Performance of nanofluids using artificial neural network

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Abstract-In this study, neural network was used for simulation and prediction of thermal efficiency of solar collectors when we use various nanofluidsas absorbers in solar collectors. Effects of nanoparticle size, temperature and mass flowrate on the thermal efficiency of nanofluids were studied, and the standard efficiency curves of collector under different operating conditions were compared to the experimental data. Different networks and many runs were trying to obtain good performance. Good agreement between the numerical predictions and experimental data was observed.

Index Terms-Neural networks, nanofluids.

1 INTRODUCTION

The sun is a continuous fusion reactor in which hydrogen is turned into helium. The sun's total energy output is 3.8 $\times 10^{20}$ MWwhich is equal to 63 MW/m^2 of the sun's surface. The solar radiation strikes our planet for 30 min is equal to the world energy demand for one year. A good use of solar energy is in its benefits. Solar energy is clean and can be supplied without any environmental pollution. The future of our planet will be negatively affected if humans keep degrading the environment. Three environmental problems are internationally known; these are the acid precipitation, the stratospheric ozone depletion, and the global climate change. The solar energy systems decrease the environmental pollution. This is achieved by the reduction of the effects of air pollutants on the human, environment, public health, agriculture and on ecosystems. In addition to that the solar energy is considered a prime agent and a significant factor in economic development. A worldwide research and development in the field of solar energy resources is carried out during the last two decades [1- **3**].

Nanofluids are a mixture of liquid (base fluid) and nanoparticles (nanometer sized material). Nanofluids containing small amounts of nanoparticles have substantially higher thermal conductivity than base fluids. Nanofluid was first discovered by Choi. Nanofluids have significantly better heat transfer characteristics than the conventional fluids depending upon the concentration of nanoparticle and its size. The enhancement in thermophysical properties of nanofluids attracted scientists to use it as an absorber in solar collectors. Several comprehensive articles summarized the effect of using nanofluids as absorbers on the efficiency of solar collectors [4 -8].

Artificial neural networks can be used for prediction of performance of various energy systems such as solar collectors at high speed and accuracy. There is a little reported work about modeling of thermal conductivity of nanofluids using artificial neural network. Esfe et al. [9] used the neural network method to predict the thermal conductivity of MgO/ethylene glycol (EG) nanofluids in a temperature range of 25–55 °C. Many studies have been conducted on using ANN in simulation and prediction of the performance of the thermal conductivity of nanofluids where different nanoparticles and base fluids are used. For example, the readers can refer to the most recent research papers and review articles in this field [10 – 15].

This paper is organized in five sections. Section 2 introduces the analysis of experimental data using nanofluids in solar collectors. Section 3 describes the artificial neural network. Section 4 presents the structure of ANN model and simulation results. Results and discussion are provided in section 5.

2 Analysis of experimental DataUsing nanofluids in solar collectors

Role of nanoparticles

More experiments become interested in the use of nanofluids due to the effectiveness of nanofluids as absorber fluids in solar device which strongly depends on the type of nanoparticles and base fluid, volume fraction of nanoparticles , PH values ,properties of nanofluids, temperature of liquid, size and shape of nanoparticles.

Said et al.[16] investigated the thermal conductivity of ethylene glycol (EG) and EG+H_2O based AL_2O_3 nanofluids prepared by using ultrasonic dispersion method from 25°c to 80°c .

To improve the performance of solar thermal systems. Liu et al. [17] observed 15.2% -22.9% enhancement in thermal conductivity using 0.06% grapheme in the temperature range from 25 to 200°c .

The effect of PH of multiwall carbon nanotubes (MWCNTs)-H2O nanofluid on the efficiency of a flate-plate solar collector wasinvestigated byYousefiet al.[18]

Karami et al. [19] investigated the cooling of water based Boehmitenanofluid in a hybrid photovoltaic cell .

3 Artificial Neural Network (ANN)

An ANN consists of two types of basic components, namely, neuron and link. A neuron is a processing element and a link is used to connect one neuron with another. Each link has its own weight. Each neuron receives stimulation from other neurons, processes the information, and produces an output.The neuron has three simple sets of rules: multiplication, summation and activation. At the entrance of artificial neuron the inputs are weighted what means that every input value is multiplied with individual weight(Wm). In the middle section of artificial neuron is sum function that sums all weighted inputs and bias(b). At the exit of artificial neuron the sum of previously weighted inputs and bias is passing through activation function that is also calledtransfer function (Fig. 1.).

