Transactions of the TSME (2016) Vol. 4, No. 2, 135-147
Journal of Research and Applications in Mechanical Engineering

ISSN 2229-2152 print
DOI: 10.14456/jrame.2016.14

Research Article

HEAT TRANSFER ANALYSIS USING ARTIFICIAL NEURAL NETWORKS OF THE SPIRALLY FLUTED TUBES

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ABSTRACT:
The optimal artificial neural network model for predicting the heat transfer coefficient and friction factor of the spirally fluted tube is considered. The experiment, nine test sections with different characteristic parameters of: helical rib height-to-diameter, χ/d_i = 0.12, 0.15, 0.19 and helical rib pitch-to-diameter, p/d_i = 1.05, 0.78, 0.63 are tested. The developed artificial neural network model shows the mean square error (MSE) of 0.0123 and the correlation coefficient (R) of 1.00 in modeling of overall experimental data set. The predicted results obtained from the optimize ANN model are verified with the testing experimental data and good agreement is obtained with errors of ±2.5%, ±15% for the Nusselt number and friction factor, respectively. In addition, the optimal ANN model results are found to be more accurate than the predicted results obtained from the published correlation.

Keywords: *Artificial neural network; spirally fluted tube, heat transfer and pressure drop*

1. INTRODUCTION

Heat transfer enhancement techniques are applied to improve the heat exchanger devices which the spirally fluted tube has been used as one of passive heat transfer enhancement techniques to facilitate the desire flow modification for augmenting heat transfer. The spirally fluted tubes are the most widely used tubes in several heat transfer applications. There are many papers presented the heat transfer and pressure drop in the tube with helical ribs [19]. In addition, Sablani [1] developed a non-iterative procedure using an artificial neural network for calculating the fluid-to-particle heat transfer coefficient in fluid–particle systems. Mittal and Zhang [2] predicted the food thermal process evaluation parameters using neural networks. Islamoglu [3] applied a new approach for the prediction of the heat transfer rate of the wire-on-tube type heat exchanger use of an artificial neural network model. Wang et al. [4] Generalized neural network correlation for flow boiling heat transfer of R22 and its alternative refrigerants inside horizontal smooth tubes. Compared with the experimental data, the average, mean and root-mean-square deviations of the trained neural network were 2.5%, 13.0% and 20.3%, respectively. Scalabrin et al. [5] proposed a new model for predicting the heat transfer of the mixtures flow boiling by using artificial neural networks. Yigit and Ertunc [6] predicted the outlet air temperature and humidity of a wire-on-tube type heat exchanger using neural networks. Zdaniuk et al [7] used an artificial neural network approach to correlate experimentally determined Colburn j-factors and Fanning friction factors for liquid water flow in the straight tubes with internal helical fins. Ermis et al. [8] applied the feed-forward back-propagation artificial neural network algorithm for phase change heat transfer analysis in a finned-tube, latent heat thermal energy storage system. Xie et al. [9] analyzed the heat transfer of shell-and-tube heat exchangers by artificial neural networks approach. Kurt et al. [10] estimated the thermal

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performance of hot box type solar cooker by using artificial neural network. Tahavvor and Yaghoubi [11] determined the natural convection heat transfer and fluid flow around a cooled horizontal circular cylinder having constant surface temperature by using Artificial Neural Network. Xie et al. [12] predicted the performance predictions of laminar and turbulent heat transfer and fluid flow of heat exchangers having large tube-diameter and large tube-row by artificial neural networks. Taymaz and Islamoglu [13] predicted the laminar convection heat transfer in converging–diverging tube using back-propagation neural network. Alizadehdakhel et al. [14] applied the CFD and artificial neural network modeling to consider the two-phase flow pressure drop. Gao et al. [15] predicted the performance prediction of wet cooling tower using artificial neural network under cross-wind conditions. Bar et al. [16] predicted the pressure drop using artificial neural network of non-Newtonian liquid in piping components. Kumar and Balaji [17] estimated the heat generation from multiple protruding heat sources on a vertical plate under conjugate mixed convection by using ANN. Wu et al. [18] studied the predicting the performance characteristics of a reversibly used cooling tower under cross flow conditions for heat pump heating system in winter using artificial neural network technique. Reza [19] applied the artificial neural network to predict the heat transfer and flow characteristics in the helically coiled tube. Khairul et al. [20] numerically studied the convective heat transfer of nanofluids in the spirally corrugated helically coiled heat exchanger by using fuzzy logic technique.

