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Application of ANN and ANFIS to predict the effect of fatty acids on the performance of CA composite membranes in removal of pesticides from water

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ABSTRACT

Modeling of the membrane separation processes in removal of hazardous components like pesticides from water would be beneficial to predict the membrane performance in treatment of the polluted water sources. In this paper, the computational intelligence (CI) methods such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) are used to model and predict the effect of fatty acids on the performance of cellulose acetate composite membrane in treatment of aqueous solutions containing nitrophenols as an important class of pesticides. For this purpose, membrane, feed and solution pH are selected as the inputs, and the membrane efficiency is selected as the output of the proposed CI models. Comparison between the proposed ANN and ANFIS models and the experimental data shows that the proposed CI models are very efficient and fast tools, and there is a good agreement between the experimental and our models with a minimum error. The overall mean relative error percentages obtained for the ANN and ANFIS models are less than 2.05% and 1.12% for flux (less than 1.49% and 0.47% for rejection), respectively, which declare the high reliability of the proposed models.

Keywords: Artificial neural network; Adaptive neuro-fuzzy inference system; Modeling; Composite membrane; Nitrophenol pesticides; Water treatment

1. Introduction

Water sources have been always exposed to a variety of pollutants influencing water physical and chemical qualities in negative and harmful ways. In this way, one of the most effective kinds of pollutants has always been pesticides. Meanwhile, nitrophenols as one of the important types of nitroaromatic pesticides have been extensively observed in the effluents released into water sources by some industries manufacturing various applicable and commercial chemical compounds such as dye, drug, fungicides, pesticides, ammunition and various chemical plants. More importantly, nitrophenol compounds might reach the groundwater reservoirs as a result of gravitational settlement of aerosols via rain and snow. It should be stated here that nitrophenols can be categorized as hazardous compounds due to their detrimental influences on human nervous system [1,2]. To tackle their unwanted impacts on human being and wildlife, there have been some conventional treatment methods such as oxidation with chlorine, ozone, potassium permanganate, hydrogen peroxide and also adsorption on activated carbon; however, these methods lack sufficient efficiency and often produce toxics chemicals as by-products [2–4]. By the same token, membrane-based removal of pesticides from polluted effluents is an efficient and economic treatment approach. In this connection, cellulose acetate (CA) has been one of the most applicable polymers to prepare various types of polymeric membranes due to its environmental-friendly property, low price and also high hydrophilicity; however, its dense skin layer and low porosity of support layer might reduce flux permeated through CA membrane [5,6]. It was

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proved that introducing additives with amphiphilic properties into the dope solution could improve membrane structure and performance thanks to changing penetration rate of non-solvent (water) into the casted polymeric film during phase inversion process [6]. In this regard, fatty acids as one of the amphiphilic additives were added into CA membrane matrix with the aim of causing considerable improvement in membrane characteristics that eventually resulted in a better performance in removal of pesticides from water [5]. Computational intelligence (CI) methods such as artificial neural network (ANN) and adaptive neuro-fuzzy inference system (ANFIS) have been used for estimating physical and chemical data in many studies recently [7–24]. Reviewing the literature revealed that no study has been published to discuss the application of ANN [25,26] and ANFIS [27,28] in predicting the effect of fatty acids on the performance (i.e., flux and rejection) of CA nanofiltration membrane in treatment of aqueous solutions containing nitrophenols as an important class of pesticides.

2. Experimental method

In the experimental section of this study, three different types of fatty acids (palmitic acid, oleic acid and linoleic acid) with various concentrations (0.5, 1, 1.5 and 2 wt%) were embedded into the matrix of CA membrane. To this end, common phase inversion method was used by the researches to fabricate composite membranes. Equally important, several nitrophenol pesticides with a variety of chemical compounds including *p*-nitrophenol (PNP), 2,4-dinitrophenol (DNP), 2-methyl-4,6-dinitrophenol (DNOC), 3,5-dinitrosalicylic acid (DNSA) and 4-nitrophenol phosphate disodium salt hexahydrate (NPP) were employed in this study with the intent of evaluating performance of the prepared membranes. In this regard, the experiments were conducted by use of solutions containing each one of the aforementioned nitrophenols (0.1 mM) at acidic (4.5), neutral (7.0) and basic solution pHs (8.0) [5]. A batch type, dead-end stirred cell, was applied to conduct the filtration tests and to determine the composite membrane efficiency. It is worth mentioning here that the most applicable parameters indicating membrane performance are flux and rejection. In general, the amount of the permeated solution through a membrane can be determined by flux that could be calculated using the following equation:

$$\mathrm{Flux}\left(\mathrm{kg/m^2.h}\right) = {}^{Q}\!/_{A.\Delta t} \tag{1}$$

where Q, A and Δt are quantity of permeated solution through the membrane (kg), active surface of membrane (m^2) and sampling time (h), respectively.

