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Optimal COP prediction of an intermittent solar adsorption refrigeration system operating with AC–methanol for ice production using ANNs

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Abstract— **this paper presents the modeling of performance of a solid adsorption solar refrigerator working with activated carbon methanol pair using artificial neural networks (ANNs) approach; this approach has the advantages of computational speed, low cost for feasibility, and ease of design by operators with little technical experience. For that, a feed-forward multi-layer neural network with Levenberg–Marquardt training algorithm was developed to predict the performance of this kind of refrigerators. Different networks were trained and tested with different network parameters using training and testing data sets. Using validating data set the network having the highest regression coefficient (r2) and the lowest mean square error was selected. To confirm the network generalization, an independent data set was used and the predictability of the network was statistically assessed. Statistical analyses showed that the neural network predictions had an excellent agreement ($r^2 \approx 1$) with experimental data.**

Keywords— Solar refrigeration; Performance; Adsorbent; Adsorbate; Modelling; Adsorption/Desorption ; Artificial neural network.

I. INTRODUCTION

The use of solar energy for environmental control is receiving much attention as a result of the projected world energy shortage. Refrigeration is particularly attractive as a solar energy application because of the near coincidence of peak cooling loads with the available solar power. Solar refrigeration has the potential to improve the quality of life of people who live in areas with electricity insufficient. It is usually used for storage of agricultural products, food and medicines (e.g. vaccines) in remote areas. Solar cooling to produce ice accumulates latent heat, thus leading to smaller volume of ice-makers. The adsorption system is one of the promising solar thermal refrigeration methods, and it is environmentally friendly along with low cost and low maintenance requirements [1]. Adsorptive processes have been applied extensively for gas separation and catalysis, but it is only recently that adsorptive processes have been widely studied for refrigeration and heat pumps, [2].

Despite a large potential market, existing solar refrigeration systems are not competitive with electricity-driven refrigeration systems because of their high capital costs. Improvements such as reduced collector area, improved system performance, and reduced collector cost will lower the cost of solar components. Several solar refrigeration systems have been proposed and are under development such as

sorption systems including liquid/vapor, solid/vapor absorption, adsorption, vapor compression and photovoltaic-vapor/compression systems. Most of the above mentioned systems have not been economically justified, [2].

Solar refrigeration is highly dependent upon environmental factors such as cooling water temperature, air temperature and solar radiation. The energetic conversion efficiency is low, and solar cooling and refrigeration are not yet competitive economically with the conventional systems. This article details the various research aspects of adsorption refrigeration, which includes adsorption mechanism, the criteria to choose an appropriate working pair, thermodynamic analysis of several refrigeration cycles, adsorbent properties and various solar powered adsorption refrigeration systems based on various cooling technologies, [2].

As can be seen from the literature review, it is clear that there are studies related with experimental adsorption systems, solar refrigeration and approach ANN in absorption systems and solar energy process. However, recently, to solve the solar energy problems the application of ANN continues to expand [2]. The aim of the present work discusses two main ideas; first the use of a multilayer feed-forward neural network model to predict efficiently the coefficient of performance values of a solar intermittent refrigeration system for ice production operating with the activated carbon/methanol.

II. PRINCIPLE OF ADSORPTION

Adsorption occurs at the surface interface of two phases, in which cohesive forces including electrostatic forces and hydrogen bonding, act between the molecules of all substances irrespective of their state of aggregation [3]. Unbalanced surface forces at the phase boundary cause changes in the concentration of molecules at the solid/fluid interface. The process of adsorption involves separation of a substance from one phase accompanied by its accumulation or concentration at the surface of another. The adsorbing phase is the adsorbent, and the material concentrated or adsorbed at the surface of that phase is the adsorbate.

Adsorption processes can be classified as either physical or chemical, depending on the forces causing the adsorption process. Physical adsorption (physisorption) occurs when Van der Waals forces bind the adsorbing molecule to the solid phase, these intermolecular forces are as same as ones that bond molecules to the surface of a liquid. Molecules that are physically adsorbed to a solid can be released by applying heat; therefore, the process is reversible. Chemical adsorption (chemisorption) occurs when covalent or ionic bonds are formed between the adsorbing molecules and the solid substance. The bonding forces of chemical adsorption are much greater than that of physical adsorption. Thus, more heat is liberated. This bonding leads to change in the chemical form of the adsorbed compounds and hence, it is irreversible. For this particular reason, most of the adsorption processes applicable to the thermal system or cooling machine mainly involve physical adsorption.