As mentioned review above, there are many papers presented the thermal devices analysis by using artificial neural network. However, there is not paper concerned the heat transfer characteristics and friction factor of the fluted tube using ANN. The main purpose of this paper is to analyze and predict the heat transfer coefficient and friction factor of the horizontal double tube with helical ribs using artificial neural network. The optimal ANN approach has been applied to show its capability in the representation of the thermal performance of the heat exchangers.

2. ARTIFICIAL NEURAL NETWORKS APPROACH

The artificial neural network has been got great attention due to a simplicity, flexibility, availability a various training algorithms. The processors are analogous to biological neurons in human brain which are connected to each other by weighted links over which signals can pass. Neuron receives multiple input parameters from other neurons in proportion to their connection weights and generates the output parameters. Due to a simple in structure and easily analyzed mathematically, the feed forward neural network has been become the most popular in engineering applications. As shown in Fig. 1, this ANN configuration has one input layer, one hidden layer and one output layer. A set of input parameter is supplied to the input nodes for the feed forward process and the information is transferred forward through the network to the nodes in the output layer. The nodes perform non-linear input–output transformations by means of sigmoid activation function. The mathematical background, however, the procedures for training and testing the optimize ANN model can be found in the text by Haykin [21]. ANN configuration model as shown in Fig. 1, the input parameters are the hot and cold water mass flow rates, hot and cold water inlet temperatures, helical ribs pitch to diameter ratio, p / d_i and helical ribs depth to diameter ratio, χ / d_i while the output parameters are the heat transfer rate, the heat transfer coefficient and friction factor.

For training and testing the neural networks results, input data patterns and corresponding targets are required. Based on the experimental conditions [22], the artificial neural network processes are run. The experimental results 819 data point [22] are used for training and testing of the ANN model. In developing a ANN model, the available data set is divided into two dataset: the first dataset [20%] is used for training the ANN model, and then it is validated with the another dataset [80%]. The ANN training process can be performed by comparing with the predicted results of the ANN model to the input data. In order to minimize the error between the predicted output results and the input data, the weights and biases are changed. The back propagation algorithm is used in the study scheme. The proposed ANN model configuration is set by selecting the number of hidden layer and the number of nodes in hidden layer. The number of nodes in the input and output layers can be determined from physical variables which the calculation procedure of the optimize ANN model as shown in Fig. 1.

