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Youness El Hamzaoui, *Autonoumus University of Morelos State*
J.A Hernandez, *Autonoumus University of Morelos State*
Abraham Gonzalez Roman, *Autonoumus University of Morelos State*
José Alfredo Rodríguez Ramírez, *Autonoumus University of Morelos State*

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ANN and ANFIS Models for COP Prediction of a Water Purification Process Integrated to a Heat Transformer with Energy Recycling

Youness El Hamzaoui, J.A Hernandez, Abraham Gonzalez Roman, and José Alfredo Rodríguez Ramírez

Abstract

The aim of this study is to demonstrate the comparison of an artificial neural network (ANN) and an adaptive neuro fuzzy inference system (ANFIS) for the prediction of the coefficient of performance (COP) for a water purification process integrated in an absorption heat transformer system with energy recycling. ANN and ANFIS models take into account the input and output temperatures for each one of the four components (absorber, generator, evaporator, and condenser), as well as two presures and LiBr+H2O concentrations. Experimental results are performed to verify the results from the ANN and ANFIS approaches. For the network, a feedforward with one hidden layer, a Levenberg-Marquardt learning algorithm, a hyperbolic tangent sigmoid transfer function and a linear transfer function were used. The best fitting training data set was obtained with three neurons in the hidden layer. On the validaton data set, simulations and experimental data test were in good agreement (R2>0.9980). However, the ANFIS model was developed using the same input variables. The statistical values are given in as tables. However, comparaison between two models shows that ANN provides better results than the ANFIS results. Finally this paper shows the appropriateness of ANN and ANFIS for the quantitative modeling with reasonable accuracy.

KEYWORDS: water purification, absorption heat transformer, COP prediction, artificial neural network, adaptive neuro fuzzy inference system, memership functions

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1. Introduction

The absorption heat transformer is a system that consists of a thermodynamic device capable of producing useful heat at a thermal level superior to the one in the source (Torres, 1997). This heat transformer plays a special role in the process industries to minimize the energy consumption, because, it could be used in any other system that requires a temperature greater than the one provided by the origin. In addition, an absorption heat transformer is used extensively and regularly in water purification process. It is known that the coefficient of performance (COP) is a very important variable for determining the performance of an absorption heat transformer according to Equation (1). This COP is defined as the heat delivered in the absorber per unit of heat load supplied to generator and evaporator (Huicochea et al., 2004).

$$COP = \frac{Q_{AB}}{Q_{GE} + Q_{EV}} \tag{1}$$

However, to describe the behavior of the COP, Siqueiros and Romero (2007) have used a thermodynamic model to simulate COP values for a water purification process integrated to an absorption heat transformer. This model was based on a set of assumptions as a heat loss, pressure drops in the tubing, whenever these considerations are so difficult to be fulfilled in practice. Thus, controlling this process is impossible according to the thermodynamic model in steady-state. Therefore in practice an artificial intelligence tools such as an artificial neural network (ANN) can provide a new approach to process without take into account any previous assumptions (Hernandez et al., 2008 and Hernandez et al., 2009). ANN is a collection of interconnecting computational elements which function like neurons in biological brain. It has the ability to model processes by learning from input and output data, without mathematical knowledge of the process, requiring less formal statistical training, ability to estimate important parameters with only based on the poor available information, ability to implicitly detect complex nonlinear relationships between dependent and independent variables, ability to detect all possible interactions between predictor variables, ability to approximate virtually any function in stable and efficient way, performs better when there is non linear spatial trends in the database and its availability of multiple training algorithms. Consequenly, the COP could be calculated on-line, when the input variables are well known in the water purification process integrated to the heat transformer with energy recycling.

Fuzzy propositions are statements that pertain with fuzzy variables. The concept of a fuzzy set is the basis of a fuzzy logic. A fuzzy set is a set without a crisp, clearly defined boundary. Adaptive neuro fuzzy inference system (ANFIS) and ANN can be viewed as strong tools in the statistical pattern recognition algorithm and to prepare an equivalent model by virtue of their capabilities of function approximation and classification (Singh et al., 2007). Fuzzy models offer advantages over mathematical ones, the inference process is close to human thinking and it is easier to deal with complex non-linear systems. Moreover, these approaches can be useful to non-expert modeling people.

The ANFIS function can be studied through the fuzzy toolbox of Matlab (Jang, 1993). ANFIS stands for adaptive neuro-fuzzy inference systems and tunes a fuzzy inference system with a back-propagation algorithm based on collection of input/output data. The fuzzy modeling and identification toolbox constructs Takagi–Sugeno fuzzy models from data by means of product-space fuzzy clustering using the Gustafson– Kessel algorithm (Babuska, 1998). Fuzzy systems have gained increasing popularity in engineering over the past few decades, finding a large variety of applications in control theory, pattern recognition, power systems and expert predictions systems (Jang and Gulley, 1996). In addition to the above advantages, fuzzy models can be combined with neural networks to create ANFIS which the advantages are: It is computationally efficient, it works well with linear techniques, it works well with optimization and adaptive techniques, it has guaranteed continuity of the output surface, it is well suited to mathematical analysis. We have found limited published work in relation to the modeling of energy use and energy efficiency for heating and cooling process. In the literature, there are a lot of studies about ANN and ANFIS interested in the energy systems. Kalogirou (2000) examined applications of ANN for energy systems. Bechtler et al (2001a) illustrated an ANN model for estimation the steady-state performance of a vapour-compression heat pump. Swider (2003) made a comprehensive comparison of empirically based models for steady state modeling of vapour-compression liquid chillers. Yang et al (2003) developed an optimized ANN model to determine the optimal start time for a heating system in a building. Arcaklıoglu et al (2004) determined the performance of a vapour-compression heat pump using ANN. Ertunc and Hosoz (2006) used the ANN approach to estimate various performance parameters of an R134a refrigeration system employing an evaporative condenser. Ceylan and Aktas (2008) have presented a hazelnut dryer through heat pump using ANN. Hernández et al. (2008) developed a forcasting model for a water purification process integrated in an absorption heat transformer using ANN to obtain on line prediction of COP. Sahu et al (2008) developed the prediction model of spontaneous heating susceptibility of coals with fuzzy expert system and ANN. Esen and Inalli (2010) described the applicability of ANN and ANFIS to estimating the performance of a vertical ground source heat pump system. On the other hand, in general exists others techniques trying to solve diverse problems of simulation and optimization in the chemical engineering process, as monte carlo method, genetic algorithms, particles swarm optimization, inverse neural network (Chang et al., 2011; El Hamzaoui et al., 2010; El Hamzaoui et al., 2011; Gharebagh and Mostoufi, 2004; Hamidipour et al., 2005; Hernández et al., 2009; Iranshahi et al., 2004; Mostoufi et al., 2005 and Cortés et al., 2009).

This paper presents the COP prediction for the integration of a water purification process in a heat transformer with energy recycling, with the help of adaptive neuro fuzzy inference system and compared with commonly used prediction tool like artificial neural networks. Statistical analysis has been carried out to estimate the statistical parameters of COP values. The validation of the models is made up through experimental data reported by (Morales, 2005).

