PREDICTIVE ANALYSIS OF HEAT TRANSFER CHARACTERISTICS OF NANOFLUIDS IN HELICALLY COILED TUBE HEAT EXCHANGER USING REGRESSION APPROACH

by

Mukesh Kumar PERYIASAMY CHOKKIYEE[a*], Rajappa BALASUBRAMANAIN[b], and Durgadevi VELUSAMY[c]

[a] University College of Engineering, Dindigul, Tamil Nadu, India
[b] University College of Engineering, Pattukkottai, Tamil Nadu, India
[c] M. Kumarasamy College of Engineering Karur, Tamil Nadu, India

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Nanofluids are the combination of base fluid and nanoparticles which offer higher thermal conductivity resulting higher heat transfer. In this research article, soft computing tool is used to find the accurate Nusselt number of coiled tube heat exchanger handling Al_2O_3/H_2O nanofluids at three different volume concentrations and at different mass flow rate in terms of Dean number. The input predictor variables used in this model are convective heat transfer coefficient, thermal conductivity of nanofluids, and Dean number and the output response variable is Nusselt number. Linear regression, generalized linear regression, and Lasso and elastic-net regularized generalized linear models methodologies are taken to predict the Nusselt number. It is observed that the linear regression method shows an accurate agreement with experimental data with root mean square error value of 0.05614 and regression coefficient value is 0.99. It is studied that the experimental data holds good accordance with the predicted data given by the trained network. The average relative errors in the prediction of Nusselt number and heat transfer coefficients are found to be 0.3% and 0.2%, respectively.

Key words: *nanofluids, nusselt number, neural network, heat exchanger computational modelling*

Introduction

In the past decades, much research have been done on prediction of thermal and flow properties of various heat transfer fluids in the thermal systems , in particular, the heat exchangers by using soft computing tools. The core objectives of those works are to cut down the experimental expenses, time and efforts. The reasons behind this works are due to fast becoming and rapid increasing of cooling demand because of the increasing interest in technological developments. At the same time, the development of alternate heat transfer fluids to transfer the current fluids with the increasing interest area called nanotechnology. The prime concern over the applications of nanotechnology in thermal systems is to enhance the heat transfer rate by using nanoparticles. Choi [1] was the first one who reported that the suspended nanosized particles in the conventional heat transfer fluids, nanofluids, enhance the thermal conductivity over the current fluids. Since then, quantum amount research works have been

* Corresponding author, e-mail: pcmukeshkumar1975@gmail.com

widely performed and reported the nanofluids have the increasing importance and gained much attention for the past two decades in the field of heat transfer. The estimation of thermal conductivity of nanofluids with different experimental techniques have been reported and presented that they are expensive and time taking process. Moreover the estimation of thermal conductivity and viscosity come across much controversial and much debatable. Therefore the prediction of thermal and flow properties have been emerged into the thermal systems with the soft computing techniques to reduce the experimental hurdles and to get the accurate results.

Until now, much attention has been paid to predict the thermophysical properties and heat transfer coefficient of nanofluids using different soft computing algorithms**.** The major concern over the thermal systems is the pumping power which leads to the power consumption. In particular, the pressure drop in heat exchangers has gained much momentum and the ways and means of estimating when the heat transfer is allowed to flow through the pipe. Avudaiappan *et al.* [2] developed the model for finding the thermal conductivity of nanofluids by taking the temperature, particle volume fraction, and nanoparticles thermal conductivity as the inputs. This work has taken the effect of particle cluster size on the prediction of ANN model. The data of this work was validated by the experimental data of the some other authors and its own. Finally it is has been concluded that the predicted model shows very good agreement with the experimental data. In the same way, Esfe *et al.* [3] employed the soft computing tools for prediction of thermal conductivity of Cu/TiO_2-water/EG hybrid nanofluid at 0.1 to 2% particle volume concentration involving the temperature range 30-60 °C. This involved two different approaches such as artificial neural network and correlation. This paper found the mean square error (MSE) is $2.62 \cdot 10^{-5}$ and the correlation coefficient is 0.999. Further this paper found the MSE of the correlation model is $1.3310 \cdot 10^{-4}$ having the 0.995 correlation coefficient. The two models showed acceptable range of error in predicting thermal conductivity. However the model developed by ANN highly accurate performance. Although most of the research works on heat exchangers at different types have been published by using ANN and genetic algorithm (GA). However very limited works on solar collector using nanofluids. Kavitha and Kumar [4] is one among them who dealt with the solar collector using ANN. In his research paper, the thermal efficiency of flat plate solar collector was predicted by changing the solar radiation heat flux and mass-flow rate, inlet temperature of Ag/H_2O nanofluid. The predicted thermal efficiency have been compared with the experimental results and found the predicted data agrees well with the experimental data with less than 2%.