Neurons are organized into a sequence of layers. The first and the lastlayers are called input and output layers, respectively, and the middle layers are called hidden layers see Fig.(2).

An important property of neural networks is their ability to learn from input data with or without a teacher. In a supervised learning process, the adjustment of weights is done under the supervision of a teacher; that is, precise information about the desired or correct network output is available from a teacher when given a specific input pattern. Error-correction is the most common form of supervised learning. *Error* is defined as the difference between the desired response and the actual response of the network. The learning involves adjusting weights, based on the error, until the network output gets as close as possible to the target value.The proposed ANN was trained using the R Prop optimization technique. This optimizationis considered the best algorithm, measured in terms of convergence speed, accuracy and robustness with respect to training parameters [20-25].

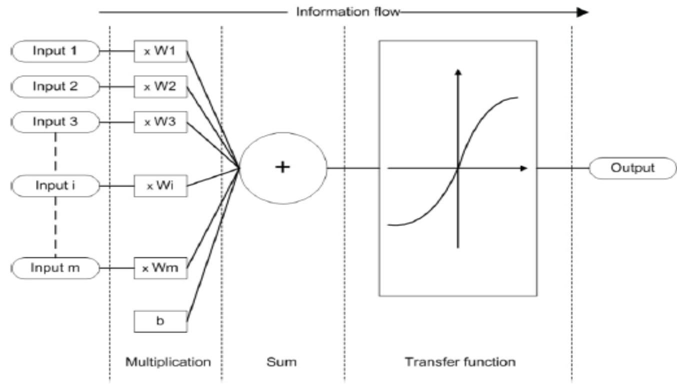

Fig. 1.Working principle of an artificial neuron.

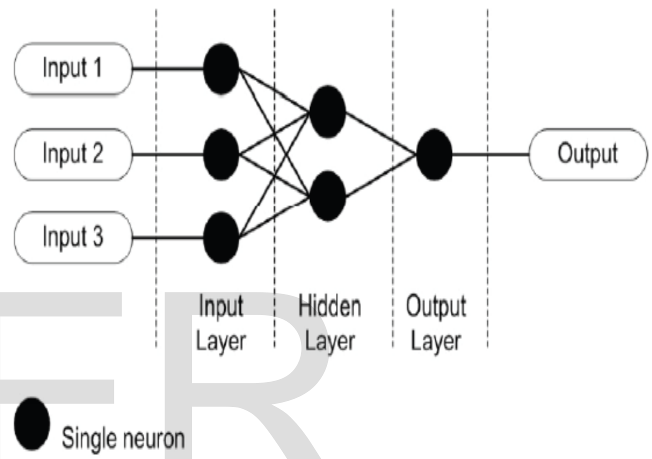

Fig. 2.Example of simple artificial neural network.

4Structure of ANN model and simulation results

As the nature of the experimental is completely different from each other, authors choose to internally model the problem with Five individual neural networks training separately using experimental data (see Fig. 3 and table 1). In the training process, 55,70,97,200 and 272 epochs was found to achieve minimum error of $3x10^{-11}$,$2.5x10^{-12}$,$4.2x10^{-11}$, $4.2x10^{-6}$ and$2.7x10^{-13}$ errors respectively.The parameters of the five ANN are given in table 1. For work completeness, the final equations which describe the five neural networks are given in Appendix A , B and C.

No	Structure of ANN	First ANN	Second ANN	Third ANN	Fourth ANN	Fifth ANN
1	Inputs	Volume Fraction	Volume Fraction	Temperature Concentration	MWCNT PH	flow rate Concentration
2	Outputs	Thermal conductivity	thermal conductivity	thermal Conductivity	Efficiency	Temperature
3	No. of hidden layers	3	3	3	4	2
4	No. of neurons	50,20,30	50,35,50	70,35,50	11,6,7,12	50,30
5	No. of epochs	55	70	97	200	272
6	Training algorithm	trainrp	trainrp	trainrp	trainrp	trainrp
7	Performance	$3x10^{-11}$	$2.5x10^{-12}$	$4.2x10^{-11}$	$4.2x10^{-6}$	$2.7x10^{-13}$
8	Transfer function	logsig	logsig	logsig	logsig	logsig
9	Output function	purelin	purelin	purelin	purelin	purelin

