modeling problem is a troublesome work in general. On the other hand, studies of fuzzy neural networks that combine both advantages of the fuzzy systems and the learning ability of the neural networks have been carried out. These techniques can improve the matter of fuzzy modeling by the learning ability of neural networks and have been reported since around the beginning of 1990s [3,4]. Fuzzy neural networks can be applied not only for simple pattern classification but also meaningful fuzzy if-then rules creation; therefore, they can be put into practice for various applications. In the early stage of fuzzy neural network researches, *Lin et al.,* [3] proposed one of the current prima models that decide the initial fuzzy model by *Kohonen's* self-organizing algorithm [9] and carry out parameter adjustment by back propagation algorithm. Also as a representative example, *Jang et al.,* [10] proposed ANFIS in 1993.

ANFIS applies a neural network in determination of the shape of membership functions and rule extraction. However, since it needs to divide the input data space in advance, accuracy of the system depends much on the achievement of this pre-processing. *Wang et al.,* [11] reported an approach to acquire fuzzy rules by dividing input space. These techniques, however, do not consider the output data space, so the obtained rules should not be always reasonable. Since the architecture and behavior of ANFIS are very applicable [12], it has been adopted as a basic component for interpretation researches [13,14]. However, its fuzzy modeling for the target task is not always sufficient.

Many systems that aim at excellent fuzzy modeling and carry out input selection, rule creation and parameter estimation have been proposed [5-8, 15, 16]. Elimination of unnecessary rules and selection of efficient input elements can contribute to the performance improvement, reduction of calculation cost and analysis of the obtained rules that is one of the most important merits of fuzzy systems. In these researches, *Linkens et al.,* [7, 8] reported effective input selection and rule creation method and showed the excellent results on their experiments. In addition, since the algorithms are complicated and their algorithms and results are presented only for single output system, they have difficulty if they are employed for many applications. Generally, many fuzzy neural network models have common problems derived from their fundamental algorithm. For example, the systems that use gradient decent method sometimes reduce the width of the membership function to negative during the learning. The systems that employ basic fuzzy inference theory make the degree of each rule extremely small and often make it underflow when the dimension of the task is large. In such a situation, the learning and inference cannot be carried out correctly.

Dynamic modeling of ultrafiltration performance of colloidal systems (such as milk) is an important criterion in designing of a new process, due to the complex nature of the phenomena itself. In order to dynamically model cross flow ultrafiltration of milk, a neuro-fuzzy modeling tool (ANFIS) can be utilized. Through this means we would be able to predict permeate flux and total hydraulic resistance as a function of transmembrane pressure, pH, temperature, fat, molecular weight cut off, and processing time. Hence in this paper, an adaptive fuzzy inference neural network (ANFIS) is used to enhance the shortcomings of the conventional models.

STRUCTURE OF ANFIS IN MILK ULTRA-FILTRATION SYSTEM

An ANFIS can divide input-output data space and provide appropriate rules automatically. Fig. 1 shows the structure of ANFIS for milk ultrafiltration. It consists of three layers. The first layer is the input (I) layer, second is the intermediate (hidden layer) or rule-layer, and last is output (O) layer. The I and O layer consists of the input-part and the output-part. Each node in the rule-layer represents one fuzzy rule. Weights from the input-part to the rule-layer and those from the rule-layer to the output-part are fully connected and they store fuzzy if-then rules. Membership functions as premise part are expressed in the weights. Each weight from the rule-layer to the output-part corresponds to the estimated value of