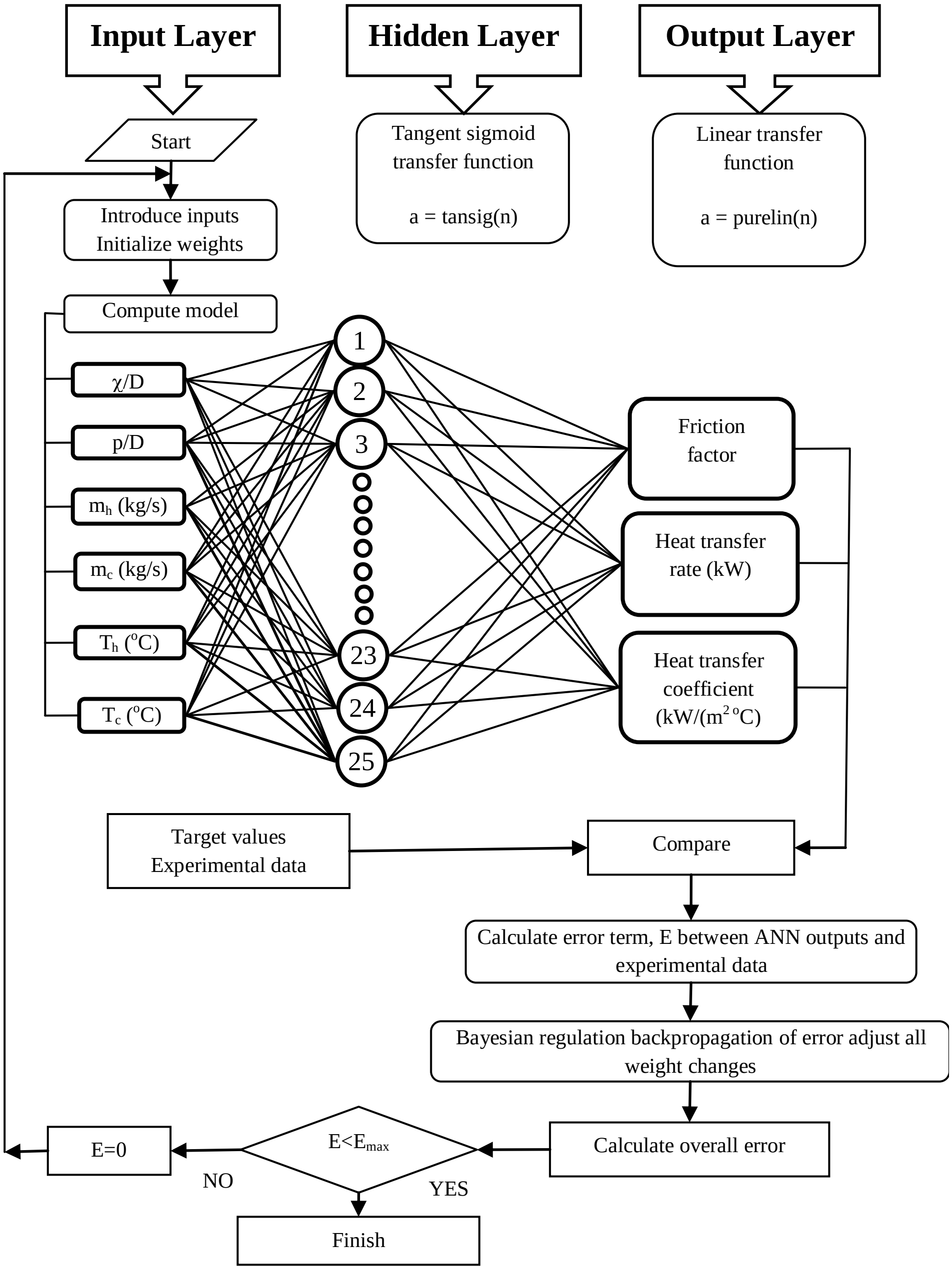

Fig. 1. Proposed optimal ANN model configuration.

3. Results and Discussion

3.1 ANN performance analysis

In order to obtain the accuracy of the optimal ANN model, the correlation coefficient (R) and the mean square error (MSE) are used as the characteristic parameters to obtain the agreement of training and predicting process of the optimal ANN model. Correlation coefficient is a measurement of how well the variation in the predicted outputs which is explained by the measured data, and the R value between the measured data and predicted output results is defined by [15,23] as follows:

$$R = \frac{cov(a,p)}{\sqrt{cov(a,a)\cdot cov(p,p)}} \tag{1}$$

where $cov(a, p)$ is the covariance between a and p sets which represent the measured data and the predicted results obtained from ANN, respectively, and is calculated from:

$$cov(a,p) = E\left[\left(a-\mu_a\right)\left(p-\mu_p\right)\right] \tag{2}$$

where E is the expected value, μ_a and μ_p are the mean value of a set and p set, respectively. In addition, $cov(a, a)$ and $cov(p, p)$ are the auto covariances of a and p sets, respectively, and are expressed as follows:

$$cov(a,a) = E\left[\left(a-\mu_a\right)^2\right] \tag{3}$$

$$cov(p,p) = E\left[\left(p-\mu_p\right)^2\right] \tag{4}$$

The correlation coefficient ranges between −1 and +1. The R values closer to +1 indicate a stronger agreement of training and predicted results, while the values closer to −1 indicate a stronger negative relationship between training and predicting process.

The mean square error is calculated from [15,23] as follows:

$$MSE = \frac{1}{N}\sum_{i=1}^{N}\left(a_i - p_i\right)^2 \tag{5}$$

where a_i and p_i are the experimental results and predicted results of i set, and N is the number of data patterns.