Much attention has been paid to replace the traditional coolant with the future coolant nanofluids in an automobile field. However the accurate determination of thermophysical properties on different nanofluids faced many shortcomings. In recent years, there has been an increasing interest in data driven modelling for prediction of thermal conductivity and viscosity of nanofluids. In the same way Zhao [5] had detailed review on soft computing based models in estimating the core properties of nanofluids namely thermal conductivity and viscosity. Finally they summarized that the ANN method gives suitable solution for finding the thermal conductivity and viscosity of nanofluids, heat transfer in automobile radiator is improved by using nanofluids and many different opinions on Nusselt number and power for pumping arises based on the existing the literature. Hojjat [6] revealed the similarity between experimental and predicted Nusselt number using ANN when nanofluids as taken as the coolant in thermal systems. The target fluid medium was the non-Newtonian nanofluids , multi-layer perceptron, tangent sigmoid transfer function have been used for modelling. The data was trained by particle swarm optimization

(PSO) to get the Nusselt number as output. This work asserted that the ANN predicted values and experimental values show comfortable agreement. The average deviation was 0.8% and the maximum deviation was 0.8% and 5.6%.

Pradeep Mohan Kumar. K *et al.* [7] involved the applicability of using ANN model for predicting the heat transfer behaviour of TiO_2/H_2O nanofluids which passed through the heat sink in the micrio-channel. Their work has 44 channel with dimensions of length, width, and height of 4 cm, 500 μm, and 800 μm, respectively. The data set used are 23 for heat transfer coefficient and 72 for Nusselt number. The determination of thermal conductivity is based on the three existing models. The proposed model handled 0, 0.5, 1, and 2% volume concentrations and the Reynolds number range is 400-1200 and the heating rates were 50, 60, and 69 W. This work employed the particle volume concentration, Reynolds number and heating rate as input to the ANN. The Nusselt number was taken as network outcomes. Their ANN model is the good replacement of the present costly and time experiments. The revealed that the ARE of the predicting of heat transfer coefficient and Nusselt number are 0.3% and 0.2%, respectively. Zhao and Li [8] tried to predict the thermal conductivity and viscosity of alumina water nanofluids using ANN. This paper firstly prepared the nanofluids under consideration and tested the thermal conductivity and viscosity at different temperature and the same were recorded. The radial basis function (RBF) neural network has been constructed with the particle volume fraction and temperature were taken as the inputs. This paper found that the RBF neural network excellently predicts the thermophysical properties of nanofluids. The prediction of thermal conductivity error and viscosity error were found to 0.5177% and 0.5618%, respectively.

Baghban *et al.* [9] demonstrated the prediction of convective heat transfer coefficient of SiO_2 nanofluid when it passes through the channel with the aid of effective e soft computing tools such as multi-layer perceptron (MLP), ANFIS, and least squares support vector machine (LSSVM). The Reynolds number, Prandtl number, and the particle volume concentration have been taken as the input variables. The evaluation criteria namely graphical and statistical error have been considered for accurate and reliability of the model suggested. The LSSVM approach resulted the accurate estimation consisting of MSE is 59.7 and the coefficient R^2 is 0.992. They also suggested that the Prandtl number has the maximum impact on prediction of convection heat transfer coefficient with 0.524 relevancy factor. Kavitha and Mukesh Kumar [4] predicted the thermal conductivity of MWCNT water based nanofluids using two approaches namely of MLP model and support vector regression (SVR) and finally they have been compared with different evaluation criterions. They disclosed that the data extracted from experimental work and the data predicted show good agreement. This paper reported that the R^2 value for MLP 0.99 and 0.98 for SVR. They revealed that the root mean square error (RMSE) value of MLP is less in MLP model when compared with SVR model, This paper proposed that the SVR approach performs well with the available constrained data set.

Dhandayuthabani [10] numerically explained the importance of predicting the model for heat transfer problems in $Ag\text{-}MgO/H_2O$ hybrid nanofluids by using ANN. This work dealt with the rectangular microchannel and the nanofluids to predict the model for generation of entropy. The Reynolds number was in the range of 200 to 2000 and the particle volume fraction 0.005 and 0.02%. This work handled convective heat transfer and particle volume faction of coolant as input and the generation of entropy as output. It asserts that the entropy generation depends on particle volume fraction and that it increases with increasing particles volume fraction. As a result of this work, the ANN model for entropy generation holds good with the numerical data with acceptable deviation.