Table 1 Overview of all parameters in the five ANN

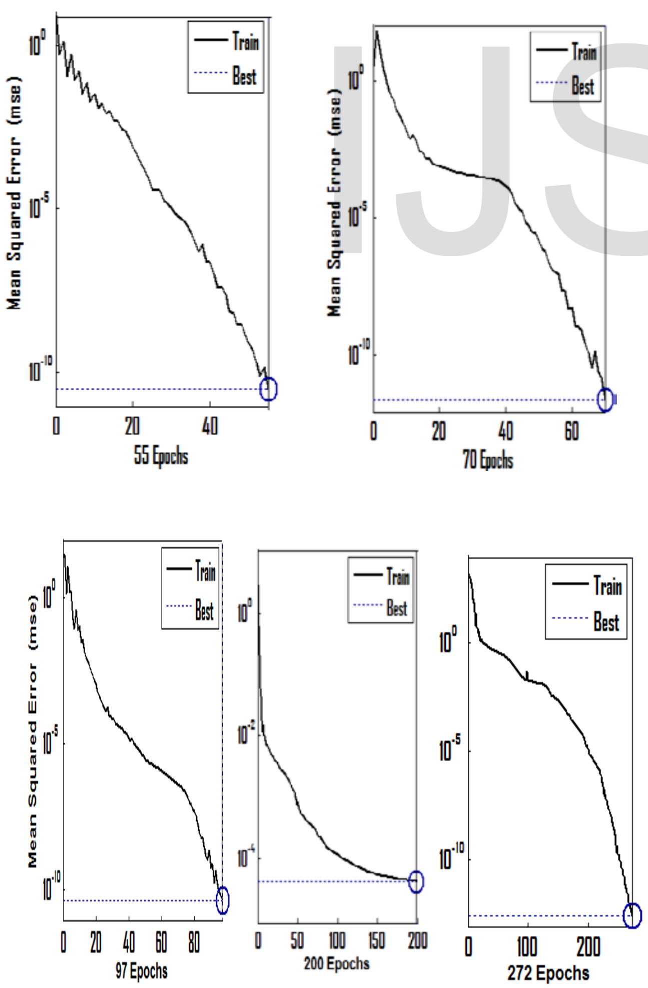

Fig.3 Performance of the five neural network

5 Results and Discussion

Nanofluid is used to improve the efficiency of several solar thermal applications. Thermal efficiency of solar collectors was simulated and predicted using artificial neural network. ANN and R Prop training algorithm were used to model the nonlinear relationship of thermal conductivity. The training procedures (performance) are shown in Fig.3 . It reveals that the training sum of squared errors is always reduced during the training procedure.The simulated results from the trained neural network and the experimental data are shown in Figs. 4,5 ,6 and 7 .Fig. (4a,b) show the simulation results of volume fraction and thermal conductivity [Al_2O_3/EG(a) and Al_2O_3/water(b)], effective model and compared with the experimental data. The simulation results show a clear and excellent match to the experimental data. Simulation and prediction of thermal conductivity as a function of temperature are shown in Fig.5. Simulation results for [HMIM]BF4 , (0.01wt% and 0.03wt%graghene) and the prediction for (0.03wt% and 0.09wt%)graghene. The efficiency of the flat plate solar collector with MWCNT nanofluid as base fluid at (ph=6.5 and 9)and water are found in Fig.6. The author simulate at ph=9 and water while predict at ph=6.5. Fig.7 show ANN model for variation of the average temperatures of the PV surface at various flow rates for water and three different concentrations of nanofluid (0.01,0.1 and 0.3wt). Results of thermal conductivity and efficiency solar cell based ANN showed almost best fitting to the experimental data for simulation and prediction. This gives the ANN the provision of wide usage in modeling of solar cell.