2. System description and experimental data

Figure. 1 shows a schematic diagram for a heat transformer. Useful heat (Q_{AB}) is the result of the reaction between working fluid vapor and absorbent solution (which comes from the evaporator and generator, respectively). After this process, a diluted water/LiBr solution, goes to the generator. In the generator, the aqueous solution receives a quantity of heat (Q_{GE}) from an external heat supply. Under these conditions, working fluid steam leaves the generator and goes through a condenser where it loses heat (Q_{CO}) and the fluid is condensed. This condensate goes to the evaporator where external heat (Q_{EV}) is supplied and the working fluid evaporates at high pressure and goes to the absorber. At the same time, a concentrated water/LiBr solution goes to the absorber, and at this point, the cycle starts again. Also, it can be observed that the heat transformer is integrated to the water purification system. The absorber gives the unique useful heat delivered (Q_{AB}) in the heat transformer. Q_{AB} is used to heat the impure water until it reaches its boiling point and partly evaporates. The two phases (liquid water and steam) leave the absorber and are separated through a phase separator. The liquid phase returns to the suction pump and the steam produced goes through an auxiliary condenser where heat is transferred as steam condenses while the heat source stream is heated (Siqueiros et al., 2007). In addition on the above of this Figure shows, also the process of water purification system integrated to a heat transformer with heat recycling in the heat source. (Huicochea and Siqueiros, 2010).

Experimental database provided by (Morales, 2005) consists of different COP values, obtained from a portable water purification process coupled to an absorption heat transformer with energy recycling. The experimental data set was obtained at different initial concentration of LiBr in LiBr+H_2O mixture, different temperatures in the absorber, the generator, the evaporator, and the condenser as well as different pressures in the absorber and the generator. The transitory and steady states were taken into account for each initial concentration of the mixture. After 2 h from start-up, data were collected for 4h. The experiments were carried out at eight different initial conditions with at least two replicates. The arrangement was 8 x 2 with 4 h of information acquisition. Thus, a database of 11882 samples was obtained. A summary of 16 operating parameters (10 levels of temperatures, 4 of concentrations and 2 of pressures) is shown in Table 1. The thermodynamic properties of the LiBr + H_2O mixture were estimated with Alefeld correlations cited by (Torres, 1997). The input and output temperatures of each component (AB, GE, CO and EV) were obtained experimentally. At the same time, the pressure of two components (AB and GE) was registred with a temperature pressure acquisition system (thermocouple conditioner and Agilent equipment with commercial software). The input and output concentrations in the AB and GE were established by a refractometer (refraction index). In this process, LiBr + H_2O mixture was used as the working mixture in the absorber and generator, while only H_2O was used in the evaporator and condenser.

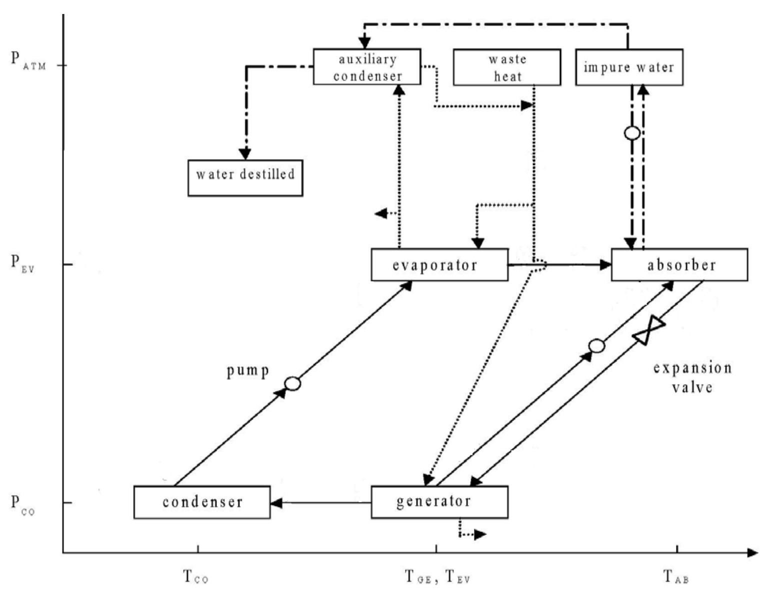

Fig. 1 Schematic diagram of the integration of the water purification process to an absorption heat transformer with energy recycling. The continuous line (-) represents the absorption heat transformer, the line and point (- . -) are the water purification process and the dotted lines (….) are the recycling energy.

Table 1 Experimental operation range conditions studied to obtain the COP values

Variables	Mean±Standard deviation	Limiting conditions
Operation parameters, °C		
$T_{in.GE-AB}$	88.60±1.99	76.29-91.53
$T_{in.EV-AB}$	83.96±2.39	74.56-89.93
$T_{out.AB-GE}$	93.85±2.28	84.31-98.27
$T_{in.AB-GE}$	87.17±1.53	74.99-92.58
$T_{out.GE-CO}$	88.60±1.99	76.29-91.53
$T_{out.GE-AB}$	82.03±0.88	77.03-83.89
$T_{in.CO}$	48.67±3.47	40.37-65.03
$T_{out.CO}$	30.44±1.53	26.77-33.79
$T_{in.EV}$	35.57±7.70	28.52-85.33
$T_{out.EV-AB}$	83.96±2.40	74.56-89.93
Operational parameters, %		
$X_{in.AB}$	53.84±1.31	51.66-55.36
$X_{out.AB}$	52.77±1.33	50.75-54.36
$X_{in.GE}$	52.76±1.32	50.75-54.36
$X_{out.GE}$	55.01±1.03	53.16-56.07
Operational parameters, in Pascal (Pa) (absolute)		
P_{AB}	8.64±1.12	7-11.5
P_{GE}	20.54±0.49	19-21.10

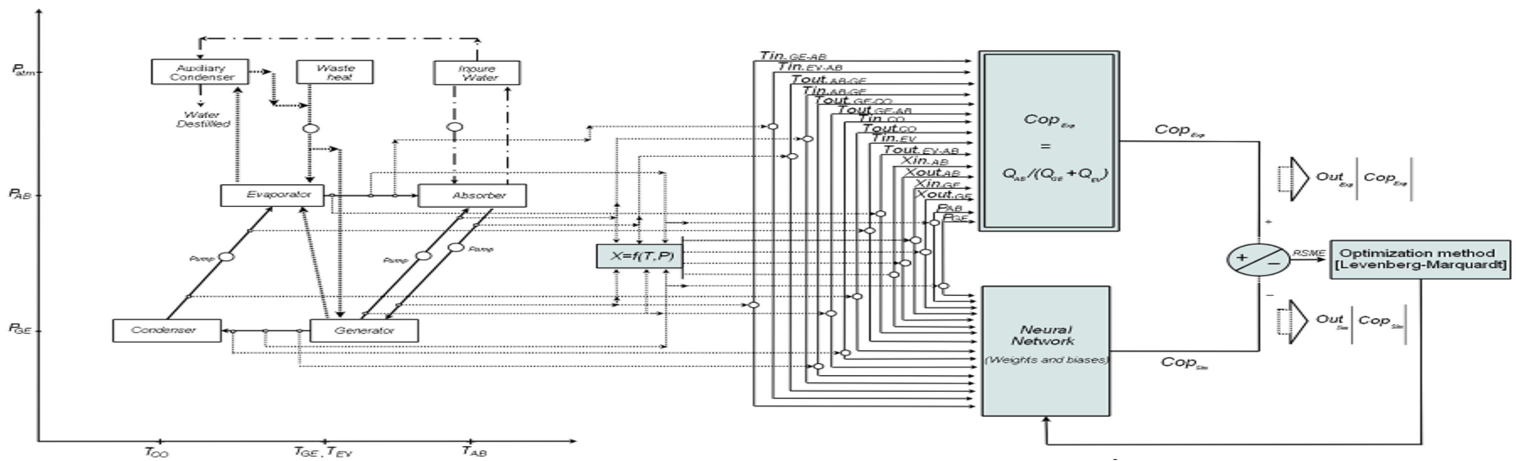

Fig. 2 Recurrent network architecture for COP values and procedure used for neural network learning