3.2 Backward propagation algorithm selection

There are many training functions can be adopted in the training process which the backward propagation algorithms are used in the present study. Due to higher stability and faster convergence rate than other training algorithms, the Levenberg–Marquardt algorithm with a minimum MSE and R is used to act as the training function. For all backward propagation algorithms, a three-layer ANN model with a tangent sigmoid transfer function (tansig) for hidden layer and a linear transfer function (purelin) for output layer are used which the 25 neurons are used in the hidden layer for all backward propagation algorithms.

3.3 ANN structure optimization

The most important step in development of an ANN model is the determination of the optimal number of hidden layers and the numbers of neuron in each hidden layers which the suitable numbers of hidden neurons are often determined by trial and error process. Determination of an optimal number of hidden neurons depends on the correlation complexity between independent and dependent variables being handled by ANN, number of training and testing dataset which are available and amount of noise which exists in the dataset [24,25]. However, large numbers of hidden neurons require high computation times and often result in over-fitting, while low numbers of hidden neurons cannot relate dependent/dependent to independent/independent variables with acceptable accuracy [24,25]. Although, smaller network, which has fewer weights and biases usually have better generalization capability, two different strategies, i.e., network growing and network pruning are proposed [24,25] for the evaluation of an optimal number of hidden neurons. The network growing method starts with a small network and increases hidden neurons until a desired accuracy is achieved, while the network pruning strategy commences with a large number of hidden units, and then reduces the extra neurons through the training stage [24,25]. Network growing strategy is more efficient than pruning algorithms where the majority of the learning time devoted to the networks which are bigger than necessary [26].

In this section, the heuristic design principle of acquiring decision factors to determine the quantity of hidden nodes and the configuration of hidden layers is presented. There are three empirical correlations for determination of number in hidden layer [27] as follows;

$$\sum_{i=0}^{n} C_N^i \quad > k \tag{6}$$

where K is the simple number, if i > N, $C_N^i = 0$ = 0.

$$N \ = \sqrt{m+n} + c \tag{7}$$

where c is a constant which belongs to [28,29].

$$N \ = log_2 n \tag{8}$$

For one hidden layer of ANN model, the correlation for calculation of node number in hidden layer is proposed by [30] as follows;

$$N \ = \sqrt{mn} \tag{9}$$

For put forward, the empirical correlation [31] for determination the node number in hidden layer can be expressed as;

$$N \ = \sqrt{0.43mn + 0.12m^2 + 2.54n + 0.77m + 0.86} \tag{10}$$

Which *N* is the node number in hidden layer, n is the node number in input layer and m is the node number in the output layer. The three neurons are used in the hidden layer as an initial guess. With an increase in the number of neurons, the networks give several correlation coefficient (R) and different mean square error (MSE) values for the training process.

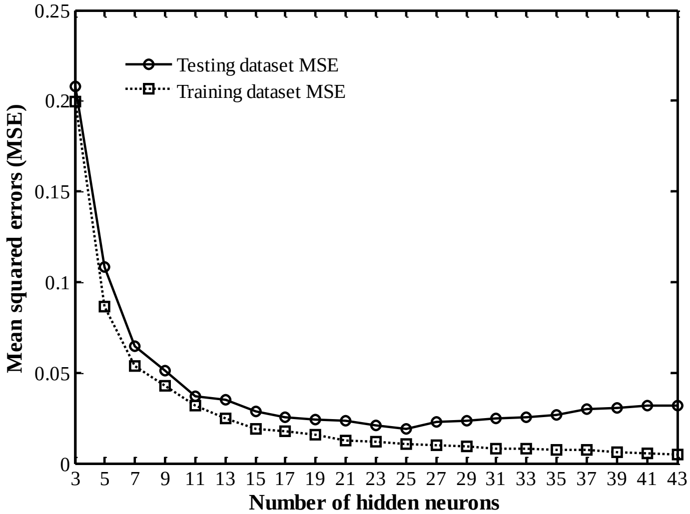

Fig. 2. MSE of various ANN models over training and testing subset.