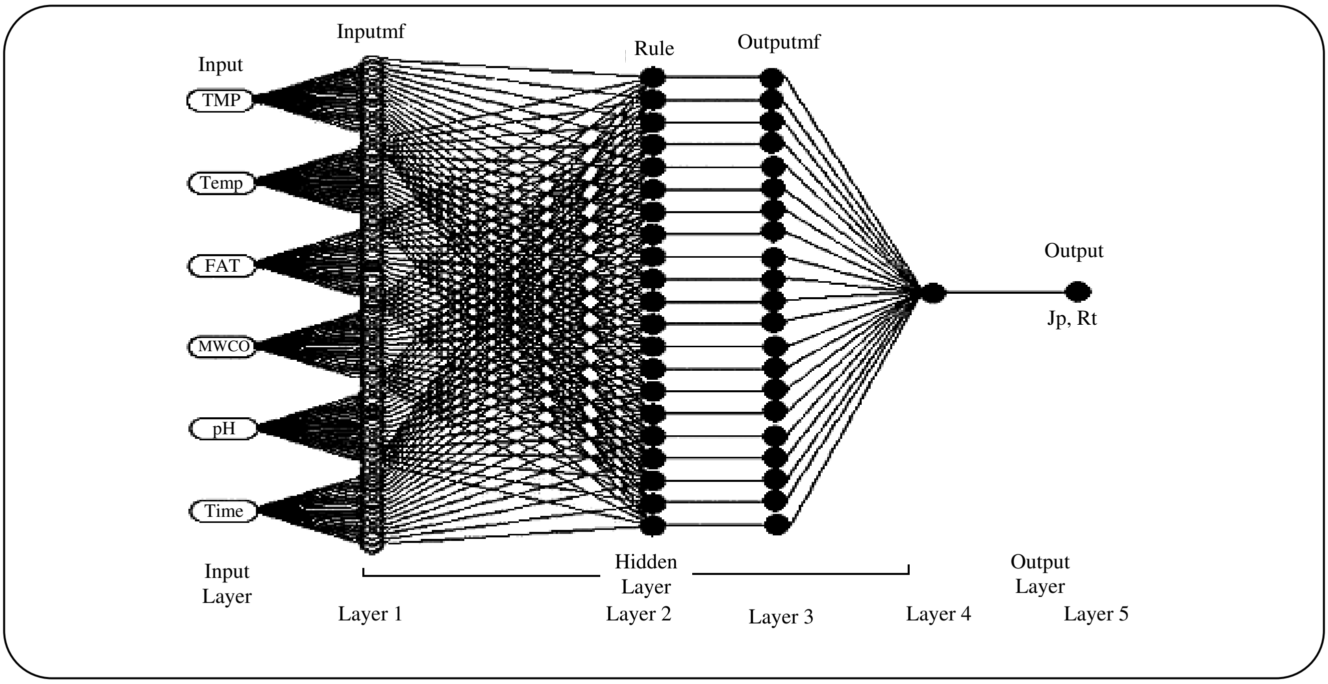

Fig. 1: ANFIS architecture of a six-input-one-output with 21 rules in milk ultrafiltration system.

each rule. In short, the weights from the input-part to the rule-layer indicate if-parts of fuzzy if-then rules and those from the rule-layer to the output-part indicate then parts. The shapes of membership functions are adjusted automatically in the learning phase.

ADAPTIVE NEURO-FUZZY INFERENCE SYSTEM (ANFIS)

From Sugeno Fuzzy Model, Adaptive Neural-Fuzzy Inference System (ANFIS) was proposed by *Roger Jang* in 1992 [17]. The architecture of a six-input twenty one-rule ANFIS is shown as Fig. 1. In ANFIS architecture, a FIS is described in a layered, feed-forward network structure where some of the parameters are represented by adjustable nodes and the others as fixed nodes. The raw inputs are fed into the layer 1 nodes that represent the membership functions (mf) which is twenty one in this study for each input.

For a first-order Sugeno fuzzy model, a common rule set with two fuzzy if-then rules is the following:

Rule 1: If x_1 is A_1 and x_2 is B_1 and … x_6 is f_1, then $f_1= p_1x_1 + q_1x_2 + … + k_1x_6 + r_1$

Rule 2: If x_1 is A_2 and x_2 is B_2 and … x_6 is f_2, then $f_2= p_2x_1 + q_2x_2 + … + k_2x_6 + r_2$

The ANFIS has five layers, in which node functions of the same layer have the same function type as described below: (Note that Oij, denotes the output of the ith node in the jth layer.)

Layer 1: Every node *i* in this layer is an adaptive node with node function:

$$\mu_A(x)=\exp-\left[\frac{x-x^*}{\sigma}\right]^2 \tag{1}$$

where $\{x^*,\sigma\}$ are premise parameters updated through hybrid learning algorithm and x is input variable. At least in the basic ANFIS method these parameters are not adjustable.