Table 2 Comparison of 10 backpropagation algorithms with three neurons in the hidden layer

Backpropagation algorithms	Function	RMSE	R^2	RSD %	Best linear equation
Levenberg-Marquardt	*trainlm*	9.5219×10^{-7}	0.998	2.9343×10^{-4}	Y=0.998X+0.306
Batch gradient descent	*traingd*	8.3247×10^{-6}	0.988	0.0026	Y=0.986X+0.927
Batch gradient descent with momentum	*traingdm*	7.8918×10^{-5}	0.987	0.0243	Y=0.988X+0.837
Polak-Ribiere conjugate gradient	*traincgp*	7.9934×10^{-5}	0.979	0.0246	Y=0.957X+2.53
Scaled conjugate gradient	*trainscg*	6.4627×10^{-4}	0.974	0.1992	Y=1.020X-0.783
BFGS quasi-Newton	*trainbfg*	6.9871×10^{-4}	0.971	0.2153	Y=0.982X+1.23
Powell-Beale conjugate gradient	*traincgb*	6.9997×10^{-4}	0.965	0.2157	Y=0.960X+2.03
One step secant backpropagation	*trainoss*	6.9287×10^{-3}	0.782	2.1352	Y=0.617X+45.3
Fletcher-Reeves conjugate gradient	*traincgf*	6.4159×10^{-2}	0.725	19.7716	Y=0.425X+34.8
Variable learning rate	*traingdx*	6.9781×10^{-1}	0.718	215.0416	Y=0.386X+38

3. Materials and methods

3.1. Artificial neural network

The databases previously mentioned in the section 2 was successfully used to train the ANN model using backpropagation procedure, in order to predict the COP in water purification systems integrated to a heat transformer with energy recycling. On the other hand, as illustreted in Figure 2, we have proven that three layers ANN and three neurons in the hidden layer, could successfully predict the experimental results about the COP's system prediction in this article.

However, in order to determine the best backpropagation training algorithm, ten backpropagation algorithms were studied, Table. 2 shows a comparison of different backpropagation training algorithms. Levenberg-Marquardt backpropagation training algorithm could have smaller mean square error $(RMSE)$ and relative standard deviation (RSD), respectively. In addition, we found training with Levenberg Marquardt algorithm can run smoothly in computer with lower expanded memory specification (EMS), and the training time is quickly, than the other backpropagation algorithms. Because, the Levenberg-Marquardt algorithm was designed to approach second order training speed without having to compute the Hessian matrix. When the performance function has the form of a sum of squares (as is typical in training feed-forward networks), then the Hessian matrix can be approximated as:

$$H = J^T J \tag{2}$$

And the gradient can be computed as:

$$g = J^T e \tag{3}$$

Where J is the Jacobian matrix that contains first derivatives of the network errors with respect to the weights and biases, and e is a vector of network errors. The Jacobian matrix can be computed through a standard backpropagation technique that is much less complex than computing the Hessian matrix. The Levenberg- Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton like up date:

$$X_{k+1} = X_k - \left[J^T J + \mu I\right]^{-1} J^T e \tag{4}$$

When the scalar μ is zero, this is just Newton's method, using the approximate Hessian matrix. When μ is large, this becomes gradient descent with a small step size. According to Hagan and Menhaj (1994), Newton's method is faster and more accurate near an error minimum, so the aim is to shift toward Newton's method as quickly as possible, thus μ is decreased after each successful step (reduction in performance function) and is increased only when a tentative step would increase the performance function. In this context, the performance function is always reduced at each iteration of the algorithm (Khataee and Kasiri., 2010). That's why for these arguments, the Levenberg-Marquardt algorithm was considered the training algorithm in the present study.

However, the performance of the ANN model was statistically measured by the root mean square error *(RMSE)*, relative standard deviation *(RSD)* and regression coefficient *(R^2)*, which are calculated with the experimental values and network predictions. These calculations are used as a criterion for model adequacy obtained as follows:

$$RMSE = \sqrt{\frac{\left(\sum_{n=1}^{N}\left(y_{q,pred} - y_{q,\exp}\right)^2\right)}{N}} \tag{5}$$

$$RSD = \frac{RMSE}{y_m} \times 100 \tag{6}$$

$$R^2 = 1 - \frac{\sum_{n=1}^{N}\left(y_{n,pred} - y_{n,\exp}\right)^2}{\sum_{n=1}^{N}\left(y_{n,\exp} - y_m\right)^2} \tag{7}$$

Where N is the number of data points, $y_{n,pred}$ is the network prediction, $y_{n,\exp}$ is the experimental response, y_m is the average of actual values and n is an index of data.

The Figure 2 mentioned below depicts also, the recurrent network architecture for a COP values and procedure used for neural network learning.
the performance of the network. Therefore, the network having minimum *RMSE*, minimum *RSD* and maximum R^2 was selected as the best ANN model.
According to (Hernandez et al., 2008), the proposed model is represented by the following equation:

$$COP = \sum_{s=1} \left[W_o(1,s). \left(\frac{2}{1+\exp\left(-2.\left(\sum_{k=1} \left(IW(s,k).In(k) \right) + b1(s) \right) \right)} - 1 \right) \right] + b2 \tag{8}$$

Where s is the number of neurons in the hidden layer, k is the number of the input, and IW, W_o and b are weights and bias, respectively. Table 4 shows the adjustable parameters $\left(IW, W_o, b1\, and\, b2 \right)$ of the proposed model. However, the equation (8), can be expressed as follow:

$$COP = 2\left[\frac{W_o(1)}{1+e^{X_1}} + \frac{W_o(2)}{1+e^{X_2}} + \frac{W_o(3)}{1+e^{X_3}} \right] - \left(W_o(1) + W_o(2) + W_o(3) \right) + b_2 \tag{9}$$

It seems clear, according to equation (9), that it is possible to simulate the COP in water purification systems integrated to a heat transformer with energy recycling. However, in many cases, the problem is that this COP calculated by ANN is not ideal in the system, and therefore it is necessary that its input variables are well known when giving a required COP.

3.2. Adaptive network based fuzzy inference system (ANFIS)

An adaptive network, as its name implies, is a network structure consisting of nodes and directional links through which the nodes are connected. Moreover, parts or all of the nodes are adaptive, which means each output of these nodes depends on the parameters pertaining to this node and the learning rule specifies how these parameters should be changed to minimize a prescribe error measure (Jang, 1993). For simplicity, we assume the fuzzy inference system under consideration has two inputs x and y and one output z. Suppose that the rule base contains two fuzzy if then rules of Takagi and Sugeno's type:

Rule 1: $If\left(x\ is\ A_1 \right) and \left(y\ is\ B_1 \right) then \left(f_1 = p_1 x + q_1 y + r_1 \right).$

Rule 2: $If\left(x\ is\ A_1 \right) and \left(y\ is\ B_1 \right) then \left(f_2 = p_2\, x + q_2\, y + r_2 \right).$

Where A_i and B_i are the fuzzy sets, f_i are the outputs within the fuzzy region specified by the fuzzy rule, p_i, q_i and r_i are the design parameters that are determined during the training process. The ANFIS architecture to implement these two rules is shown in Figure 3, in which a circle indicates a fixed node, whereas a square indicates an adaptive node (Guler and Ubeyli, 2005).