As the other fundamental element representing the membrane capability in separation process, rejection is defined as the membrane efficacy in retaining unwanted materials. In this study, rejection (Rej (%)) of pollutants (nitrophenols) was measured as follows:

$$\mathrm{Rej}(\%) = \left(1 - \frac{C_P}{C_F}\right) \times 100 \tag{2}$$

where C_p (mM) and C_F (mM) are concentration of nitrophenol in the permeate and feed, respectively [5].

3. Modeling based on ANN and ANFIS

3.1. Artificial neural network

ANN is based on the operation of biological neural networks [25,26]. The basic processing element of ANN structure is the artificial neuron, in which the synapses of the biological neurons are modeled as the weights. The weights can be adjusted using the backpropagation rule, which is an error-minimization technique. Multi-layer perceptron (MLP) network is the most widely used ANN structure, which consists of at least three layers (i.e., one input layer, one output layer and one or more hidden layers) [25,26]. As shown in Fig. 1, each layer has a number of neurons. In Fig. 1, X_1, X_2, ..., X_n are the inputs, Y_1, Y_2, ..., Y_n are the outputs, where n is the number of inputs and m is the number of outputs. In this figure, tth neuron of the hidden layer has the following equation:

$$\theta_t = f\left(\sum_{k=1}^{n}\left(X_k W_{kt}\right) + b_t\right) \quad t = 1,2,\ldots,i \tag{3}$$

where f is the hidden layer activation function (usually Tansig function); b is the bias term and W is the weighting factor. Also, jth neuron in the output layer has the following equation:

$$y_i = \sum_{k=1}^{i}\left(\theta_k W_{kj}\right) + b_j \qquad j = 1,2,\ldots,m \tag{4}$$

3.2. Adaptive neuro-fuzzy inference system

ANFIS is a fuzzy inference system (FIS) implemented using ANN, which merges the advantages of both fuzzy system and ANN network [27,28]. With a FIS, which has two inputs x and y and one output f, a single fuzzy if-then rule for the first-order Sugeno model is given by:

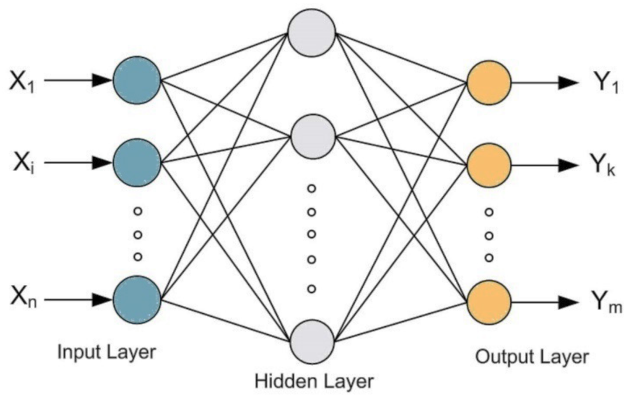

Fig. 1. MLP structure.

Rule #1: if x is A_1 and y is B_1, then $f_1 = p_1x + q_1y + r_1$

Rule #2: if x is A_2 and y is B_2, then $f_2 = p_2x + q_2y + r_2$

where p_i, q_i and r_i (i = 1, 2) are the linear output parameters named consequent parameters.

Fig. 2 shows the ANFIS structure. Each ANFIS structure has five layers described as follows [27,28]:

Layer 1: Every adaptive node in this layer has a node function given by the following equations:

$$O_{1,i} = \mu_{A_i}(x), \quad i = 1,2 \tag{5}$$

$$O_{1,i} = \mu_{B_{i-2}}(y), \quad i = 3,4 \tag{6}$$

where i is the membership grade of a fuzzy set (A_1, A_2, B_1, B_2) and $O_{1,i}$ is the output of the node i in the layer 1. A typical membership function is Gaussian function given by:

$$\mu_A(x) = \exp\left(-\frac{(x-c)^2}{2\sigma^2}\right) \tag{7}$$

where c and σ are called the premise parameters.

Layer 2: The nodes in this layer are fixed nodes, which multiply all incoming signals and represent the firing strength of a rule. The outputs of layer 2 are given by:

$$O_{2,i} = w_i = \mu_{A_i}(x)\mu_{B_i}(y), \quad i = 1,2 \tag{8}$$

Layer 3: The fixed nodes in this layer are called the normalized firing strength. They calculate the ratio of the ith rule's firing strength to the sum of all rule's firing strengths given by:

$$O_{3,i} = \overline{w}_i = \frac{w_i}{w_1 + w_2}, \quad i = 1,2 \tag{9}$$

Layer 4: The adaptive nodes in this layer have the node functions given by the following equation:

$$O_{4,i} = \overline{w}_i f_i = \overline{w}_i(p_ix + q_iy + r_i), \quad i = 1,2 \tag{10}$$

where $\overline{w}_i$ is a normalized firing strength from layer 3, and $\{p_i, q_i, r_i\}$ is the consequent parameters set.