Layer 2: Every node i in this layer is a fixed node labeled $\prod$, whose output is the product of all the incoming signals:

$$O_{2,i} = \omega_i = \prod_{i=1}^{6}\mu_h(x_i) = \mu_{A_i}(x_1)\times...\times\mu_{B_i}(x_6) \tag{2}$$

Where x,…, x_6 are input variables and n is nodes number.

Layer 3: Every node i in this layer is a fixed node labeled N. The ith node calculates the ratio of the ith rule's firing strength to the sum of all rules' strengths.

$$O_{3,i} = \overline{\omega}_i = \frac{\omega_i}{\sum_{i=1}^{n} \omega_i} \qquad (3)$$

This layer implements a normalization function to the firing strengths producing normalized firing strengths.

Layer 4: The single node in this layer is a fixed node labeled $\sum$, which computes the overall output as the summation of all incoming signals:

$$\text{Overalloutput} = O_4 = \sum_i \overline{\omega}_n f_i = \frac{\sum_i \omega_i f_i}{\sum_i \omega_i} \qquad (4)$$

where $f_i = p_i x_1 + q_i x_2 + \ldots + k_i x_6 + r_i$, $x_1, x_2, \ldots, x_6$ are input variables, $\{p_i, q_i, \ldots, k_i, r_i\}$ are consequent parameters updates through Recursive Least-Squares Estimation (LSE). The fifth layer represents the aggregation of the outputs performed by weighted summation. It is not adjustable.

HYBRID LEARNING RULE: COMBINING BP AND LSE

A hybrid-learning algorithm that is proposed is as follows [18]:

- In the forward pass, node outputs go forwards until layer 3 and the consequent parameters are identified by the least squares method.
- In the backward pass, the error signals propagate backward and the premise parameters are updated by gradient descent.

These procedures are summarized in table 1.

MATERIALS AND METHOD

Experimental set-ups

The pilot plant membrane system used in this study (as illustrated in Fig. 2) was equipped with a feed tank (20 lit), centrifugal pump, flow meter, spiral wound module, two pressure gauges, tubular heat exchanger, two control valves and temperature sensor (as are described in table 2). The two pressure gauges adopted in this work was used to measure the pressure at the inlet and outlet of the module. Temperature probe was attached to the feed tank and used for monitoring the temperature during each run. The temperature of feed was continuously controlled, monitored and adjusted by the rate of the heat exchanger.

Table 1: Two passes in the hybrid learning procedure for ANFIS.

Backward pass	Forward pass	
Gradient descent	Fixed	Premise parameters
Fixed	Least-squares estimator	Consequent parameters
Error signals	Node outputs	Signals

Table 2: Technical specification of the system adopted in this work.

Module type	Spiral wound
Membrane length	470 mm
Module outside diameter (O.D.)	52 mm
Membrane effective surface area	0.33 m^2
Membrane type	Polysulfone amide
Molecular weight cut off (MWCO)	10, 20 and 50 KDa
Pure water flux range	25 – 40 lit/hr
pH range	2 - 11
Pressure range	0.5 – 3 atm
Fluid circulation rate	2 – 12.5 m^2/hr
Pump power	1.5 KW

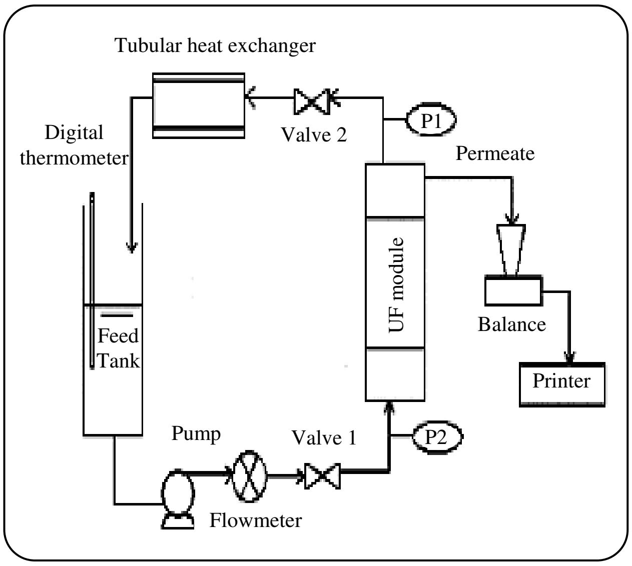

Fig. 2: Schematic flow diagram of the ultrafiltration pilot plant.