Layer 1: Every node i in this layer is a square node with a node function

$$O_i^1 = \mu_{A_i}(x), i=1,2 \tag{13}$$

$$O_i^1 = \mu_{B_i}(y), i=3,4 \tag{14}$$

where x is the input to node i, and A_i is the linguistic label (small, large, etc.) associated with this node function, and where $\mu_{A_i}(x)$, $\mu_{B_{i-2}}(y)$ can adopt any fuzzy membership functions (MFs). Usually we choose $\mu_{A_i}(x)$ to be bell-shaped with maximum equal to 1 and minimum equal to 0, such as

$$\mu_{A_i} = \frac{1}{1+\left\{\left(\frac{x-c_i}{a_i}\right)^2\right\}^{b_i}} \tag{15}$$

Where a_i, b_i and c_i are the parameter set. Parameters in this layer are refferred to as premise parameters.

Layer 2: The nodes in this layer are fixed. These are labelled M to indicate that play the role of a simple multiplier. The outputs of these nodes are given by

$$O_i^2 = w_i = \mu_{A_i}(x)\mu_{B_i}(y)\ i=1,2 \tag{16}$$

which are the so-called firing strengths of the rules.

Table 3 Adjustable parameters obtained (weights and bias) in the proposed model with S=3, K=16

IW(s,k)	Wi(1,1)	Wi(1,2)	Wi(1,3)	Wi(1,4)	Wi(1,5)	Wi(1,6)	Wi(1,7)	Wi(1,8)	Wi(1,9)	Wi(1,10)	Wi(1,11)	Wi(1,12)	Wi(1,13)	Wi(1,14)	Wi(1,15)	Wi(1,16)
	1.04	1.62	-8.54	1.79	7.15	-1.19	-1.09	2.51	-0.003	-2.34	242.39	-159.45	-172.58	20.83	-19.47	-65.58
	Wi(2,1)	Wi(2,2)	Wi(2,3)	Wi(2,4)	Wi(2,5)	Wi(2,6)	Wi(2,7)	Wi(2,8)	Wi(2,9)	Wi(2,10)	Wi(2,11)	Wi(2,12)	Wi(2,13)	Wi(2,14)	Wi(2,15)	Wi(2,16)
	20.07	-6.46	-46.46	6.32	26.42	-16.54	-14.63	37.45	0.32	4.41	-216.87	135.77	115.08	10.27	17.52	-47.03
	Wi(3,1)	Wi(3,2)	Wi(3,3)	Wi(3,4)	Wi(3,5)	Wi(3,6)	Wi(3,7)	Wi(3,8)	Wi(3,9)	Wi(3,10)	Wi(3,11)	Wi(3,12)	Wi(3,13)	Wi(3,14)	Wi(3,15)	Wi(3,16)
	-3.74	-0.11	3.51	-0.54	0.64	0.34	-0.02	0.001	0.003	0.11	-0.43	-7.14	12.61	3.29	-0.15	-1.11
$W_o(s)$	$W_o(1)$	$W_o(2)$	$W_o(3)$													
	-0.18	0.02	-0.88													
b1(s)	b1(1)	b1(2)	b1(3)													
	129.09	-17.75	-6.49													
b2	0.24															

Where:

$$\begin{aligned} X_1 = -2.(&IW_{i(1,1)}.Tin_{GE-AB} + IW_{i(1,2)}.Tin_{EV-AB} + IW_{i(1,3)}.Tout_{AB-GE} + IW_{i(1,4)}.Tin_{AB-GE} + IW_{i(1,5)}.Tout_{GE-CO}\ldots \\ &\ldots\ldots\ldots + IW_{i(1,6)}.Tout_{GE-AB} + IW_{i(1,7)}.Tin_{CO} + IW_{i(1,8)}.Tout_{CO} + IW_{i(1,9)}.Tin_{EV} + IW_{i(1,10)}.Tout_{EV-AB}\ldots \\ &\ldots\ldots\ldots + IW_{i(1,11)}.Xin_{AB} + IW_{i(1,12)}.Xout_{AB} + IW_{i(1,13)}.Xin_{GE} + IW_{i(1,14)}.Xout_{GE} + IW_{i(1,15)}.P_{AB} + IW_{i(1,16)}.P_{GE} + b1_{(1)}) \end{aligned} \tag{10}$$

$$\begin{aligned} X_2 = -2.(&IW_{i(2,1)}.Tin_{GE-AB} + IW_{i(2,2)}.Tin_{EV-AB} + IW_{i(2,3)}.Tout_{AB-GE} + IW_{i(2,4)}.Tin_{AB-GE} + IW_{i(2,5)}.Tout_{GE-CO}\ldots \\ &\ldots\ldots\ldots + IW_{i(2,6)}.Tout_{GE-AB} + IW_{i(2,7)}.Tin_{CO} + IW_{i(2,8)}.Tout_{CO} + IW_{i(2,9)}.Tin_{EV} + IW_{i(2,10)}.Tout_{EV-AB}\ldots \\ &\ldots\ldots\ldots + IW_{i(2,11)}.Xin_{AB} + IW_{i(2,12)}.Xout_{AB} + IW_{i(2,13)}.Xin_{GE} + IW_{i(2,14)}.Xout_{GE} + IW_{i(2,15)}.P_{AB} + IW_{i(2,16)}.P_{GE} + b1_{(2)}) \end{aligned} \tag{11}$$

$$\begin{aligned} X_3 = -2.(&IW_{i(3,1)}.Tin_{GE-AB} + IW_{i(3,2)}.Tin_{EV-AB} + IW_{i(3,3)}.Tout_{AB-GE} + IW_{i(3,4)}.Tin_{AB-GE} + IW_{i(3,5)}.Tout_{GE-CO}\ldots \\ &\ldots\ldots\ldots + IW_{i(3,6)}.Tout_{GE-AB} + IW_{i(3,7)}.Tin_{CO} + IW_{i(3,8)}.Tout_{CO} + IW_{i(3,9)}.Tin_{EV} + IW_{i(3,10)}.Tout_{EV-AB}\ldots \\ &\ldots\ldots\ldots + IW_{i(3,11)}.Xin_{AB} + IW_{i(3,12)}.Xout_{AB} + IW_{i(3,13)}.Xin_{GE} + IW_{i(3,14)}.Xout_{GE} + IW_{i(3,15)}.P_{AB} + IW_{i(3,16)}.P_{GE} + b1_{(3)}) \end{aligned} \tag{12}$$

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

$$O_i^3 = \bar{w}_i = \frac{w_i}{w_1 + w_2} \quad i = 1,2 \tag{17}$$

For convenience, outputs of this layer will be called normalized firing strengths.
Layer 4: In this layer, the nodes are adaptive nodes. The output of each node in this layer is simply the product of the normalized firing strength and a first order polynomial (for a first order Sugeno model). Thus, the outputs of this layer are given by:

$$O_i^4 = \bar{w}_i f_i = \bar{w}_i \left(p_i x + q_i y + r_i \right) \; i = 1,2 \tag{18}$$

Parameters in this layer will be referred to as consequent parameters.
Layer 5: The single node in this layer is circle node labelled $\sum$ that computes the overall output as the summation of all incoming signals, i.e.,

$$O_i^5 = \sum_{i=1}^{2} \overline{w_i} f_i = \frac{\sum_{i=1}^{2} w_i f_i}{w_1 + w_2} \tag{19}$$

It can be seen that there are two adaptive layers in this ANFIS architecture, namely the first layer and the fourth layer. In the first layer, there are three modifiable parameters $\{a_i, b_i, c_i\}$, which are related to the input MFs. These parameters are the so-called premise parameters. In the fourth layer, there are also three modifiable parameters $\{p_i, q_i, r_i\}$, pertaining to the first order polynomial. These parameters are so-called consequent parameters (Despange and Massart, 1998; Jang, 1993; Sengur, 2008a; Sengur, 2008b; Varol et al., 2007).