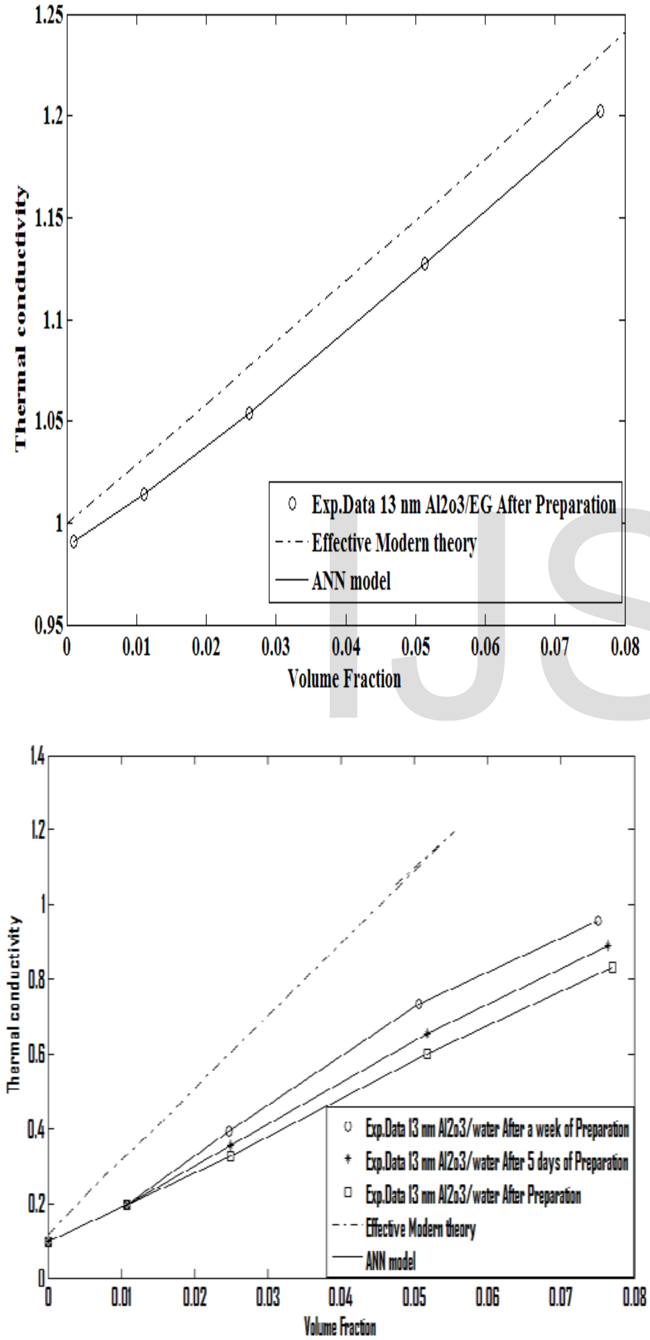

Fig.4 ANN for thermal conductivity of Al_2O_3/EG(a) and Al_2O_3/water(b) nanofluids at different volume fractions

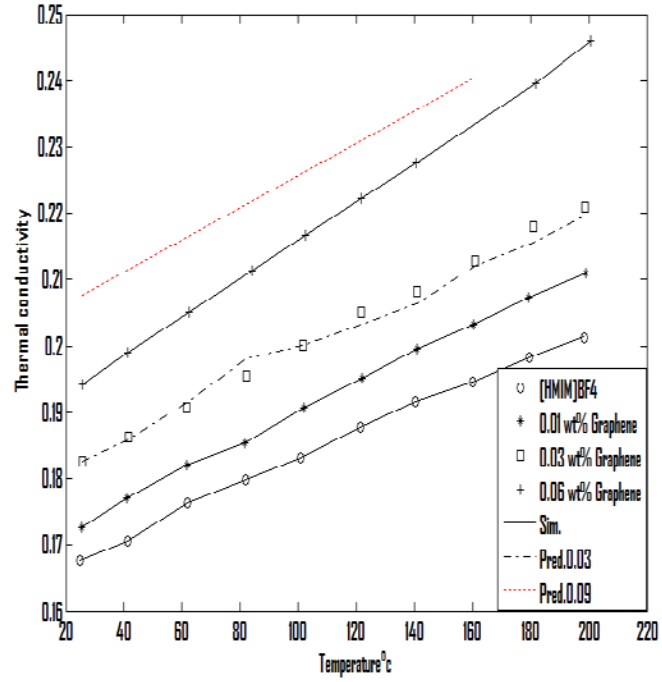

Fig.5 Simulation results for Thermal conductivity of [HMIM]BF4 and the GE-dispersed lonanofluids as a function of temperature