Many researches have focused on the thermophysical properties prediction by applying the soft computing tools like ANN for the decades. However, the same have been done with different angle to predict the thermal conductivity and viscosity of ferromagnetic nanofluids. Esfe [11] was the first one who applied ANN to study the thermophysical of ferromagnetic nanofluids by considering the temperature and size of the particles and volume fraction. In particular the thermal conductivity and viscosity have been predicted by his work. It has been concluded that the 2% is the maximum error for thermal conductivity and 2.5% is the maximum error viscosity prediction. This paper suggested that the experimental and predicted data fit well. The combined model of ANN and GA to predict the thermal conductivity, viscosity heat transfer coefficient and pressure drop of CuO nanofluid based on paraffin when it is allowed to flow in a circular pipe for the first time by Bagherzadeh *et al.* [12], Dinesh *et al.* [13], and Bahiraei and Majd [14]. This work involved the multi-objective optimization method. It is found that multi-objective optimization by GA gives satisfied fitness of the out puts under consideration. Until now, a little importance has been paid to predict the heat transfer coefficient and Nusselt number in coiled tube heat exchangers handling Al_2O_3/H_2O based nanofluids with regression models. Therefore, this paper focuses to predict the model for thermal behaviour of coiled tube heat exchanger employing the nanofluids by regression approach.

Theoretical background of Nusselt number

The prime importance the Nusselt number is to identify the convective heat transfer mode contribution to heat transfer in thermal systems. Mathematically, Nusselt number, and Dean Number are estimated by using:

$$\mathrm{Nu} = h_\mathrm{i}\, D/k_\mathrm{nf} \tag{1}$$

$$\mathrm{De} = \mathrm{Re}\sqrt{\frac{D}{2R_\mathrm{c}}} \tag{2}$$

where h_i [Wm^{-2}K^{-1}] is the inner heat transfer coefficient, D – the inner diameter of the coiled tube, k_nf – the thermal conductivity of nanofluids, Re – the Reynolds number, and R_c is the radius of curvature of the tube. The convection heat transfer mode relies on the types of the liquid medium, temperature, density and flow velocity of the medium and heat transfer surface properties. It is reported that the convective heat transfer is the most complex phenomena.

Methods and materials

Preparation of nanofluids

The Al_2O_3/H_2O nanofluids have been prepared without dispersing the stabilizer and with the two step methods by Ultra sonicator. The prepared samples have been studied with SEM image to ascertain the uniform dispersion of nanoparticles. The sample prepared are 0.1, 0.4, and 0.8% of particle volume concentrations. This paper is the continuation of earlier experimental research work Mukesh Kumar [15] and Saravankumar *et al.* [16].

Specifications of the experimental section

The important dimensions of the test section are: internal diameter of coiled tube, d_i, = 9 mm, external diameter of coiled tube, d_o = 10.5 mm, coil inner diameter, D_c = 93 mm, coil outer diameter, D_e = 111 mm, coiled tube pitch, b = 17 mm, internal diameter of shell, D_i = 120 mm, number of coil turns, n = 13. The flow rate on tube side is varied in the range of 0.03-0.05 kg per second by using valve arrangement. The range of Dean number is: 1600 < De < 2700.

Network model

Figure 1 shows the steps to be followed to select the network. Heat exchanger is one of the basic applications in heat transfer analysis. There are large numbers of phenomena associated with the heat exchangers like heat and flow geometries, turbulence in the flow, and existence of hydrodynamic, and thermal entrance regions, non-uniform local heat transfer rates, fluid temperatures, and heat conduction along tube walls, natural convection within the tubes and between fins. Linear function is a relationship between variables; linear regression (LR) is used to demonstrate the relationship between the predictor variables and outcome variables. If (x_1, y_1), (x_2, y_2) … (x_n, y_n) are the observed data pair it can be represented in the linear model:

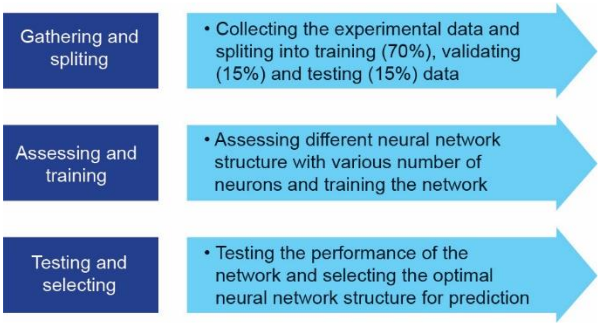

Figure 1. Steps to select the network

$$y_i = \beta_0 + \beta_1 x_i + \varepsilon_i \tag{3}$$

where β_0 and β_1 are two constants, their values are unknown and it represents the intercept and slope of y and ε_i – the error term represents as Gaussian noise: $\varepsilon \sim N(0, \sigma^2)$.