Table 3: Input-output value samples used in this work.

TMP	TEMP	FAT	MWCO	PH	TIME	JP	RT
150	30	0.1	20	6.67	4.5	6.75E-06	2.4E+13
150	40	0.1	20	6.67	9.5	6.5E-06	3.25E+13
150	50	0.1	20	6.67	28	5.5E-06	4.25E+13
200	40	0.1	20	6.67	8.5	7.7E-06	3.65E+13
150	30	0.1	20	6.43	30	5e-6	3.25E+13
150	30	0.1	20	6.25	0	5e-6	3.25E+13
150	30	0.1	20	5.97	7.5	3.9E-06	4E+13
50	40	0.1	20	6.67	1	5.5E-06	1.25E+13
100	40	0.1	20	6.67	5.5	4.75E-06	2.85E+13
150	40	1.2	20	6.67	10.5	6e-6	3.5E+13
150	40	2.4	20	6.67	13	5.8E-06	3.5E+13
150	40	3.3	20	6.67	23	5.5E-06	3.7E+13
100	40	0.1	10	6.67	22	2.1E-06	6.55E+13
100	40	0.1	50	6.67	22	9E-07	2.38E+14

In order to compute the weight of the permeate every 30 seconds, an electronic balance and a container were adapted to record and weight of the permeate.

Total hydraulic resistance and permeate flux

The total hydraulic resistance (RT) can be expressed by *Darcy's* law [19] (assuming that the osmotic pressure is minute):

$$Rt = \frac{TMP}{\mu\ J_P} \tag{5}$$

and permeate flux by [20]:

$$J_P = \frac{1}{\mu} . \frac{TMP}{Rt} \tag{6}$$

where μ_p is the permeate viscosity, J_p the permeate flux and TMP the transmembrane pressure which can be calculated by the following equation:

$$TMP = \frac{1}{2}(P_I + P_o) - P_P \tag{7}$$

where P_i and P_o are the inlet and outlet pressures, respectively and P_p is permeating pressure

ANALYTICAL METHOD

In order to measure the permeate and retentate fat percentage of the samples, a device called Lactostar from Funke Gerber Company was employed. Viscosity and density of permeate samples were measured using an Ostwald U-tube capillary viscometer and a 25 ml densitometer, respectively at 40 ^oC for each run. A pH meter (3010, Jenway Ltd., UK) was adopted to measure the skim milk, permeate, retentate and flushing solutions samples (distillate water and NaOH solution) at 25 ^oC during the process. All measurements were carried out at least two times for each test run.

Experimental procedure

Reconstituted skim milk was prepared by adding medium heat skim milk powder to warm water (about 50 ^oC) in a blender. The average composition of skim milk samples is recorded in table 3.

Table 4: The ANFIS data used in this study.

	J_p	R_t
# of nodes	205	191
# of linear parameters	98	91
# of nonlinear parameters	168	156
# of parameters	266	247
# of training data pairs	228	228
# of checking data pairs	270	270
# of fuzzy rules	14	13
error tolerances	0	0
# of epochs	20	20

The same batch of powdered milk was used in all runs to ensure that changes in measured parameters did not result from variation in the milk composition. The effect of varying TMP (50, 100, 150, 200,250 KPa), TEMP (30, 40, 50 ^{o}C), FAT (0.1, 1.2, 2.4, 3.3 %), MWCO (10, 20, 50 KDa), and PH (6.67, 6.43, 6.25, 5.97) on flux and total hydraulic resistance were studied in a batch mode and at a constant temperature.

RESULTS AND DISCUSSION

In this work, the applications of ANFIS for the dynamic prediction of permeate flux and total hydraulic resistance in the ultrafiltration of milk process has been performed for different operating conditions. The results of the modeling for J_p and Rt are demonstrated underneath:

Method of applications

The ANFIS data that are used for J_p and Rt are shown in table 4. The total number of fitting parameters is 399, which includes 147 for the premise and 252 for the consequent. The generation of FIS method is a subtractive clustering. The value adopted for influence, squash factor, accept ratio and reject ratio is 0.5, 1.25, 0.5 and 0.15, respectively.