Adsorption is an exothermic process accompanied by evolution of heat, the quantity of heat release depends upon the magnitude of the electrostatic forces involved, latent heat, electrostatic and chemical bond energies. The heat of adsorption is usually 30–100% higher than the heat of condensation of the adsorbate. In general adsorption is stronger than condensation to liquid phase. Hence, if a fresh adsorbent and adsorbate in liquid form coexist separately in a closed vessel, transport of adsorbate from the liquid phase to the adsorbent occurs in the form of vapor. The liquid temperature becomes lower while the adsorbent temperature rises. Air-conditioning and refrigeration utilize this phenomenon to obtain a cooling effect [4].

Heat of adsorption is either derived from adsorption isotherms, generally referred to as either the isosteric heat (the energy released in the adsorption process), or, as the differential heat of adsorption determined experimentally using a calorimetric method. Differential heat of adsorption for some adsorbent/adsorbate pairs are given in Table I. The performance of adsorbents used in physisorption is governed by surface properties, such as surface area, micro-pores and macro-pores, size of granules in powders, crystals or in pellets. Adsorbents having

special affinity with polar substances like water are termed 'hydrophilic'. These include silica gel, zeolites and porous or active alumina. Non-polar adsorbents, termed 'hydrophobic', have more affinity for oils and gases than for water. These substances include activated carbons, polymer adsorbents and silicalites. The general term 'sorption' is used when both adsorption and absorption occurs simultaneously. 'Desiccants' are a type of adsorbent having special affinity for water and have been used extensively for dehumidification or drying in air processing applications.

Adsorbents are characterized by surface properties such as surface area and polarity. A large specific surface area is preferable for providing large adsorption capacity, but the creation of a large internal surface area in a limited volume inevitably gives rise to large numbers of small sized pores between adsorption surfaces. The pore size distribution of micropores which determines the accessibility of adsorbate molecules to the internal adsorption surface is important for characterizing adsorptivity of adsorbents. Materials such as zeolite and carbon molecular sieves can be engineered specifically for precise pore size distributions and hence'tuned' for a particular separation.

III. EXPERIMENTAL DATA

During the experimental test runs, the main evaluating parameters such: temperatures, solar radiation and pressures were recorded every 1 min. In order to predict the coefficient of performance of the intermittent solar refrigeration system by using the artificial neural network the experimental database consisted of 400 data.

Ten input parameters were used. These were: the amount of the methanol and the mass of the activated carbon used, produced ice, the insolation, ambient temperature, condenser and the evaporator surfaces, the tilted angle, latitude and longitude, and (v) the solar coefficient of performance as an output. All the data were taken from the literature.

IV. ARTIFICIAL NEURAL NETWORK

Neural network layering

The neurons are grouped into distinct layers and interconnected according to a given architecture. As in nature, the network's function is determined largely by the connections between elements (neurons), each connection between two neurons has a weight coefficient attached to it. The standard network structure for an approximation function is the multiple-layer perception (or feed-forward network).

The feed-forward network often has one or more hidden layers of sigmoid neurons followed by an output layer of linear neurons. Multiple-layers of neurons with nonlinear transfer functions allow the network to learn nonlinear and linear relationships between input and output vectors.

The linear output layer lets the network produce values outside the -1 to +1 range [5]. For the network, the appropriate notation is used in two-layer networks [6]. A simplified sketch of the network's structure and behavior is presented in Fig. 3.

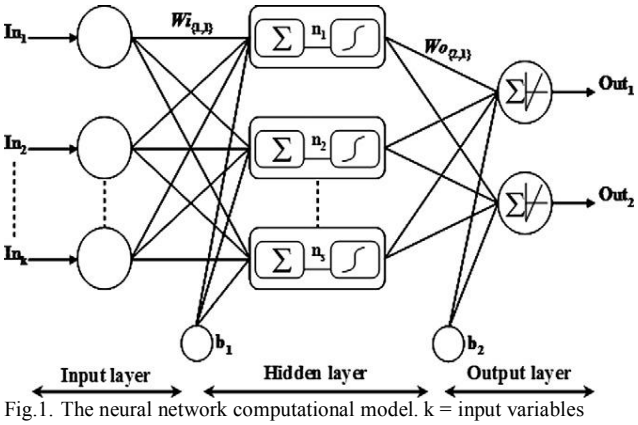

Fig.1. The neural network computational model. k = input variables number; In = input variable; Out = output variables; thick lines = weights and biases.