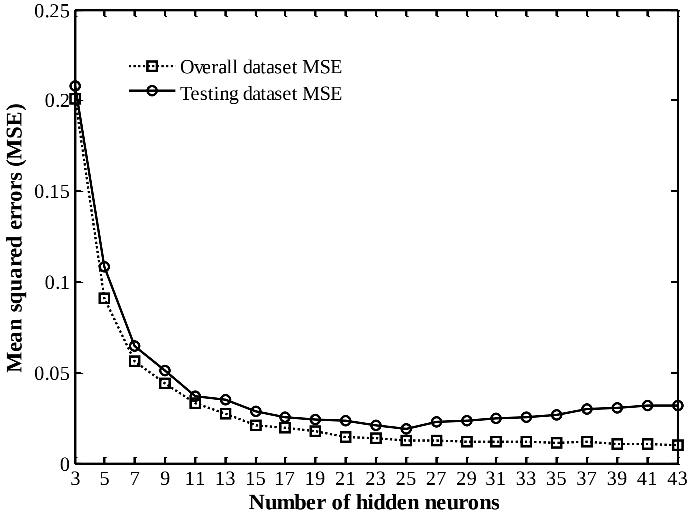

Fig. 3. MSE of various ANN models for testing and overall (training + testing) data set.

Figures 2-3 show the variation of mean square error (MSE) of the optimize ANN model with number of hidden layer for testing and overall (training+testing) dataset, respectively. It can be seen that the MSE (Testing) continuously decreases with increasing hidden layer from 3 to 25. The MSE reaches it minimum value as the hidden layer of 25. When the number of hidden layers exceeded 25, the MSE slightly increases. Figure 4 shows the variation of R (testing) with number of hidden neurons for the testing and overall (training+testing) dataset. It can be seen from the figure that the R values rapidly increases as number of hidden neurons increase from 3 to 15 and then slightly increase with increasing hidden neurons from 15 to 25. With 25 hidden neurons, the R value reaches it maximum value and then the R value tends to decrease as shown in Fig. 4. It can be said that increasing the number of hidden layer more than 25 results in over-fitting of the ANN model over training data set and also cannot generalize the rules to test data set as well. Therefore, the neural network containing 25 hidden layers is chosen as the best case. In addition, the training process is stopped after 1000 iterations for the Levenberg–Marquardt algorithm because the MSE and R values converge after 1000 epochs as shown in Fig. 5.

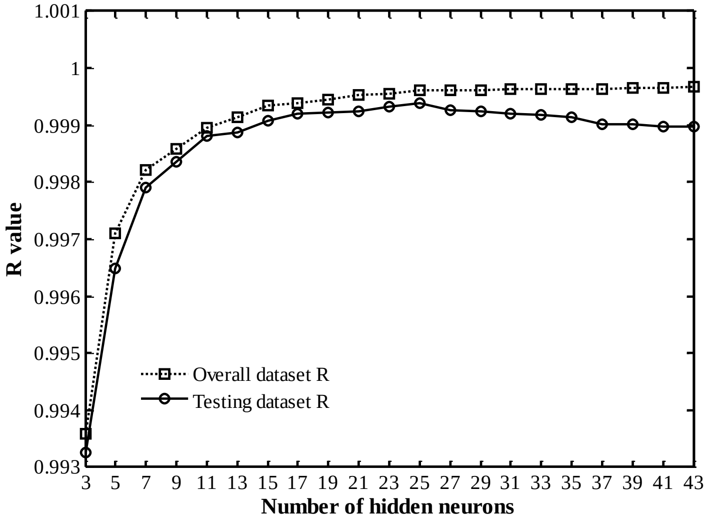

Fig. 4. R values of various ANN models for testing and overall (training + testing) data set.