Model training and testing

The model was trained with part of the database extracted from the experimental work described above (2560 data). The database was initially divided into two sections (i.e., the training and the testing data). The training data set was also broken up into two parts, a training set and a checking set. The advantage of neuro-fuzzy model is that one can adopt fewer numbers of data for modeling purposes. The use of checking sets in ANFIS learning, alongside with the training set is a highly recommended technique to guarantee the model generalization and to avoid over-fitting the model to the training data set. The Gaussian membership function is bounded between 0 and 1, in order to normalize the input and output data. The success of training process was accomplished using 120, 40 training epochs (iterations) for J_p and Rt, respectively. The ANFIS network was able to achieve training, checking RMSE of 0.0278 and 0.787, respectively for Jp. Moreover, training and checking RMSE of 0.029 and 0.598, respectively were achieved for Rt. Figs. 3a and b exhibits the training and checking of the RMSE achievements with ANFIS for J_p and Rt.

The results of modeling using ANFIS for the permeate flux (J_p) and total hydraulic resistance (Rt) at data set are shown in Figs. 4a and b, respectively. It can be seen that the magnitudes of both J_p and Rt vary significantly with index (data) values. These figures also exhibit that the complex behavior (non-linearity) of J_p and Rt profiles is well reproduced by the ANFIS. As shown in Fig. 4, there is an excellent agreement between the predictions (solid lines) and the experimental data. Furthermore, a plot of the predicted value against the desired values for flux and total hydraulic resistance are also exhibited in Figs. 5 a and b. In this figure, for each desired value, a predictive value can be obtained and a comparison between them will enable us to evaluate its deviation. The ability to predict Jp and Rt could significantly reduce the computation time and the amount of practical work required before designing a new membrane process. The previous studies have substantiated that the hybrid learning approach is supposed to converge better and faster than BP.

During the ANFIS training, the training set up can predict the analytical forms of prod (i.e., product) and probor operators for the connectors AND and OR, the min for the IF-THEN implication, the max for the ELSE aggregation and the defuzzification method wtaver (i.e., weight average) produced for the crisp output.

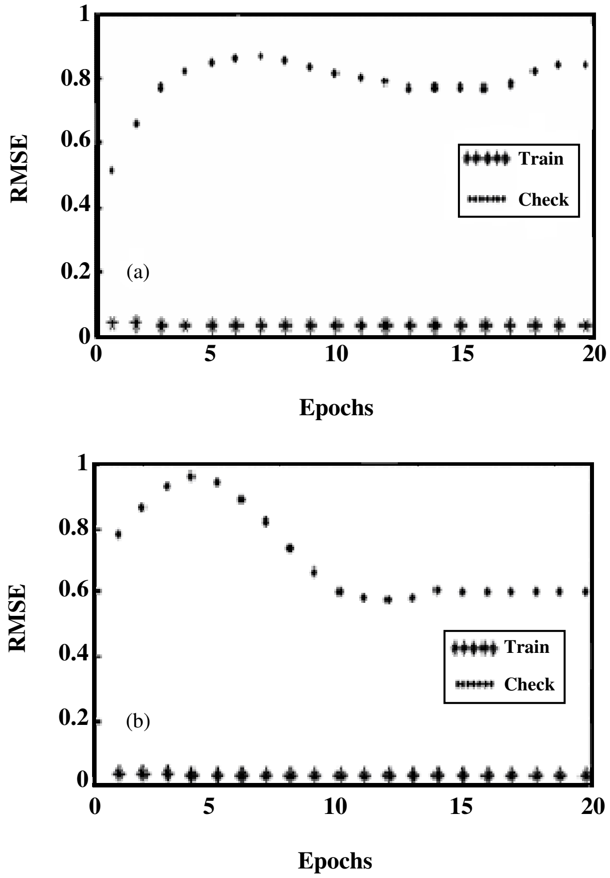

Fig. 3: Training and checking of the RMSE achievements with ANFIS for: (a) J_p and (b) Rt respectively.