Layer 5: This layer has a fixed node, which computes the overall output as the summation of all incoming signals:

$$O_{5,i} = \sum_i \overline{w}_i f_i = \frac{\sum_i w_i f_i}{\sum_i w_i}, \quad i = 1,2 \tag{11}$$

3.3. Modeling approach

In general, there are several parameters influencing on the membrane performance (flux and rejection) in removal of pesticides from aquatic media. Meanwhile, the effects of membrane type, feed properties and operating conditions could be extensively dominating due to this fact that any alteration in these parameters would make changes in membrane flux and/or rejection [5]. In order to create an appropriate model to precisely anticipate membrane performance in the present paper and also to achieve an acceptable level of optimization, three previously mentioned parameters effective on the membrane efficacy are supposed as the model inputs. In this regard, accurate models based on ANN and ANFIS structures are presented in order to model and predict the effect of fatty acids on the performance of CA nanofiltration composite membrane in treatment of aqueous solutions. In these CI models, the input parameters are defined as the membrane type (different kinds of fatty acids with various concentrations and properties), feed (nitrophenol pesticides with different chemical characteristics) and solution pH (acidic, neutral and basic). Moreover, flux and rejection (membrane efficiency) are considered as the output parameters of the models. In Fig. 3, the simplified overview of the proposed CI models is shown.

The data set required to train and test the proposed CI models is obtained using the experimental study [5]. The total number of the used samples to develop the CI models was 195, which about 70% and 30% of them were applied for training and testing, respectively. Also, a set of 14 data is used to validate the proposed models as the validation data set. MATLAB 7.0.4 software was employed for developing

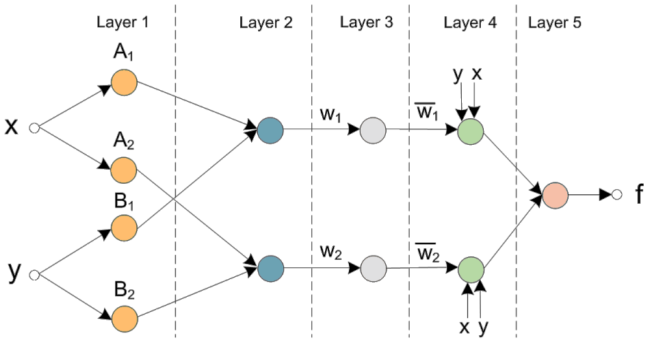

Fig. 2. An ANFIS structure.

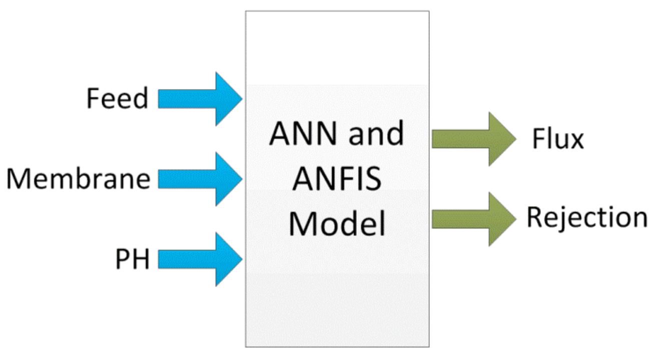

Fig. 3. Proposed CI model.

the proposed models. Different ANN and ANFIS configurations were tested and optimized to obtain the best ANFIS and ANN models. To obtain the best ANN structure, many different structures were tested with one, two and three hidden layers. Also, the number of neurons in each hidden layer was changed from 1 to 12, and the number of epochs for each MLP structures was changed from 50 to 450. In order to obtain the best ANFIS models, input membership function type, the number of input membership functions and the number of epochs were changed. Then, the ANN and ANFIS structures are trained and tested with the training and testing data. To compare the outputs of the developed structures with the experimental, we used mean relative error percentage (MRE%) defined in Eq. (12). This process is continued until the best ANN and ANFIS models are obtained with the minimum MRE% for training and testing data. The specifications of the best proposed ANN and ANFIS models are shown in Tables 1 and 2, respectively. In Table 1, Trainlm is a network training function that updates weight and biases values according to the Levenberg–Marquardt optimization.

Table 1
Specification of the best proposed ANN model

Neural network	MLP
Number of hidden layer	2
Number of neurons in the input layer	3
Number of neurons in the first hidden layer	10
Number of neurons in the second hidden layer	10
Number of neurons in the output layer	2
Learning rate	0.5
Number of epochs	150
Adaption learning function	Trainlm
Activation function	Tansig

Table 2
Optimal architectures and specifications of the proposed ANFIS models

Specification	ANFIS model for rejection	ANFIS model for flux
Type	Sugeno	Sugeno
Inputs/outputs	3/1	3/1
No. of input membership functions	18 for each input	28 for each input
No. of output membership functions	18	28
Input membership function type	Gaussian	Gaussian
Output membership function type	Linear	Linear
No. of fuzzy rules	18	28
No. of non-linear parameters	216	336
No. of linear parameters	72	112
No. of epochs	250	300

Trainlm is often the fastest backpropagation algorithm in the MATLAB software toolbox and is strongly recommended as a first-choice supervised algorithm, although it does require more memory than other algorithms. In addition, learning rate is an important parameter in the training procedure of MLP networks, which is carefully selected to ensure that the weights converge to a response fast enough without producing oscillations.