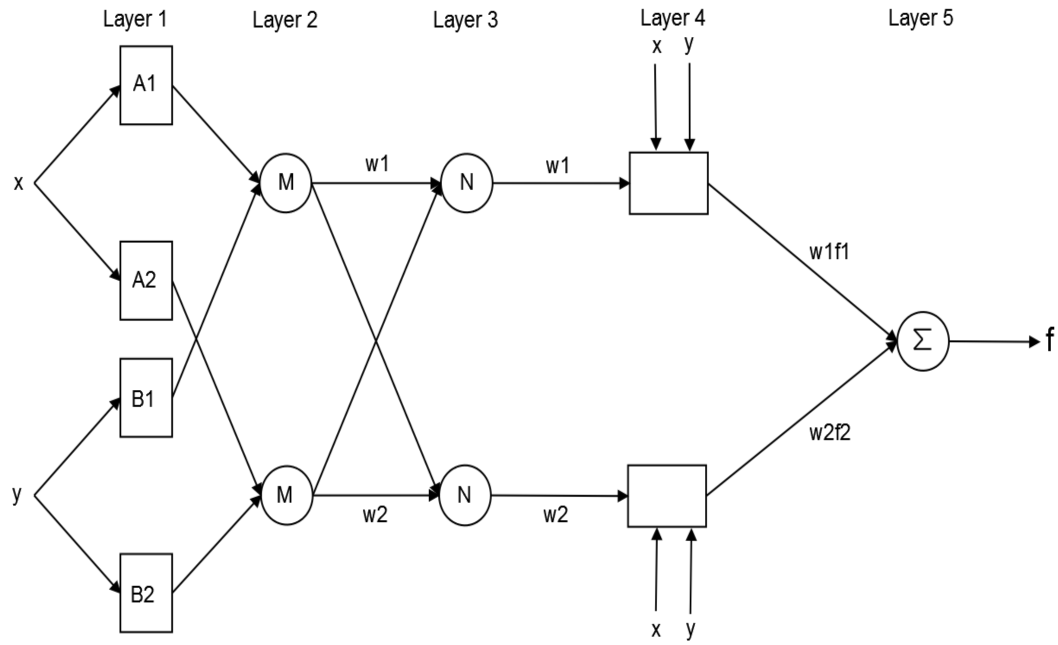

Fig. 3 ANFIS architecture

3.2.1. Learning algorithm of ANFIS

The aim of the training algorithm for this architecture is tune all the changeable parameters to make the ANFIS output match the training data. Note here that parameters a_i, b_i and c_i of the membership function (MF) are fixed, and describe the sigma, slope and center of the bell MFs respectively. According to (Guler and Ubeyli, 2005), the output of the ANFIS model can be written as:

$$f = \frac{w_1}{w_1 + w_2} f_1 + \frac{w_2}{w_1 + w_2} f_2 \tag{20}$$

Substituting Equation (19) into Equation (20) yields:

$$f = \bar{w}_1 f_1 + \bar{w}_2 f_2 \tag{21}$$

Substituting the fuzzy if-then rules into Equation (21), it becomes:

$$f = \bar{w}_1 (p_1 x + q_1 y + r_1) + \bar{w}_2 (p_2 x + q_2 y + r_2) \tag{22}$$

After rearrangement, the output can be written as:

$$f = (\overline{w_1}x)p_1 + (\overline{w_2}y)q_1 + (\overline{w_1})r_1 + (\overline{w_2}x)p_2 + (\overline{w_2}y)q_2 + (\overline{w_2})r_2 \tag{23}$$

which is a linear combination of the changeable consequent parameters p_1, q_2, r_1, p_2, q_2 and r_2. The least squares method can be used to identify the optimal values of these parameters easily. When the premise parameters are not fixed, the search space becomes larger and the convergence of the training becomes slower. A hybrid algorithm combining the least squares method and the gradient descent method is adopted to solve this problem. The hybrid algorithm is composed of a forward pass and a backward pass. The least squares method (forward pass) is used to optimize the consequent parameters with the premise parameters fixed. When the optimal consequent parameters are found, the backward pass starts immediately. The gradient descent method (backward pass) is used to adjust optimally the premise parameters corresponding to the fuzzy sets in the input domain. The output of the ANFIS is calculated by employing the consequent parameters found in the forward pass. The output error is used to adapt the premise parameters by means of a standard back-propagation algorithm. It has been proven that this hybrid algorithm is highly efficient in training the ANFIS (Despange and Massart, 1998; Esen and Inalli, 2010; Jang, 1993; Sengur, 2008a; Sengur, 2008b; Varol et al., 2007).

3.3 ANN and ANFIS models for case study

ANN model, Multi-layered Perceptron/Back-propagation (MLP/ BP) with the Levenberg-Marquardt learning algorithm was developped over this manuscript. On the other hand, the ANFIS model was also developed using the same input variables.

The data set was divided into three separate data sets randomly the training data set and the testing data set. The training data set was used to train the ANN model and ANFIS model. However, the testing data set was used to verify the accuracy and the effectiveness of the trained ANN and ANFIS model for a water purification process integrated to an absorption heat transformer system with energy recycling.

In this study, in input layer, there are 10 levels of temperatures, 4 of concentrations and 2 of pressures. The coefficient of performance of the system (COP) is in output layer. The COP of system is the output variable of the ANN and ANFIS models.

The inputs of the model were normalized in the (0.1, 0.9) range . So, all the input data set X_i (from the training, validation and test sets) were scaled to a new value x_i as follows:

$$x_i = 0.8\left(\frac{X_i - X_{\min}}{X_{\max} - X_{\min}}\right) + 0.1 \tag{24}$$

However, The output values were not normalized. The block diagram of the proposed ANN and ANFIS models are given in Figurte 4. As can be seen from the block diagram, ANN and ANFIS models are adjusted, or trained, so that a particular input leads to a specific target output. Typically, many such input/target output pairs are used to train the models.

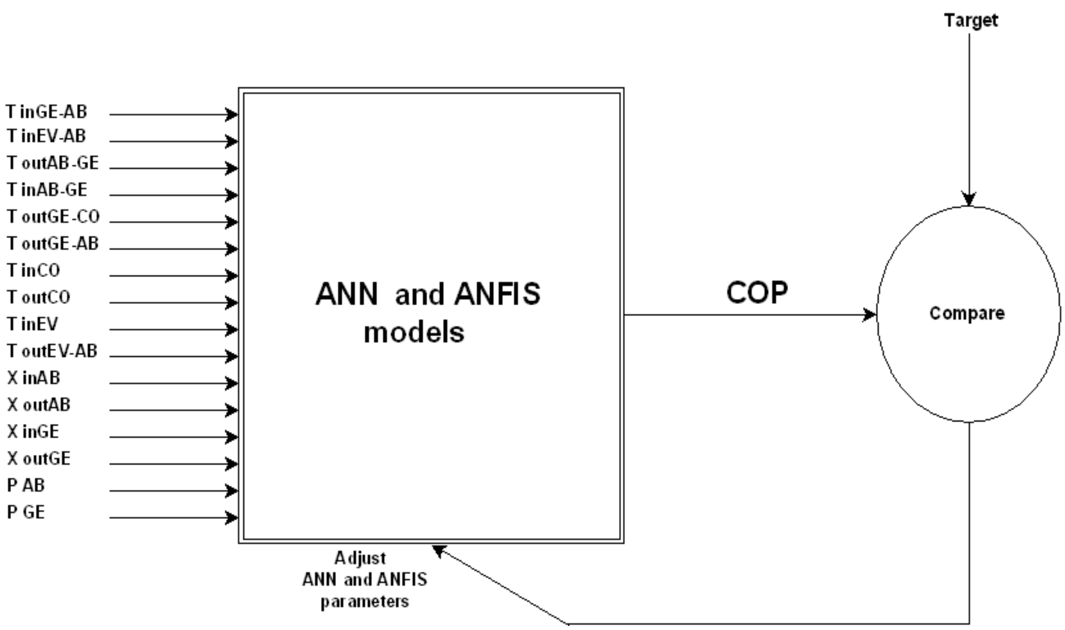

Fig. 4 ANN and ANFIS architecture used for the system

Model validation is the process by which the input vectors from input/output data sets on which the ANN and ANFIS was not trained, are presented to the trained model, to see how well the trained model predicts the corresponding data set output values.