A LR model for the *predictor* variables (x_1, x_2, …, x_p) and the response variable y has represented in:

$$y_i = f(x_{1i}, x_{2i}, \ldots, x_{pi}) + r_i \tag{4}$$

where f is the fitted regression function and r – the residual. The subscript i represents the observation number.

A generalized linear model is made up of a linear predictor and two functions namely link function and variance function. Linear predictor is represented:

$$y_i = \beta_0 + \beta_1 x_{1i} + \ldots \beta_p x_{pi} \tag{5}$$

Link function and the variance function that describes about the mean and depends on the linear predictor are represented in:

$$E(Y_i) = \mu_i \tag{6}$$

$$\text{var}(Y_i) = \phi V(\mu) \tag{7}$$

$$g(\mu_i) = \eta i \tag{8}$$

where the dispersion parameter, ϕ, is a constant.

Data set and exploratory data analysis

The proposed model was developed using R program version 3.5.3 executed in 2.60 Ghz Intel i5 processor with 4 GB primary memory. The experimental data set is split randomly in to training and test set with 75% of data used for training and the 20% for testing. The training set is used for learning the establishing a correlation between the input and the target value. The fig. 2 shows the positive correlation between the heat transfer coefficient and Nusselt number. From the correlation analysis, it is evident that there is a linear relationship between the Nusselt number and heat transfer coefficient. Also, there is a correlation between the thermal conductivity of the nanofluid and the volume concentration of the nanofluid.

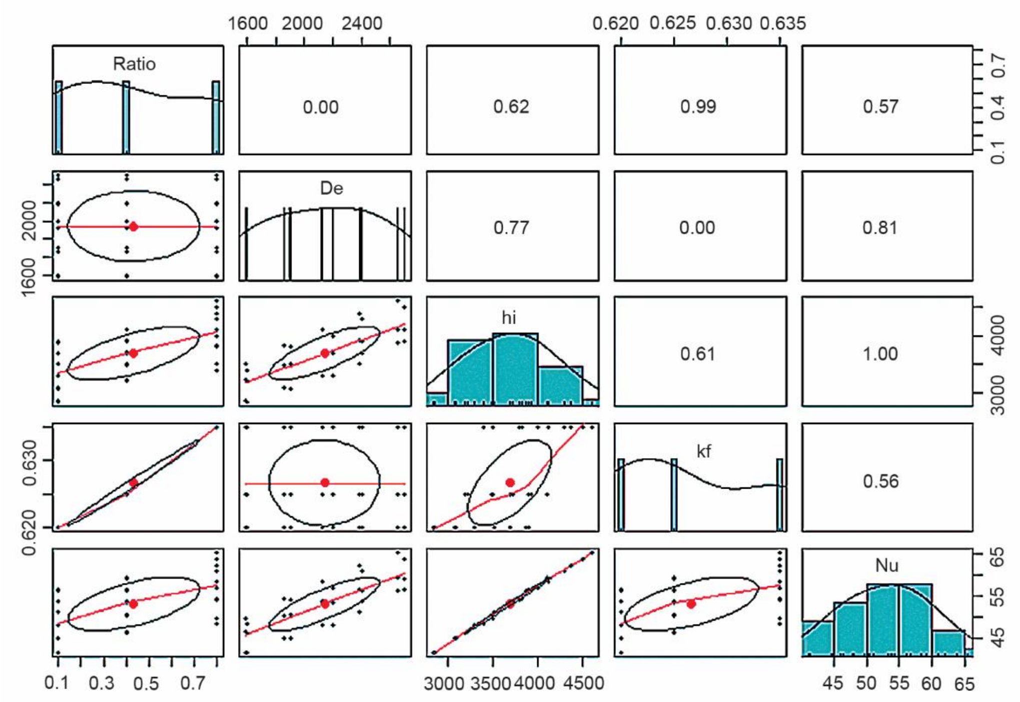

Figure 2. Correlation analysis

Results and discussions

After the model is trained with the training dataset, the testing data is used to validate the performance of the proposed model in terms of predictive accuracy of the LR model and generalized linear regression (GLR) model. The experiments are conducted for 10 independent trials and average of the result is taken as the test result. Figure 2 depicts the correlation analysis of the test. From the experimental evaluation, the MSE, MAE, MAPE, RMSE, R^2 values of linear and GLR model for predicting the Nusselt number are given in the tab. 2.