4. Results and discussion

The comparison between the experimental data and the obtained results using the proposed CI models for training and testing data are shown in Figs. 4 and 5. In these figures, the green circles show the outputs of ANN and ANFIS models in comparison with the experimental data for flux and rejection. As it can be seen, the obtained results using the proposed ANN and ANFIS models are close to the experimental data for the both outputs flux and rejection. It also seems that the ANFIS models are more accurate than the ANN model to follow the outputs in the both training and testing data. Also, the validation of the best obtained models is done. In Table 3 the comparison between the experimental and proposed ANN and ANFIS models for a set of 14 data as the validation data set is shown.

To show a better comparison between the proposed ANN and ANFIS models, we used four standard error functions, i.e., MRE%, root mean square error (RMSE), correlation factor (CF) and mean absolute error (MAE). The following equations define these standard errors:

$$\text{MRE\%} = 100 \times \frac{1}{N}\sum_{i=1}^{N}\left|\frac{X_i(\text{Exp}) - X_i(\text{Pred})}{X_i(\text{Exp})}\right| \tag{12}$$

$$\text{RMSE} = \left[\frac{\sum_{i=1}^{N}\left(X_i(\text{Exp}) - X_i(\text{Pred})\right)^2}{N}\right]^{0.5} \tag{13}$$

$$\text{CF} = 1 - \left[\frac{\sum_{i=1}^{N}\left(X_i(\text{Exp}) - X_i(\text{Pred})\right)^2}{\sum_{i=1}^{N}\left(X_i(\text{Exp})\right)^2}\right] \tag{14}$$

$$\text{MAE} = \frac{1}{N}\sum_{i=1}^{N}\left|X_i(\text{Exp}) - X_i(\text{Pred})\right| \tag{15}$$

where 'X(Pred)' and 'X(Exp)' stand for the predicted (ANN or ANFIS) values and experimental data, respectively, and N is the number of data. In Table 4, the overall (training, testing and validation) obtained errors for the proposed models in comparison with the experimental data are shown. From Table 4, it can be observed that the proposed ANFIS models are capable of predicting the both outputs flux and rejection better than the proposed ANN model. For example, the obtained MRE% using the ANN model is more than 2 times and 1.8 times bigger than the obtained MRE% using the ANFIS models for the outputs rejection and flux, respectively.

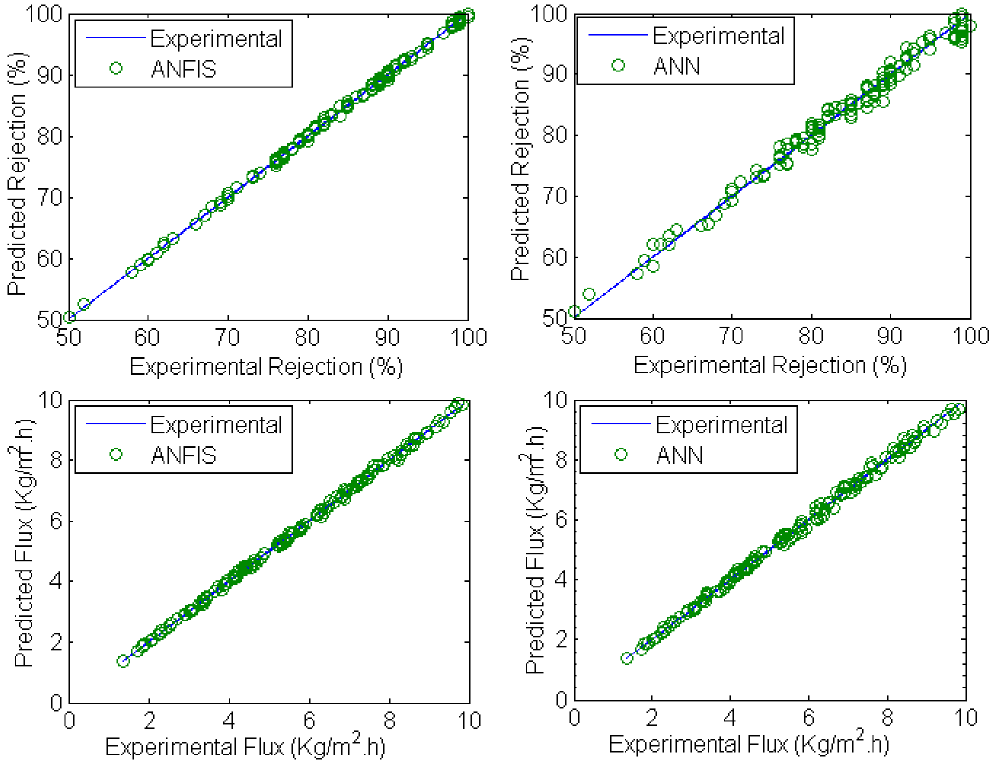

Fig. 4. Comparison between the experimental and the proposed models for training data.