Therefore, several statistical methods, such as the mean squared error *(RMSE)*, relative standard deviation *(RSD)* and the regression coefficient *(R^2)*, could be used to compare predicted and experimental values for model validation. Therefore, these statistical parameters could be estimated according to equations.

The training of the ANN models was stopped when either the acceptable level of error was achieved. Neverthless, in order to obtain the optimal model parameters, the fuzzy rule architecture of the ANFIS was designed by using different type of MFs and various number of MFs. Hybrid learning rule was used to train the model according to input/output data pairs, and the number of iterations was 10000 although it was observed that the best about the learning was completed in the first 4000 epochs.

Different types of MFs as trapezoidal membership function (trapmf), generalized bell membership function (gbellmf), triangular membership function (trimf), gaussian membership function (gaussmf) and gaussian combination membership function (gauss2mf) were used in the ANFIS model.

ANN and ANFIS were implemented by using MATLAB software package.

4. Results and discussions

4.1 Proposed neural network model

A neural network model as showed in Figure 5 with three neurons in the hidden layer (51 weights and four biases) was found to be efficient in predicting COP values for the water purification process integrated to an absorption heat transformer with energy recycling.

Similar results were obtained by (Hernandez et al., 2008), which considered the proposed method for normalizing the inputs and targets reported by (Demuth and Beale, 1998).

Figure 6 shows the experimental data versus simulated data of COP values with energy recycling. We can also observe how the simulated data have the expected relationship with regard to experimental data. The neural network was well fit to the behavior of the learning database: $RMSE = 9.5219 \times 10^{-7}$, $RSD = 2.9343 \times 10^{-4}$ and $R^2 = 0.9980$. The neural network model also fits all these unknown data very well. This figure demonstrates the ability of the model to predict the COP values at different temperatures (in AB, GE, CO and EV), pressure and initial concentration for a given validity range. This confirms the importance of the artificial neural network in simulating the performance of water purification process integrated to an absorber heat transformer with energy recycling.

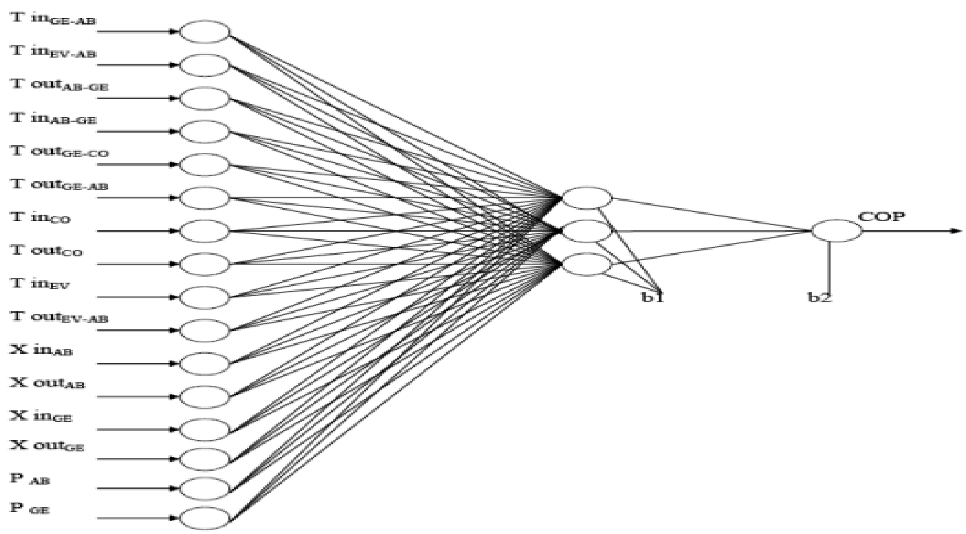

Fig. 5 Model for prediction of COP values

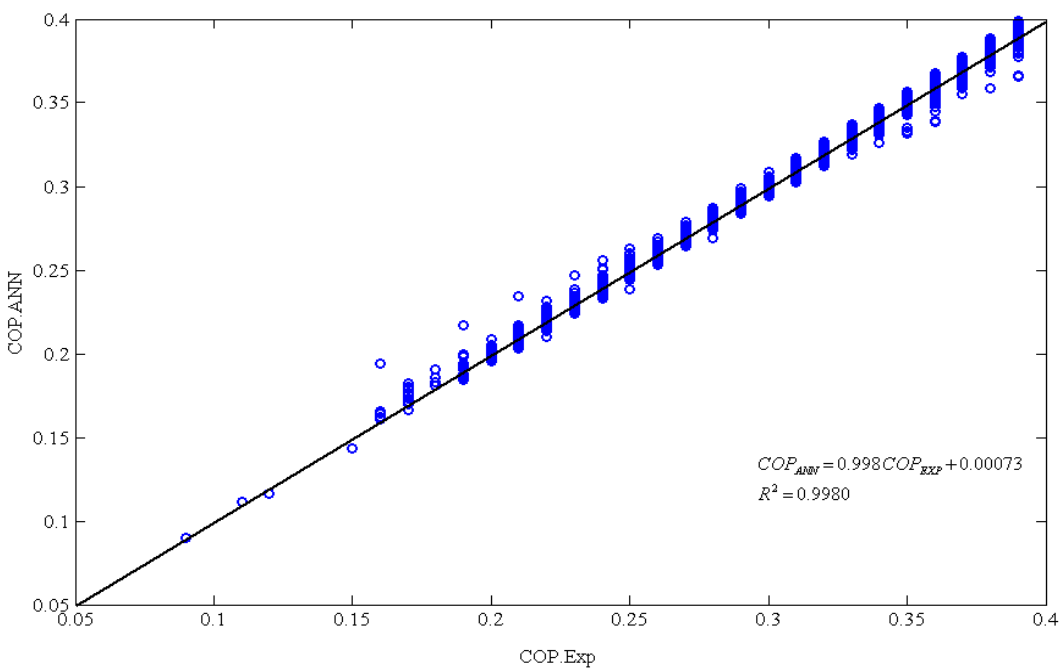

Fig. 6 Correlation of experimental and predicted (ANN) COP values

We stress that, of course, the proposed model was elaborated by the adjustable parameters of the network, called weights and biases *(IW, W_o, b1 and b2)* as mentioned above in Table 3, these coefficients play a special role because are used in the ANN model to simulate COP values. Hence, the model calculated was then validated using testing database (fresh data). However, these COP values are very complex and so difficult to predict just based on a model including assumptions. It shows that the COP prediction was correct. On the other hand, the statistical test of slope = 1 and intercept = 0, was also carried out to confirm statistically the validity of the model (Verma et al., 2005).