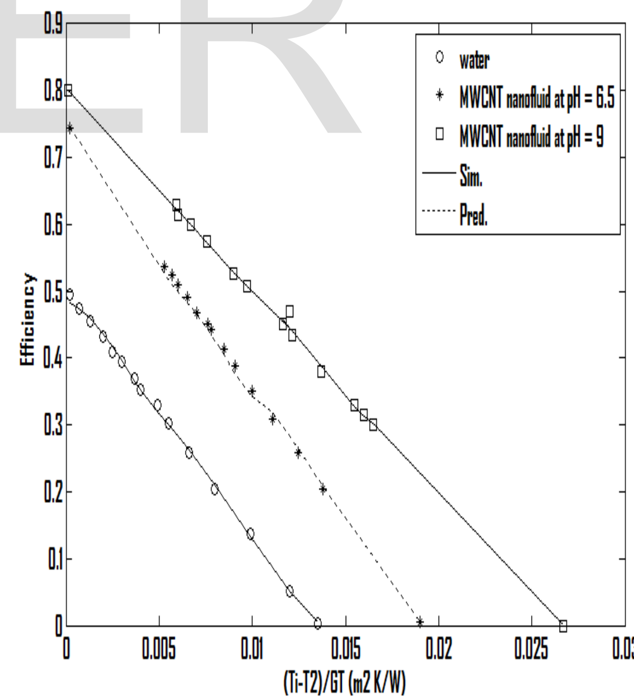

Fig.6 ANN for the efficiency of the flat plate solar collector with MWCNT nanofluid as base fluid at ph=6.5 and 9 compared with water

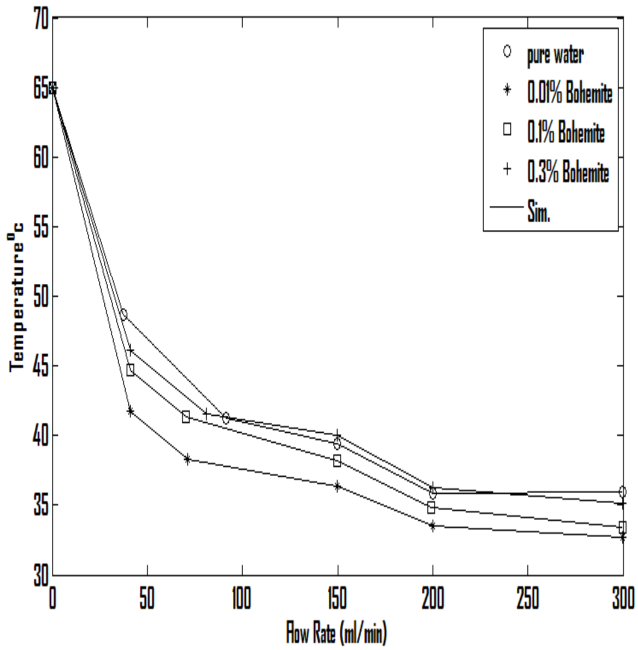

Fig.7 ANN model for variation of the average temperatures of the PV surface at various flow rates

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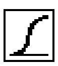
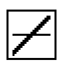
Appendix A
The equation which describe thermal conductivity
=pureline[net.LW{4,3} logsig(net.LW{3,2}logsig(net.LW{2,1}
Logsig(net.IW{1,1}A+net.b{1})+net.b{2})+net.b{3})+net.b{4}]
where

Logsig  , pureline 
A is theinput,
net.IW {1,1}:linkedweightsbetweentheinputlayerandfirst hidden layer,
net.LW {2,1}islinkedweightsbetweenthe first hidden layer and second hidden layer.
net.LW {3,2}islinkedweightsbetweenthesecondhidden layer and third layer,
net.LW{4,3} is linked weights between third hidden layer and output layer
net.b{1} isthebiasofthefirsthiddenlayer,
net.b{2} isthebiasofthesecondhiddenlayer
net.b{3}is the biasofthe third layer and net.b{4} is the bias of output layer.

Appendix B
The equation which describe efficiency
=pureline[net.LW{5,4}logsig(net.LW{4,3}logsig (net.LW {3,2}
logsig(net.LW{2,1}Logsig (net.IW{1,1}A +net.b{1}) +net.b{2})
+net.b{3})+net.b{4})+net.b{5}]

Appendix C
The equation which describe variation of the average temperatures at various flow rates
=pureline[net.LW{3,2}logsig(net.LW{2,1}
Logsig(net.IW{1,1}A+net.b{1})+net.b{2})+net.b{3}]