The number of neurons in the input and output layers is given respectively by the number of input and output variables in the process under investigation. In this work, a feed-forward is proposed, the input layer consists of ten variables and the output layer contains one variable (COP). The optimal number of neurons in the hidden layer(s) ns is difficult to specify, and

depends on the type and complexity of the task. This number is usually determined iteratively. Each neuron in the hidden layer has a bias b (threshold), which is added to the weighted inputs to form the neuron n (Eq. (6)). This sum, n, is the argument of the transfer function f.

$$n_1 = W_{i(1,1)}In1 + W_{i(1,2)}In2 + \cdots + W_{i(1,5)}Ink + b1 \quad (6)$$

The coefficients associated with the hidden layer are grouped into matrices Wi (weights) and b1 (biases). The output layer computes the weighted sum of the signals provided by the hidden layer, and the associated coefficients are grouped into matrices Wo and b2. Using the matrix notation, the network output can be given by (Eq. (7)):

$$Out = g(W_0 \times f(W_i \times In \times b1) + b2) \quad (7)$$

Hidden layer neurons may use any differentiable transfer function to generate their output. In this work, a hyperbolic tangent sigmoid transfer function (TANSIG) on hidden layer and a linear transfer function (PURELIN) on output layer were used for f and g, respectively [6]. The system adjusts the weights of the internal connections to minimize errors between the network output and target output, which can be summarized as follows: At first take a group of random numbers as the initial values of the weightsWand bias b, then compute the output of all neurons layers by layer, starting with the input layer, using the following program:

$$f = TANSIG = tanh = \frac{2}{1+\exp[-2x(n_s)]} - 1 \quad (8)$$

$$g = PURELIN = n \quad (9)$$

If considering the transfer functions, in the account that, the (Eq. (7)), may be expressed as follows:

$$Out_1 = PURELIN\{W_0 \times [TANSIG(W_i \times In_k + b1_s) + b2_1]\} \quad (10)$$

Consequently, in this work the output is the COP:

(11)

Where s is the number of neurons in the hidden layer (S = 10), k is the number of neurons in the input layer (K = 10), l is the number of neurons in output layer (l = 1), Wi, Wo and b1s, b2l are weights and biases, respectively. The Eq. (11) is not complex because is made up of a simple arithmetic operation. Therefore, it can be used for on-line estimation application for industrial processes. In this work, multilayer feed-forward ANN with one hidden layer was used for all data sets. Database sets were obtained by [7]The ANN was trained using the backpropagation algorithm. All calculations were carried out with Matlab mathematical software with the ANN toolbox. The input variables were normalized ranging from 0.1 to 0.9 in according to [8] and the following:

$$x_i = 0.8\left(\frac{x_i - x_{min}}{x_{max} - x_{min}}\right) + 0.1 \quad (12)$$

V. RESULTS AND DISCUSSION

The predictive ability assessment requires evaluation of data records excluded from the training set. Accordingly, the validation agreement vector and the validation agreement plot of the predicted versus the experimental outputs for the validation data set have been used to evaluate the predictive ability of the NN model. The plot and the parameters of the linear regression are, straightforwardly, obtained using *postreg* MATLAB function.