4.2 Development of the ANFIS

In this study ANFIS method has been used to predict the COP values for the water purification process integrated to an absorption heat transformer with energy recycling. Therefore, finding the membership function (MF) as showed in Figure 7 which the best one matches the ANFIS model to the condenser of the purification system is the first objective of the computer simulations. The second objective is finding the best appropriate number of MFs that yields the best performance. Statistical values such as *RMSE*, *RSD* and R^2 and are given in Table 4 for the heat transformer system with energy recycling for various MF types. The number of the MF is fixed to three for these simulations.

From the results presented in Table 4 for COP, 'Triangular' appear to be the best optimal MF for the ANFIS model. The *RMSE* value and *RSD* value are 9.5419×10^{-6} and 0.0029, respectively. However R^2 is 0.9897. Optimum trained ANFIS structures were selected according to the minimum *RMSE* and *RSD*, respectively and maximum R^2 values of the test set.
Used ANFIS data's in Matlab program are given as follows:

- Number of nodes: 524
- Number of linear parameters: 243
- Number of no linear parameters: 30
- Total number of parameters: 273
- Number of training data pairs: 6826
- Number of fuzzy rules: 243.

ANFIS with triangular membership function fuzzified into three fuzzy sets as: low, medium and high, was found to be efficient in predicting the coefficient of performance for a water purification process integrated to a heat transformer with energy recycling. Figure 8, presents a comparaison between, the experimental and simulated of the COP values using all data available.

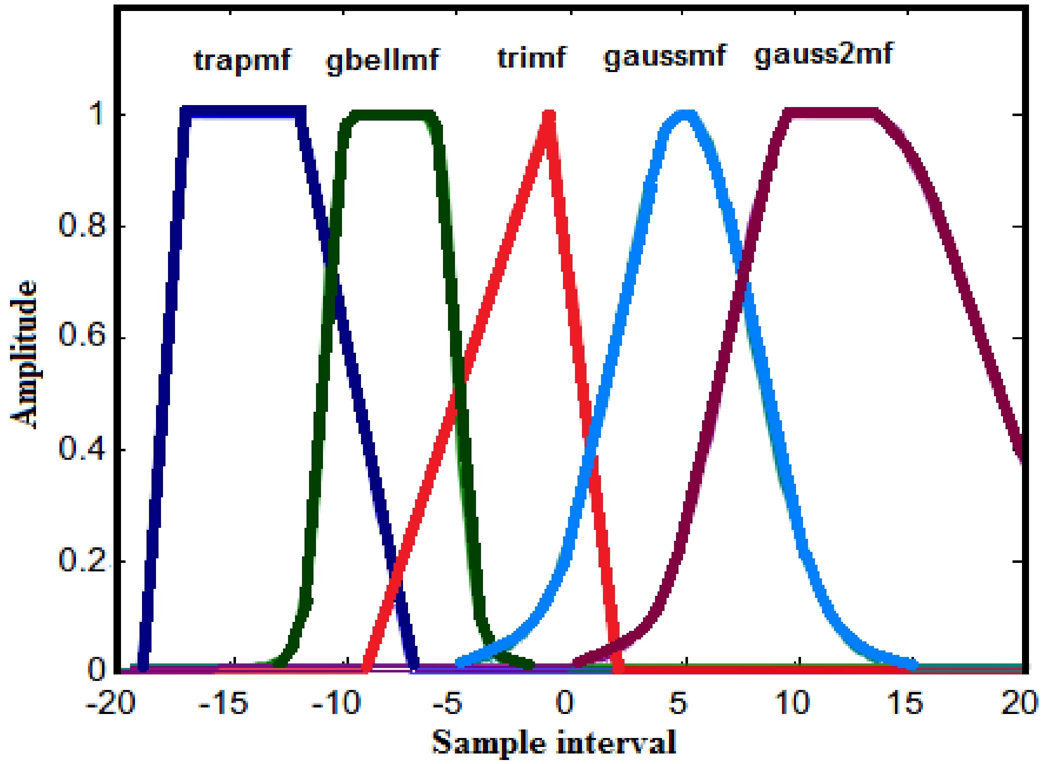

Fig. 7 Membership functions

Table 4 MF and number of MF values of COP in the proposed ANFIS model

MF[a] - MFN[b]	RMSE	%RSD	R^2
Triangular-3	9.5419×10^{-6}	0.0029	0.9897
Gbell-3	8.3257×10^{-5}	0.0257	0.9656
Gauss2mf-3	6.7318×10^{-4}	0.2075	0.9584
Gauss-3	6.3292×10^{-3}	1.9504	0.9498
Trap-3	6.6487×10^{-3}	2.0489	0.9399

[a] **Membership function**
[b] **Membership function number**

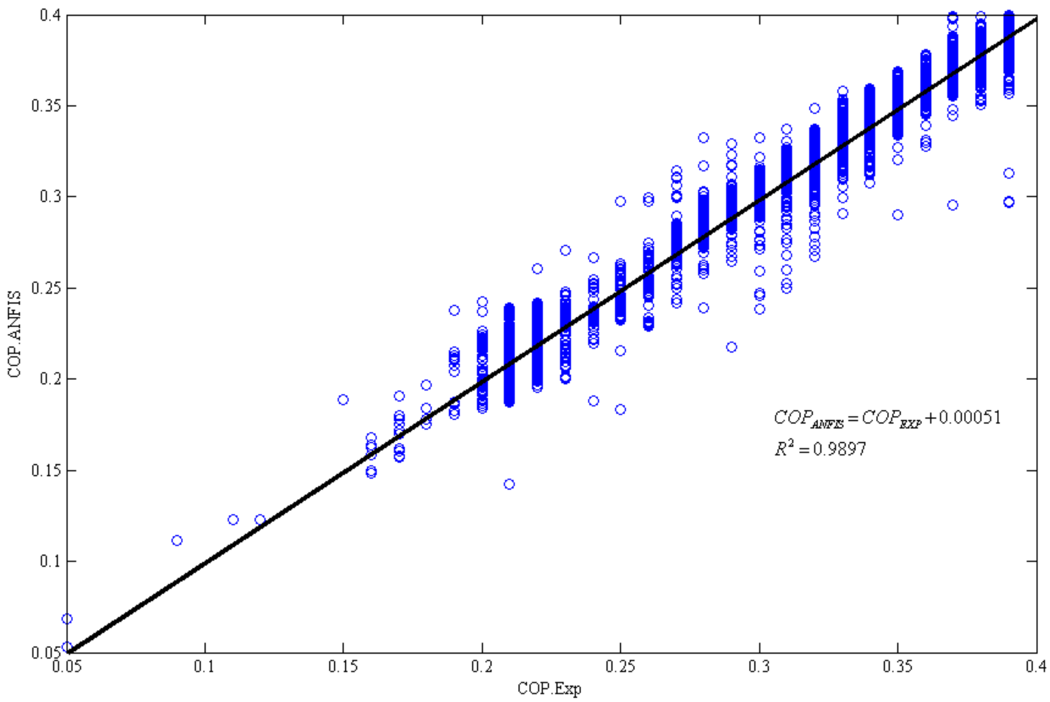

Fig. 8 Correlation of experimental and predicted (ANFIS) COP values

Experimental (COP_{Exp}) and simulated (COP_{ANFIS}) data were compared satisfactorily through a linear regression model $\left(COP_{ANFIS} = a + b\,COP_{Exp}\right)$ obtaining a regression coeficient $R^2 = 0.9897$. According to (El Hamzaoui et al., 2011), to satisfy the statistical of intercept and slope, upper and lower value of the intercepts must contain zero and upper and lower value of the slope have to include one.