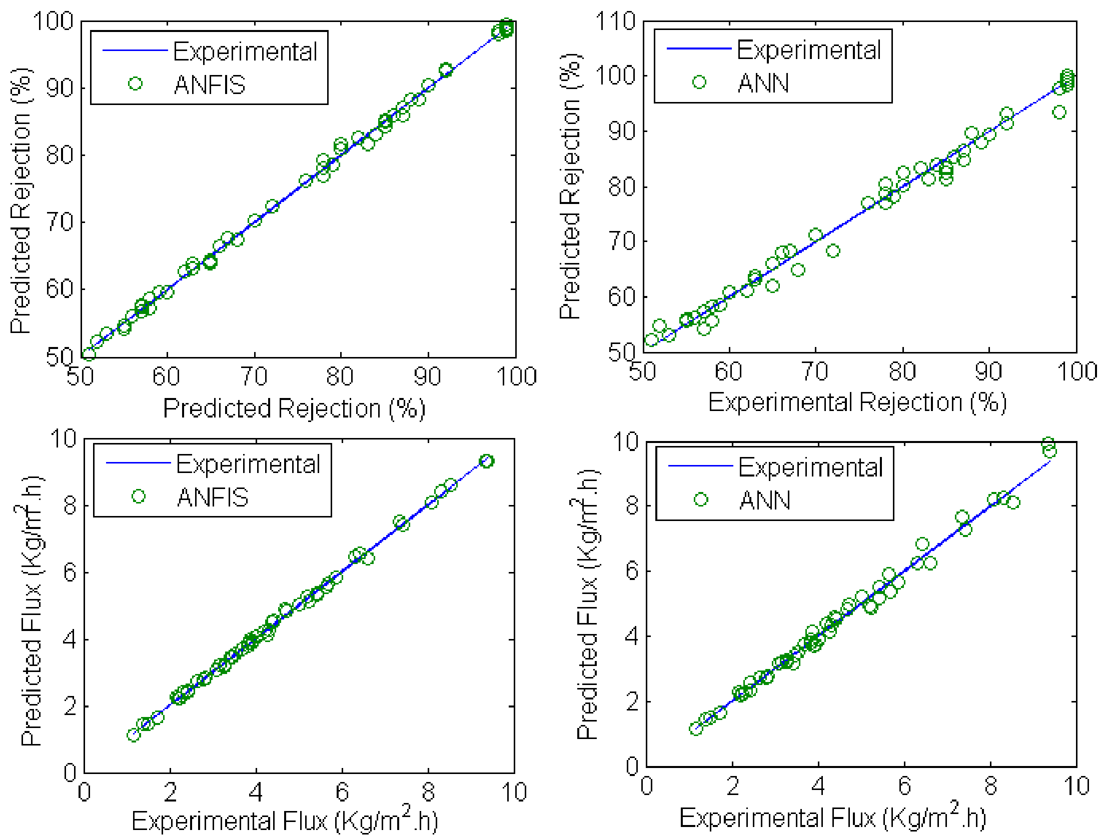

Fig. 5. Comparison between the experimental and the proposed models for testing data.

Table 3
Comparison between the experimental and proposed CI models for validation data

Inputs			Experimental		ANFIS		ANN	
Feed	Membrane	PH	Rejection	Flux	Rejection	Flux	Rejection	Flux
DNOC	2.0 wt% oleic acid	4.5	72	4.03	72.425	4.073	68.377	3.900
DNOC	0.5 wt% palmitic acid	7	82	3.95	82.887	3.899	84.393	3.845
DNOC	0.5 wt% palmitic acid	7	82	3.95	82.887	3.899	84.393	3.845
DNP	2.0 wt% linoleic acid	7	85	8.33	84.145	8.405	81.35	8.237
DNP	2.0 wt% oleic acid	4.5	80	6.63	79.214	6.591	77.719	6.393
DNP	1.5 wt% palmitic acid	4.5	78	4.19	76.943	4.211	76.959	4.385
DNSA	1.0 wt% linoleic acid	4.5	77	5.81	76.439	5.688	77.736	5.536
DNSA	1.0 wt% oleic acid	4.5	79	4.38	78.554	4.517	78.04	4.606
NPP	1.0 wt% linoleic acid	8	99	6.62	99.412	6.388	99.567	6.265
NPP	1.0 wt% oleic acid	4.5	99	4.29	98.527	4.119	98.255	4.151
NPP	2.0 wt% oleic acid	8	100	8.31	100.52	8.203	102.94	8.082
PNP	0.5 wt% linoleic acid	4.5	57	1.39	56.74	1.432	57.428	1.46
PNP	0.5 wt% linoleic acid	7	51	2.43	50.288	2.396	52.112	2.343
PNP	0.5 wt% linoleic acid	7	51	2.43	50.288	2.396	52.112	2.343