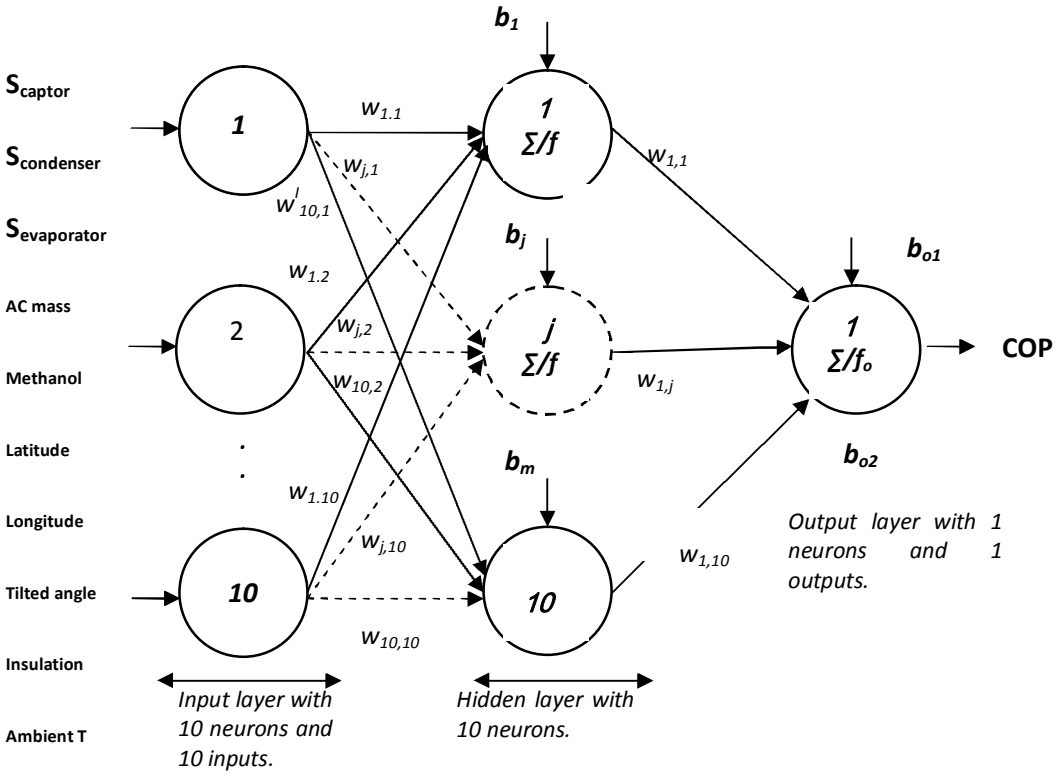

Fig.2. Model for the COP values prediction

TABLE I
STRUCTURE OF THE OPTIMISED ARTIFICIAL NEURAL NETWORKS MODEL

Type of network	Training Algorithm	Input layer	Hidden layer		Output layer	
		No. of neurons	No. of neurons	Activation function	No. of neurones	Activation function
FFBP NN	BRBP using Levenberg-Marquardt optimisation.	10	10	Logarithmic sigmoid	1	Linear

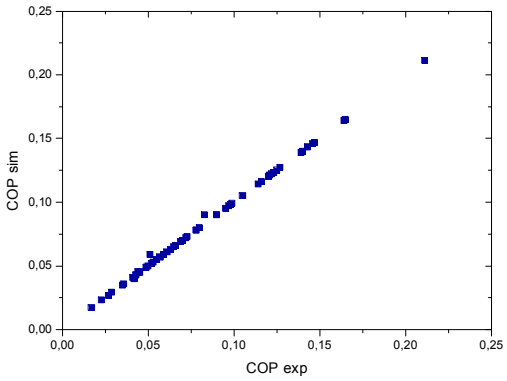

Fig. 3. Experimental versus simulated COP for database

Fig. 6 presents the COP simulated versus experimental data for the learning and testing database. It shows that the COP prediction correlated with high accuracy (r2 > 0.98). The statistical test of slope = 1 and intercept = 0 was carried out to confirm the proposed model. This statistical test presented that the slope and intercept are in 1 and 0, respectively. Experimental (COPexp) and simulated (COPsim) data of COP values were compared through a linear regression model (COPsim = a + b COPexp).

From this correlation and statistical test, it is evident that the model was successful in predicting the experimental data of COP values. This shows the importance of the artificial neural network to simulate a solar intermittent refrigeration system for ice production working with Activated carbon/methanol.

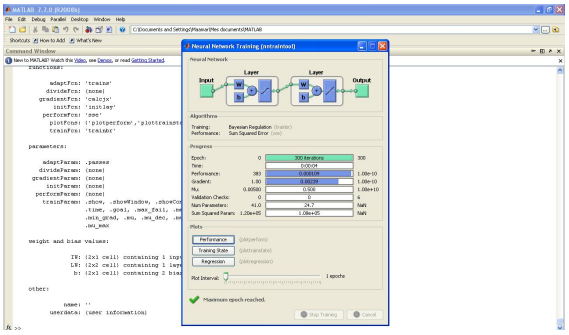

Fig.4. ANN Matlab interface

The performance of the ANN model was statistically measured by the root mean square error (RMSE) and regression coefficient, which are calculated with the experimental values and network predictions. These calculations are used as a criterion for model adequacy (see Fig. 4), obtained as follows:

Where Q is the number of data points, yq,pred is the network prediction, yq,exp is the experimental response, ym is the average of actual values and q is an index of data. Consequently, RMSE was used as the error function which measures the performance of the network. Therefore, the network having minimum RMSE and maximum R^2 was selected the best ANN model. Experimental data were split into learning (50% of experimental data set) and testing (50% of experimental data set) database to obtain a good representation of the situation diversity.

VI. CONCLUSIONS

An ANN model using back-propagation algorithm consisted of three layers with 6-6-1 neurons was successfully developed to predict the COP. Simulations based on the ANN model were performed in order to predict the system behavior under different experimental conditions. The results obtained by ANN model showed high accuracy with regard to experimental data. The correlation between the experimental data and the data obtained by using the AAN was 0.9875. Very high level of confidence to the ANN model was confirmed with the intercept and slope statistical test (99%). A sensitivity analysis was carried out to determine the contributions of each input variable in determining the COP. The optimized NN consisted of:

1. **1** hidden layer
2. **10** neurons in the input layer,
3. **10** neurons in the hidden layer and one neuron in the output layer.

The methodology presented with ANN can be used not only to simulate and optimize solar refrigerators but also different kind of solar energy systems.

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