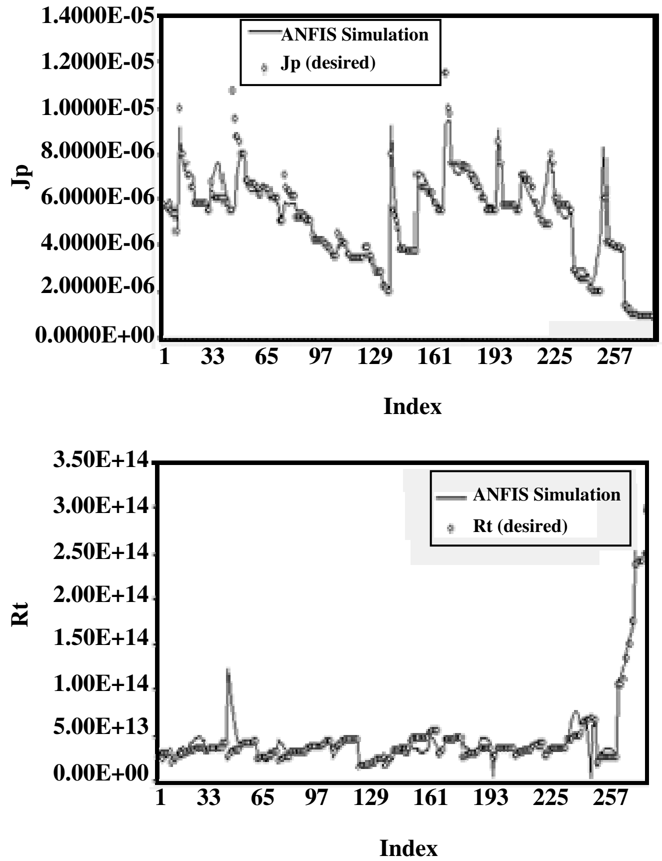

Fig. 4: Comparative studies between the desired and ANFIS predicted values for: (a) flux and (b) total hydraulic resistance, respectively.

Comparative studies between ANFIS, fuzzy and MLP

A comparison of the ANFIS with experimental values, multilayer perceptron, and FIS predicted of flux and total hydraulic resistance for a time range of 0.11 to 0.778 are shown in Figs. 6 a and b. The cascade-forward backpropagation structure used for artificial neural network prediction are composed of three layers (i.e., 3, 1 and 1 neurons in the first, second, and output layer), train function “Trainlm”, adaptive learning function “Learngdm”, and performance function "MSE". The fuzzy system was *Sugeno*, which are composed of six inputs and one output for J_p and Rt.

As shown in Fig. 6 there is an exceptionally good agreement between the ANFIS and the desired data.

CONCLUSIONS

Dynamic modeling of milk ultrafiltration performance is vital for designing purposes and a better understanding of the phenomenon itself. This paper presents the application of a class of hybrid neuro-fuzzy network for the solution of a nonlinear complex processes. Another prime objective of this work was to investigate the ability of adaptive neuro-fuzzy networks and to justify their relevance to predict the Jp and Rt characteristics for the milk ultrafiltration process.

In this study, the accomplishment of neuro-fuzzy predictors was demonstrated and their performance was illustrated using the results obtained from adaptive neuro-fuzzy networks. Furthermore, ANFIS, multilayer perceptron (MLP) and FIS were utilized for comparative purposes. The result reveals that implementation of the ANFIS approximation are advantageous over other rival methods. The result also exhibit that there is a good agreement between the checked (not used in training) and modeled data. In addition, the trained ANFIS was able to accurately capture the non-linear dynamics of milk ultrafiltration phenomenon for a new condition that has not yet been used in the training processes (tested data).