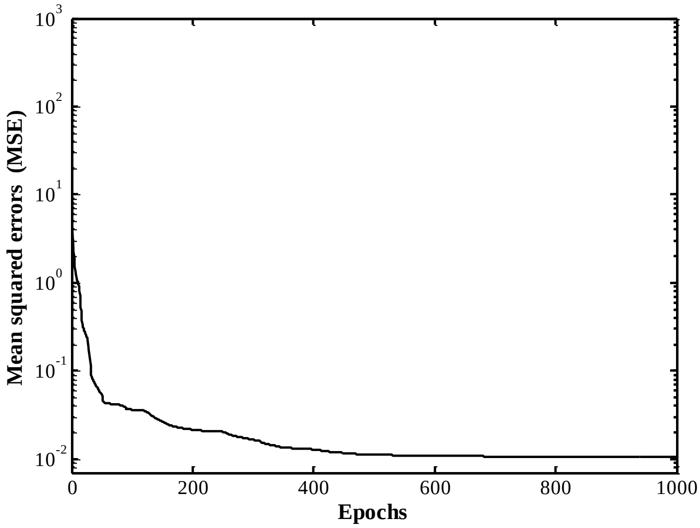

Fig. 5. MSE variation versus epochs for optimal ANN model in training.

Table 1: Evaluation of the optimal ANN model through statistical accuracy analysis

Hidden layer	No. Weight	Eff. Num	%Eff. Num	MSE (All)	MSE (Train)	MSE (Test)	R (Train)	R (Test)	R (All)
3	33	30.3	91.82	0.2010	0.1994	0.2078	0.99367	0.9933	0.994
5	53	49.3	93.02	0.0909	0.0865	0.1086	0.99726	0.9965	0.997
7	73	67.6	92.60	0.0560	0.0538	0.0649	0.99829	0.99790	0.998
9	93	85.7	92.15	0.0443	0.0425	0.0512	0.99865	0.9984	0.999
11	113	108	95.58	0.0330	0.0321	0.0368	0.99898	0.9988	0.999
13	133	125	93.98	0.0270	0.0250	0.0351	0.99921	0.9989	0.999
15	153	146	95.42	0.0209	0.0189	0.0288	0.99940	0.99908	0.999
17	173	163	94.22	0.0193	0.0179	0.0252	0.99943	0.99920	0.999
19	193	187	96.89	0.0174	0.0157	0.0244	0.99950	0.9992	0.999
21	213	201	94.37	0.0147	0.0125	0.0234	0.99960	0.9993	1.000
23	233	221	94.85	0.0137	0.0118	0.0212	0.99962	0.9993	1.000
25	253	240	94.86	0.0123	0.0106	0.0190	0.99966	0.9994	1.000
27	273	261	95.60	0.0124	0.0098	0.0229	0.99969	0.9993	1.000
29	293	281	95.90	0.0120	0.0092	0.0233	0.99971	0.9993	1.000
31	313	301	96.17	0.0116	0.0082	0.0250	0.99974	0.99920	1.000
33	333	318	95.50	0.0117	0.0082	0.0255	0.99974	0.9992	1.000
35	353	336	95.18	0.0112	0.0074	0.0267	0.99977	0.9991	1.000
37	373	356	95.44	0.0118	0.0072	0.0302	0.99977	0.999	1.000
39	393	380	96.69	0.0107	0.0058	0.0308	0.99982	0.999	1.000
41	413	393	95.16	0.0107	0.0056	0.0316	0.99982	0.999	1.000
43	433	417	96.30	0.0102	0.0048	0.0319	0.99985	0.999	1.000

3.4 Comparison of optimal ANN model with the measured overall data set

A computer program with C++ software has been developed by using the back propagation algorithm. ANN model sensitivity is examined for 21 different networks with 3, 5, 8, 9, 11,….., 39, 41 and 43 neural nodes in the hidden layer. Table 1 shows the values of MSE and R which existed between the experimental data and the predicted results obtained from optimal ANN model over training, testing as well as overall data set (training+testing). According to Table 1, the optimize ANN model shows the best predictive capability for the prediction of the heat transfer rate, the heat transfer coefficient and friction factor, MSE and R of 0.0123 and 1.00, respectively. These values of statistical criteria and error indexes confirm the excellent agreement between the measured data and the predicted results obtained from the optimal ANN model.