Table 4
Obtained errors for the proposed models

Model errors	Data	CI models			
		ANFIS		ANN	
		Rejection	Flux	Rejection	Flux
MRE%	Training	0.3565	0.9106	1.380	1.606
	Testing	0.7601	1.666	1.780	3.249
	Validation	0.8604	1.820	2.206	3.662
MAE	Training	0.2968	0.0481	1.1730	0.0893
	Testing	0.5420	0.0659	1.2955	0.1518
	Validation	0.6419	0.0828	1.7128	0.1664
RMSE	Training	0.3621	0.0642	1.4139	0.1166
	Testing	0.6518	0.0846	1.6727	0.1983
	Validation	0.6799	0.1023	2.0323	0.1861
CF	Training	0.999513	0.999549	0.992601	0.998518
	Testing	0.999069	0.999139	0.993974	0.995469
	Validation	0.999260	0.998949	0.991582	0.997494

Figs. 6–8 show a better comparison between the experimental data, the ANFIS models and the ANN model for the output flux and rejection. These figures are plotted using the training and testing data. In these figures, the type of feed and membrane are selected as X and Y axes, and flux and rejection are selected as Z axis. Also, pH is varied in three values (4.5, 7.0 and 8.0). From Figs. 6–8 it is clear that the obtained results using the both CI models are close to the experimental data. Also, the proposed ANFIS models are more accurate than the proposed ANN model. If it is assumed that a membership function in ANFIS structure is equivalent to a neuron in ANN structure (a membership function is more complicated than a neuron), it can be found that the proposed ANN model has a simpler structure (consists of 20 neurons) than the proposed ANFIS models (consist of 18 + 28 = 46 membership functions). Also, ANFIS structure is a one-output structure; thus, two ANFIS structures are needed to predict the outputs flux and rejection using ANFIS. However, due to this fact that ANN model has a multi-output structure, it is possible to use one ANN model to simultaneously predict the outputs flux and rejection. Hence, these advantages make the proposed ANN model more flexible, faster and cheaper in the hardware implementation.

One of the most advantages of the proposed ANN and ANFIS models is to present a direct mathematical equation for the relationship between the inputs (membrane and feed type and pH) and the outputs (flux and rejection). For example, a direct mathematical equation can be introduced using the ANN model presented in this paper for the relationship between the inputs (membrane and feed type and pH) and the outputs (flux and rejection). Table 5 represents the obtained equations for the outputs rejection and flux using the proposed ANN model. In Table 5, in order to determine the types of membrane and feed, a number should be assigned to each type as follows:

Types of feed:
DNOC = 1, DNP = 2, DNSA = 3, NPP = 4 and PNP = 5

Type and concentration of the added fatty acids into the matrix of membrane, which are defined as follows:

1. Pristine CA membrane,
2. Composite membrane prepared by 0.5 wt% linoleic acid,
3. Composite membrane prepared by 1.0 wt% linoleic acid,
4. Composite membrane prepared by 1.5 wt% linoleic acid,
5. Composite membrane prepared by 2.0 wt% linoleic acid,

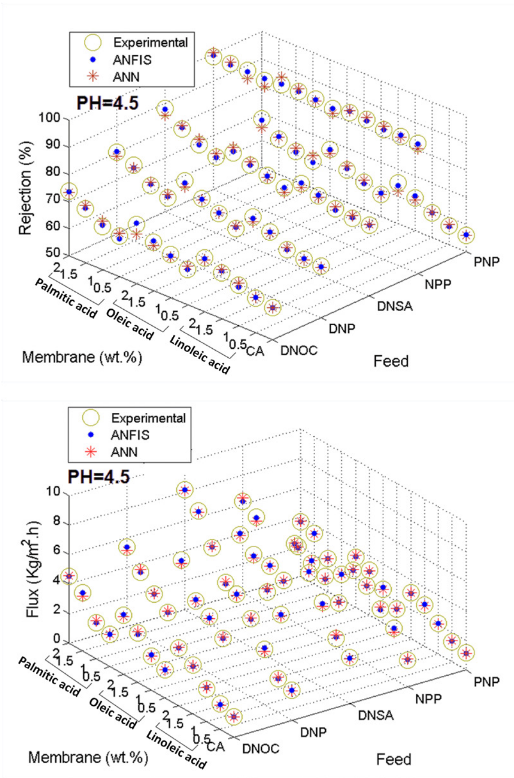

Fig. 6. Comparison between the experimental and the CI models for the outputs flux and rejection (pH = 4.5).

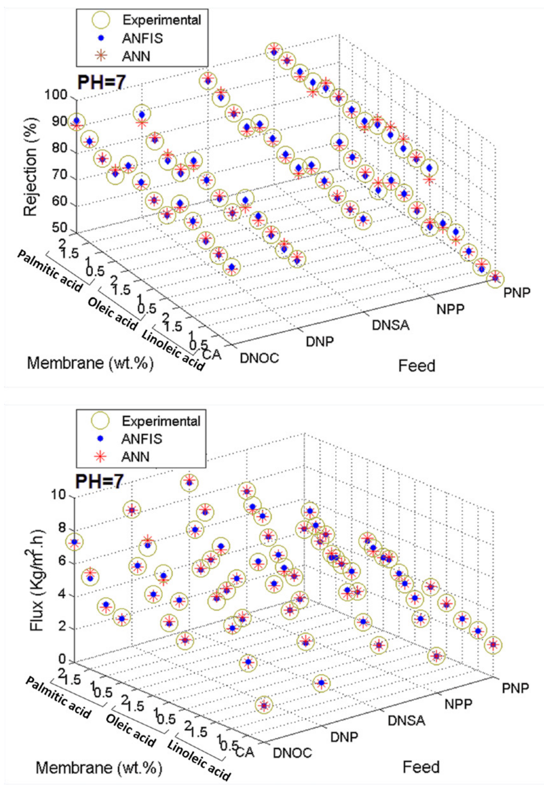

Fig. 7. Comparison between the experimental and the CI models for the outputs flux and rejection (pH = 7.0).