Table 5 shows the limits for test indicators, with slope containing the one and with the intercept containing zero. Consequently, the proposed model passed the test with 99% confidence level. This test with information mentioned above guarantees that the ANFIS has a satisfactory level of confidence.

Table 5 Intercept and slope statistical test

COP (Coeficient of performance)	
$\mathbf{a_{lower}}$	$\mathbf{a_{upper}}$
-0.0078	0.0100
$\mathbf{b_{lower}}$	$\mathbf{b_{upper}}$
0.9721	1.0021

4.3 Comparative results

The remarkable thing is that, according to the Figure 9 , there is good agreement between the predicted values by ANN and ANFS models with experimental data. Indeed, it has been an outstandingly successful models in predecting the experimental results.

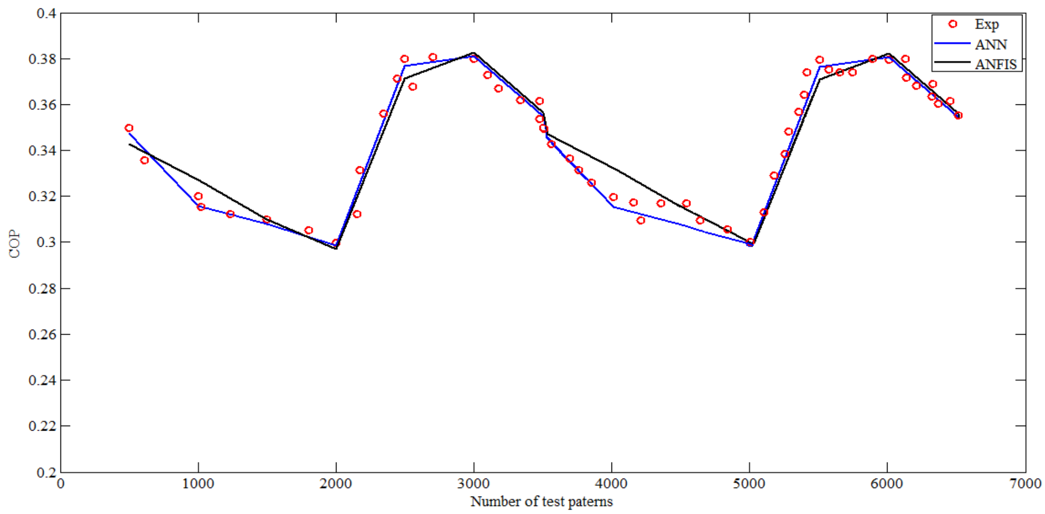

Fig. 9 COP versus number of test patterns for a water purification process in a heat transformer

These models: artificial neural network (ANN) and adaptive neuro fuzzy inference system (ANFIS), prove to be very effective in modeling the coefficient of performance of a water purification process integrated to a heat transformer with energy recycling. The smaller RMSE and RSD and larger R^2 mean better performance. However, the performance of the ANN and ANFIS on modeling COP's of the system in a heat transformer are presented in Table 6, where the two models are trained using the same training datasets and validated by the same testing datasets (fresh data). In practice, however, the calculation required for system are so complicated, that's why, all the calculations were carried out on LINUX system, Intel® D CPU 2.80 Ghz, 2.99 GB of RAM. According to the Table 6, we can distinguish the following results: The ANN model has smaller RMSE and RSD as well as bigger R^2 for the both the training and testing datasets than the ANFIS model.

In this way, the ANN achieves better performances than the ANFIS model. Therefore, ANN is a good choice for modeling the coefficient of performance of water purification process integrated to a heat transformer with energy recycling.

It is believed, also, that ANN and ANFIS could be used to handle many other types of problems about water purification process.

Table 6 Performances of ANN and ANFIS in modeling COP's of the system

Model	Training and testing database		
	RMSE	*RSD(%)*	R^2
ANN	9.5219×10^{-7}	2.9343×10^{-4}	0.9980
ANFIS	9.5419×10^{-6}	0.0029	0.9897

5. Conclusions

Due to the complexity of relationships between input and output variables for COP prediction of a water purification process integrated to a heat transformer with energy recycling, and in order to deal with this problem, this study suggests that how we may use ANN and ANFIS network for modeling COP's of the system. We also show a comparative study between ANN and ANFIS models. However, the results analysis and figures demonstrate clearly that the ANN model is better than the ANFIS model, according to the statistical evaluation criterion (RMSE, RSD and R^2 values).

Despite the important role played by ANN and ANFIS for modeling COP's behavior of a water purification process integrated to a heat transformer with energy recycling, they have demonstrated some incovenients in application. For example, the disadvantages of ANN include:

- It's "black box" nature.
- Greater computational burden.
- Proneness to overfitting and empirical nature of model development.

While, the disadvantages of ANFIS, we could mention:

- It is not intuitive.
- It has not widespread acceptance.
- It is not suited to human input.

Finally, ANN and ANFIS paradigms are demonstrated to be very powerful tools, when applied in an appropriate manner for modeling the more complicated engineering processes in which there is no obvious mathematical relationship to express their behavior.

Nomenclature

b1, b2	bias
COP	coefficient of performance, dimensionless
In	input
K	number of neurons in the input layer
LiBr	lithium bromide solution
Out	output
P	pressure, in Pascal (Pa)
Q	heat flow, in Watt
RMSE	root mean square error
S	number of neurons in the hidden layer
X	concentration, % w/w
IW, Wo	matrix weight

Input variables for artificial neural network and adaptive neuro fuzzy inference system:

$T_{in.GE\text{-}AB}$	input-temperature in the absorber that comes from generator, °C
$T_{in.EV\text{-}AB}$	input-temperature in the absorber that comes from evaporator, °C
$T_{out.AB\text{-}GE}$	output-temperature in the absorber towards generator, °C
$T_{in.AB\text{-}GE}$	input-temperature in the generator that comes from absorber, °C
$T_{out.GE\text{-}CO}$	output-temperature in the generator towards condenser, °C
$T_{out.GE\text{-}AB}$	output-temperature in the generator towards absorber, °C
$T_{in.CO}$	input-temperature of the condenser that comes from generator, °C
$T_{out.CO}$	output-temperature in the condenser towards evaporator, °C
$T_{in.EV}$	input-temperature in the evaporator that comes from condenser, °C
$T_{out.EV\text{-}AB}$	output-temperature in the evaporator towards absorber, °C
P_{AB}	pressure in absorber, in Pascal (Pa)
P_{EV}	pressure in evaporator, in Pascal (Pa)
P_{GE}	pressure in generator, in Pascal (Pa)
P_{CO}	pressure in condenser, in Pascal (Pa)
$X_{in.AB}$	LiBr (Lithium bromide) input-concentration in the absorber, % w/w
$X_{out.AB}$	LiBr (Lithium bromide) output-concentration in the absorber, % w/w
$X_{in.GE}$	LiBr (Lithium bromide) input-concentration in the generator, % w/w
$X_{out.GE}$	LiBr (Lithium bromide) output-concentration in the generator, % w/w

Sub-Index

AB	absorber
ANN	artificial neural network
ANFIS	adaptive neuro fuzzy inference system
CO	condenser
EV	evaporator
EXP	experimental
FL	fuzzy logic
GE	generator
MFs	membership functions
SIM	simulated

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