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EnergySaving on Nano Particles

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ABSTRACT

In this paper, neural network method was employed to estimate saving energy on Nano fluids. Different operational parameters such as heat flux, thermal conductivity of fluids, nanoparticle concentration and flow Reynolds number were performed to measure the effects of Nano fluids on saving energy. In order to model process, these operational parameters introduce to artificial neural network as inputs. Static factors such as mean square error and correlation coefficient were determined and indicate high performance of ANN in modeling this process. Addition of nanoparticles into the base fluid enhances the saving energy and this effect is more considerable in base fluids with lower thermal conductivity and flow with higher Reynolds number and higher heat fluxes.

Keywords: Nano Particles; Saving Energy; Artificial Neural Networks

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1. INTRODUCTION

Nano fluid, the suspension of small volume percent various types of nanoparticles into fluids, can improve poor thermal properties of fluids in advanced heat transfer systems.

Nano fluids contain 20 nm titanium dioxide with different agglomerate sizes and concentrations are synthesized by He et.al. They showed convective heat transfer coefficient increases with nanoparticle concentration and reported the higher effects in the turbulent flow regime. In the other study, they compared this data with numerical results and a good agreement was achieved [1].

For modeling the process artificial neural network in the last decade were used.

Fazeli, et al. studied the heat transfer characteristics of a miniature heat sink cooled by SiO_2–water Nano fluids experimentally and numerically. An artificial neural network (ANN) was used to simulate the heat sink performance. It was found that the results of ANN are in excellent agreement with the mathematical simulation and cover a wider range for evaluation of heat sink performance [2].

M. M. Papari et al employed neural network analysis to estimate thermal conductivity of Nano fluids consisting of multi-walled carbon nanotubes (MWCNTs) and single-walled carbon nanotubes (SWCNTs) suspended in different types of fluids. The results obtained have been compared with other theoretical models as well as experimental values. The predicted thermal conductivities are in good agreement with the literature values [3].

M. Hojjat et al synthesized three different types of Nano fluids by dispersing γ-Al_2O_3, TiO_2 and CuO nanoparticles in a 0.5% wet of carboxymethyl cellulose (CMC) aqueous solution. Thermal conductivity of Nano fluids were measured experimentally. Results show that the increase in the thermal conductivity varies exponentially with the nanoparticle concentration and temperature. Neural network models were proposed to represent the thermal conductivity as a function of the temperature, nanoparticle concentration and the thermal conductivity of the nanoparticles. These models were in good agreement with the experimental data [4].

In this paper, we have used neural network to estimate saving energy on Nano fluids. Nano fluids containing nanoparticles of various concentrations will model under the different heat flux boundary conditions in laminar and turbulent flow regimes and different heat fluxes.

1. Modeling

ANN program was written in the environment of MATLAB software. Experimental datasets, which were obtained from different references, were used to develop a three-layer feed-forward neural network model. The hyperbolic tangent sigmoid (tansig) transfer function with a back-propagation algorithm at the hidden layer and a linear transfer function (purelin) at the output layer were applied. In order to increase the numerical stability (accuracy index) of the model construction, the inputs and the target were first normalized to produce datawith zero mean and unity standard deviation, and then the principal component analysis was performed before the training stage. It was observed that the number of principal components, which accounted for 99 % of the variation, is equal to the number of original input parameters and there was no redundancy in the dataset. In the next step, the datasets were divided into three different sets: a training dataset with one-half of the data for training the ANN; a validation data-set with one-quarter of the data for validating the developed ANN; and a testing set with one-quarter of the data for testing the ANN. The division of the datasets was followed by performing various learning algorithms to select the best one. Finally, the optimization was carried out between the neuron number and MSE for the best learning algorithm. In this work, different types of statistical parameters such as mean absolute error (MAE), mean squared error (MSE), root mean squared error (RMSE), and determination coefficient (R^2) were calculated to estimate the accuracy of the process.

2. Results and discussion

2-1 Learning algorithm selection

In order to select the best back-propagation learning algorithm, different types of learning algorithm were performed. A three-layer feed-forward ANN with a tansig transfer function at the hidden layer and a purelin transfer function at the output layer was used for all the back-propagation learning algorithms. The results are given in Table 1.

Back propagation (BP) algorithm	function	MSE	R^2
Resilient back propagation (Rprop)	trainrp	0.0099	0.9899
Fletcher–Reeves conjugate gradient back propagation	traincgf	0.0031	0.9969
Polak–Ribi´ere conjugate gradient back propagation	traincgp	0.0042	0.9957
Powell–Beale conjugate gradient back propagation	traincgb	0.0039	0.9960
Levenberg–Marquardt back propagation	trainlm	**0.0010**	**0.9990**
Scaled conjugate gradient back propagation	trainscg	0.0112	0.9944

BFGS quasi-Newton back propagation	trainbfg	0.0037	0.9963
One step secant back propagation	trainoss	0.0042	0.9957
Batch gradient descent	traingd	0.0089	0.9910
Variable learning rate back propagation	traingdx	0.2186	0.7778
Batch gradient descent with momentum	traingdm	0.1061	0.8963

Table 1. Comparison of various back propagation learning algorithms

2-2 Optimization of artificial neural network

The number of hidden layer neurons is an essential parameter affecting the performance of ANNs. If the value is set too low, the network would not be trained properly, and if it is set too high, the network would be over-trained [5]. In this study, the best number of neurons in the hidden layer was determined by the trial and error method in which the number of neurons was varied from 2 to 9. The relationship between the number of neurons in the hidden layer and MSE are reported in Table 2. The minimum MSE value of 0.0008 is observed for 6 neurons in the hidden layer. Therefore, the ANN was designed with 6 neurons in the hidden layer.

Number of neurons	**MSE×10^2**
2	1.69
3	0.31
4	0.23
5	0.17
6	**0.08**
7	0.20
8	0.11
9	0.15

Table 2.Number of neurons in hidden layer with related mean square errors.

2-3 Effect of nanoparticle concentrations on saving energy

The axial profiles of the heat transfer coefficient of Nano fluids increase with increasing particle concentration. The enhancement in the high Reynolds number is more than the low Reynolds. Good agreement between experimental results and predicted data shows high accuracy of ANN in predicting this process.

2-4 Effect of heat flux on the convective heat transfer coefficient of Nano fluid

Enhancement of convective heat transfer coefficient for different power supplies show that the improvement of base fluid because of addition of nanoparticles seems to be more considerable in the turbulent flow regimes and higher heat fluxes. Comparing of experimental data and ANN results indicates that ANN could predict this process in lower heat flux better than higher one.

3. CONCLUSIONS

In this study, Experimental works has been studied on the heat transfer behavior of Nano fluids under both the laminar and turbulent flow conditions. The results were used by ANN in order to model this process. Effects of operational parameters such as nanoparticle concentrations, flow Reynolds number, type of base fluid and heat flux are investigated. The following conclusions are drawn from the results of experiments in this study:

- Addition of nanoparticles into the base fluid enhances the convective heat transfer coefficient and saving energy. The enhancement increases with increasing particle concentration.
- Saving energy due to addition of nanoparticles seems to be more considerable in the high Reynolds number.
- The use of nanoparticles as the dispersed phase in fluid can save energy in fluid and the enhancement increases with increasing heat flux.
- good agreement between experimental data and predicted results of ANN shows that ANN can be used to model this process with high accuracy except for higher heat flux.

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