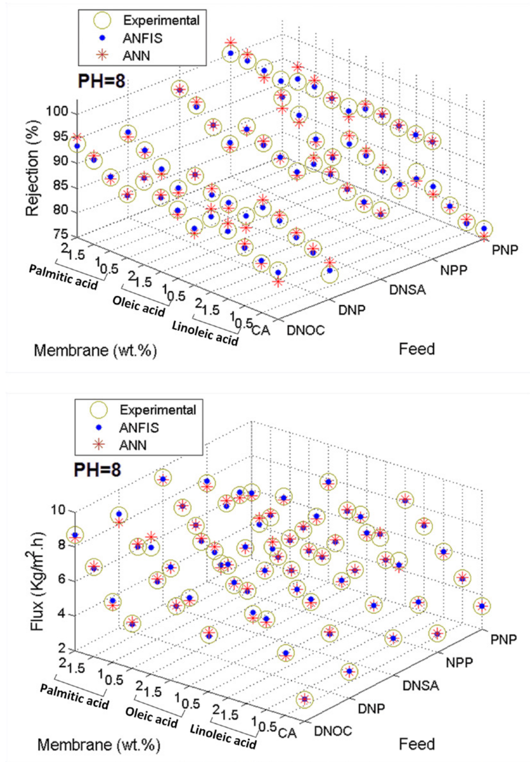

Fig. 8. Comparison between the experimental and the CI models for the outputs flux and rejection (pH = 8.0).

6. Composite membrane prepared by 0.5 wt% oleic acid,
7. Composite membrane prepared by 1.0 wt% oleic acid,
8. Composite membrane prepared by 1.5 wt% oleic acid,
9. Composite membrane prepared by 2.0 wt% oleic acid,
10. Composite membrane prepared by 0.5 wt% palmitic acid,
11. Composite membrane prepared by 1.0 wt% palmitic acid,
12. Composite membrane prepared by 1.5 wt% palmitic acid, and
13. Composite membrane prepared by 2.0 wt% palmitic acid.

Using this equation we can predict the outputs of a new data set that are not belong to the training, testing and validation data. Fig. 9 shows the obtained results for a specific application of the ANN model using the proposed equation. We obtained the plotted data in this figure using the proposed equation in <1 s, which is the other advantage of the proposed models in comparison with the experimental.

5. Conclusion

In this paper, the effects of type and concentration of fatty acids as additives on the performance (flux and rejection) of CA composite membrane in treatment of aqueous solutions (with different pHs) containing various types of nitrophenol pesticides were investigated using ANN and ANFIS. For this purpose, one ANN (MLP) structure and two ANFIS models were presented. Based on the obtained results and performed modeling, the following conclusions were drawn:

- Based on the obtained results, both proposed ANN and ANFIS models were able to accurately predict the outputs with the least error.

Table 5
Obtained equations for the output rejection and flux using the proposed ANN model

Feed = 1
Membrane = 4
pH = 8

o1 = Tansig(–0.0120 × feed + 1.170 × membrane – 0.0104 × pH – 12.722)
o2 = Tansig(–2.2030 × feed – 0.021 × membrane – 1.1125 × pH + 16.762)
o3 = Tansig(–0.3100 × feed + 0.454 × membrane + 0.8032 × pH – 6.1973)
o4 = Tansig(–0.7300 × feed + 0.033 × membrane – 0.8101 × pH + 7.1523)
o5 = Tansig(–0.7140 × feed + 0.074 × membrane + 1.0537 × pH – 3.4008)
o6 = Tansig(0.91570 × feed – 0.688 × membrane – 0.6196 × pH + 3.4774)
o7 = Tansig(–0.5890 × feed – 0.0310 × membrane + 1.3707 × pH – 7.0429)
o8 = Tansig(0.11820 × feed + 3.962 × membrane + 0.0328 × pH – 21.592)
o9 = Tansig(4.01930 × feed + 0.659 × membrane + 0.7080 × pH – 13.303)
o10 = Tansig(–0.071 × feed – 0.0660 × membrane – 0.1780 × pH + 1.4785)