Table 2. Predicting the Nusselt number by LM and GLM

Statistics	LM	GLM
MSE	0.00085499	0.000633926
RMSE	0.05582556	0.054476982
MAE	0.04965366	0.04891378
MAPE	0.0007321653	0.0006720652
R^2	0.9999478	0.9999621

Figures 3 and 4 show the cross-plots between the experimental values and predicted values of Nusselt number in the testing dataset for linear and generalized linear model, respectively. It can be evidently seen that the data points are fitted along the straight line (along a 45° line) which clearly shows that both the models have a perfect fit and is completely agreeing with the experimental data.

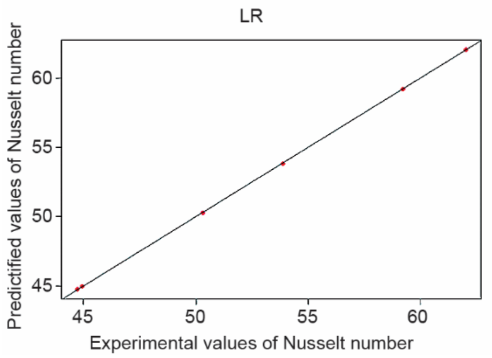

Figure 3. Experimental and predicted values of Nusselt number for LM

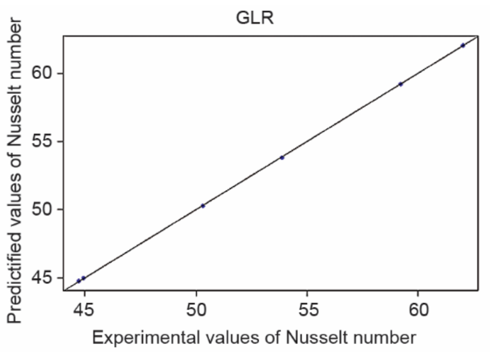

Figure 4. Experimental and predicted values of Nusselt number for GLM

Cross-validation

In order to analyse the generalization ability of the model, a *K-fold* cross validation strategy is applied to evaluate the performance of the models considered. In this paper, we have considered 2-fold, 5-fold, and 10-fold cross-validation repeated three times to evaluate the performance of the three models. During each run, one part is used for test and remaining parts are used for training the models. The results of 2-fold, 5-fold and 10-fold cross-validation with the prediction results are reported in tab. 3. It is observed from the result that R^2 value for 10-fold cross validation is higher for all the three models when compared with 5-fold and 2-fold cross-validation. It can be inferred from the cross-validation results that the performance of GLR model is better when compared with other models for a 95% confidence interval and the generalization ability of the GLM outperforms the other two models.

Table 3. Validation data

Statistics	2-fold CV			5-fold CV			10-fold CV		
	LM	GLM	GLM-NET	LM	GLM	GLM-NET	LM	GLM	GLM-NET
R^2	0.9998639	0.999904	0.9992504	0.999922	0.999922	0.999264	0.99994	0.999958	0.998806
MAE	0.05741193	0.04783835	0.1794683	0.047541	0.046774	0.185414	0.04883805	0.048707	0.18687
RMSE	0.07956434	0.06383881	0.1975090	0.061576	0.060839	0.202435	0.059374036	0.0593403	0.201481

Conclusions

In this research article, the prediction of Nusselt number of Al_2O_3/H_2O nanofluids flow in through the helically coiled tube heat exchanger at different nanofluid concentrations by using LM, GLM, and GLM_NET methods. The input predictor variables used in this models are Dean number, convective heat transfer coefficient and thermal conductivity of nanofluids. The response variable is Nusselt number in the proposed modelling. The proposed methods were modelled with different number of fold to cross validate the dataset to overcome the over fitting problem. Among the proposed models, LM model were found accurate in prediction with the RMSE 0.05614 and the regression coefficient value 0.99. This study also concludes the well-trained neural network leads to the design of heat exchangers to reduce the investment and time taken to do the real experiments.

Nomenclature

ACO – ant colony optimization algorithm
ANN – artificial neural network
GLM – generalized linear regression
GA – genetic algorithm
GLM_NET – lasso and elastic-net regularized generalized linear models methods
LM – regression
LSSVM – least squares support vector machine
MLP – multi-layer perceptron
MSE – mean square error
MAPE – mean absolute percentage error
NSGA II – non-dominated sorting genetic algorithms
RMSE – root mean square error
R^2 – regression coefficient value
RBF – radial basis function
PSO – particle swarm optimization
SA – simulated annealing
SVR – support vector regression

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