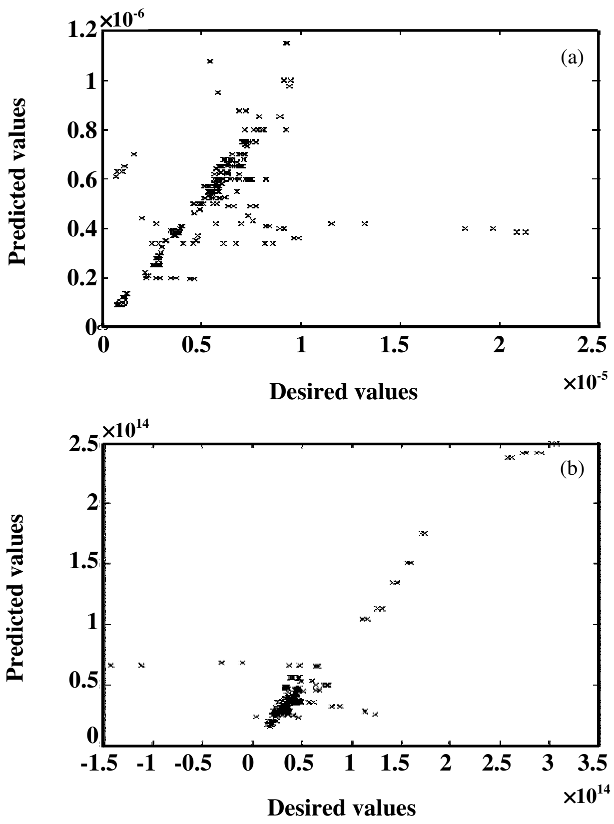

Fig. 5: Predictive versus desired values for: (a) flux and (b) total hydraulic resistance, respectively.

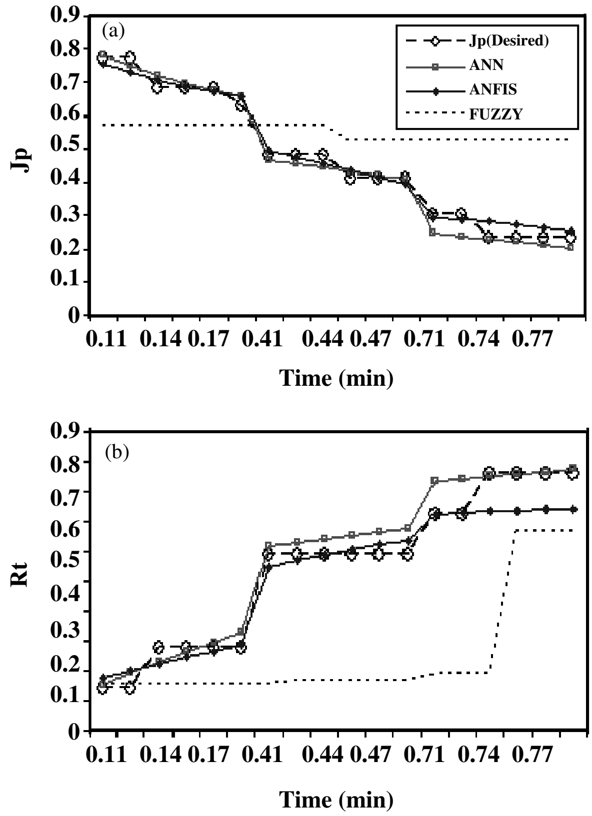

Fig. 6: Comparison between values of desired and ANFIS, MLP, and FIS predicted for: (a) flux and (b) total hydraulic resistance, respectively.

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Nomenclatures

Rt	Total hydraulic resistance, (m^{-1})
J_p	Permeate flux, (m/s)
P_i	Inlet pressure, (KPa)
P_o	Outlet pressure, (KPa)
P_p	Permeating pressure, (KPa)
μ_P	Permeate viscosity, (Kg/m.s)
X1, x2, …, x6	Input variables
$\{p_i, q_i, \ldots, k_i, r_i\}$	Consequent parameters
$\{x^*, \sigma\}$	Premise parameters
$A_1, B_1, \ldots, C_1$	Antecedent

Abbreviations

ANFIS	Adaptive neuro-fuzzy inference system
MLP	Multilayer perceptron
ANN	Artificial neural network
FISs	Fuzzy inference systems
MWCO	Molecular weight cut-off (KDa)
pH	Acidity
TMP	Transmembrane pressure (KPa)
TEMP	Temperature (°C)
Time	Time (min)
RMSE	Root mean square-error
MSE	Mean square-error
LSE	Least square-error

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