o11 = Tansig(–0.005 × o1 – 1.183 × o2 + 0.0917 × o3 + 1.3930 × o4 – 3.3452 × o5–0.065 × o6 – 0.555 × o7 – 0.0007 × o8 + 0.0047 × o9 + 0.754 × o10 + 4.42)
o12 = Tansig(1.0025 × o1 + 1.716 × o2 + 0.5433 × o3 + 12.065 × o4 + 8.6736 × o5 + 1.232 × o6 – 1.154 × o7 – 1.0875 × o8 + 0.0681 × o9 – 11.13 × o10 + 0.79)
o13 = Tansig(0.8400 × o1 + 0.692 × o2 – 3.1533 × o3 – 3.2566 × o4 + 2.7622 × o5 – 1.222 × o6 + 2.387 × o7 + 0.6133 × o8 – 0.8904 × o9 + 3.322 × o10 – 5.12)
o14 = Tansig(–0.070 × o1 + 2.261 × o2 – 0.2302 × o3 + 6.3874 × o4 – 0.5107 × o5 – 0.205 × o6 + 6.635 × o7 – 0.0777 × o8 – 0.2117 × o9 + 0.183 × o10 – 1.01)
o15 = Tansig(0.0630 × o1 – 1.090 × o2 – 0.0615 × o3 – 0.5103 × o4 – 0.4736 × o5 + 0.317 × o6 – 0.361 × o7 + 0.1451 × o8 + 0.6565 × o9 + 0.272 × o10 + 0.69)
o16 = Tansig(–16.30 × o1 – 0.392 × o2 – 1.9166 × o3 + 2.0720 × o4 + 0.1701 × o5 – 1.586 × o6 – 0.607 × o7 – 0.8926 × o8 – 2.9002 × o9 – 7.217 × o10 – 13.7)
o17 = Tansig(0.0450 × o1 + 0.203 × o2 – 0.0105 × o3 + 0.3098 × o4 + 0.1301 × o5 – 0.181 × o6 – 0.171 × o7 – 0.1616 × o8 – 0.0655 × o9 – 0.970 × o10 – 1.40)
o18 = Tansig(0.0250 × o1 – 0.804 × o2 – 0.0033 × o3 – 0.9257 × o4 + 0.1796 × o5 + 0.022 × o6 – 0.148 × o7 – 0.0169 × o8 – 0.0035 × o9 – 0.280 × o10 + 1.84)
o19 = Tansig(–3.590 × o1 – 2.679 × o2 – 7.9508 × o3 – 5.9341 × o4 – 3.1037 × o5 – 3.143 × o6 – 5.873 × o7 + 0.3899 × o8 – 0.2921 × o9 – 5.081 × o10 + 1.65)
o20 = Tansig(0.0620 × o1 + 4.450 × o2 + 0.4359 × o3 – 4.8204 × o4 + 0.9201 × o5 – 0.192 × o6 – 0.098 × o7 – 0.3125 × o8 – 1.2549 × o9 – 0.485 × o10 + 2.03)

Rejection = exp(–0.601 × o11 – 0.002 × o12 – 0.0003 × o13 – 0.249 × o14 + 0.219 × o15 + 0.0508 × o16 + 0.6457 × o17 – 1.260 × o18 – 0.0089 × o19 + 0.2060 × o20 + 5.71)
Flux = exp(–0.67898337 × o11 + 0.235 × o12 – 0.3830 × o13 + 1.562 × o14 + 3.082 × o15 + 0.5767 × o16 + 4.7243 × o17 – 0.937 × o18 – 0.2106 × o19 + 2.3734 × o20 + 2.78)

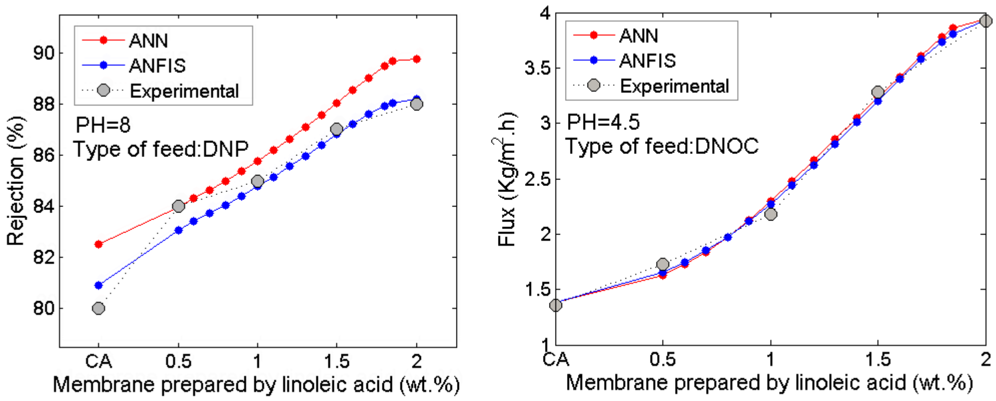

Fig. 9. Interpolation using the proposed ANN and ANFIS models.

- The proposed ANFIS models were more accurate than the proposed ANN model; however, the proposed ANN had less complex structure and was more flexible, faster and cheaper in the hardware implementation.
- Both proposed ANN and ANFIS models were very faster than the experimental method, which means that the proposed CI models can be used as the reliable and flexible tools due to their high accuracy and fast speed; therefore, they can be applied to predict the experiments precisely.

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