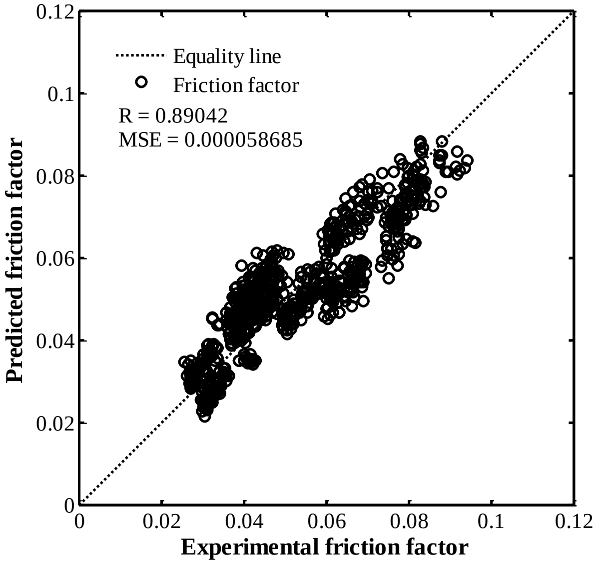

Fig. 6. Experimental friction factor vs. predicted values for the overall (training + testing) data set.

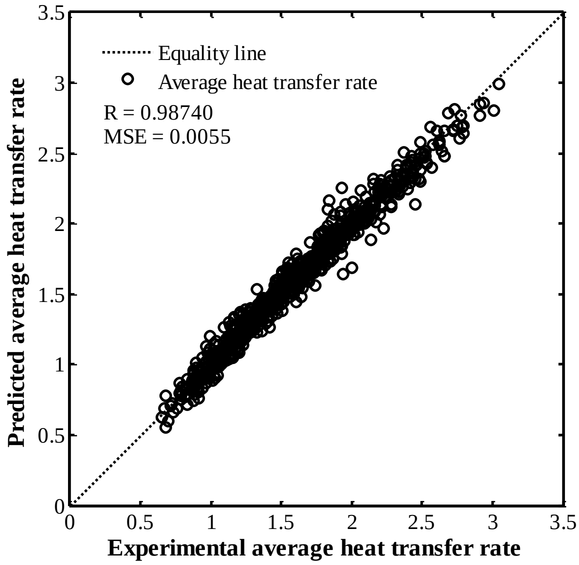

Fig. 7. Experimental average heat transfer rate vs. predicted values for the overall (training + testing) data.

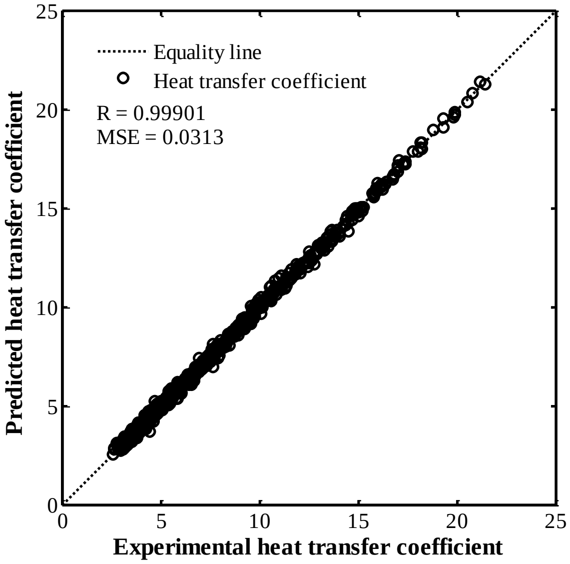

Fig. 8. Experimental heat transfer coefficient vs. predicted values for the overall (training + testing) data set.

Figures 6-8 show the comparison between the values of friction factor, heat transfer rate and the convective heat transfer coefficient which are obtained from the optimal ANN model and overall experimental data set, respectively. The optimal ANN model shows the R= 0.89042 between the predicted friction factor and the experimental results of the overall data set. The optimal ANN model has predicted the friction factor of overall data set with MSE of 0.000058685. Again, Figures 7-8 present the comparison between the heat transfer rate, the measured heat transfer coefficient overall data set and the predicted results from the optimal ANN model. It can be seen that the ANN model prediction for the heat transfer rate and the heat transfer coefficient yield a MSE of 0.98740, 0.99901, R of 0.0055, 0.0313 with the experimental overall data set, respectively. Figures 7-8 also are provided with a straight line indicating perfect prediction.

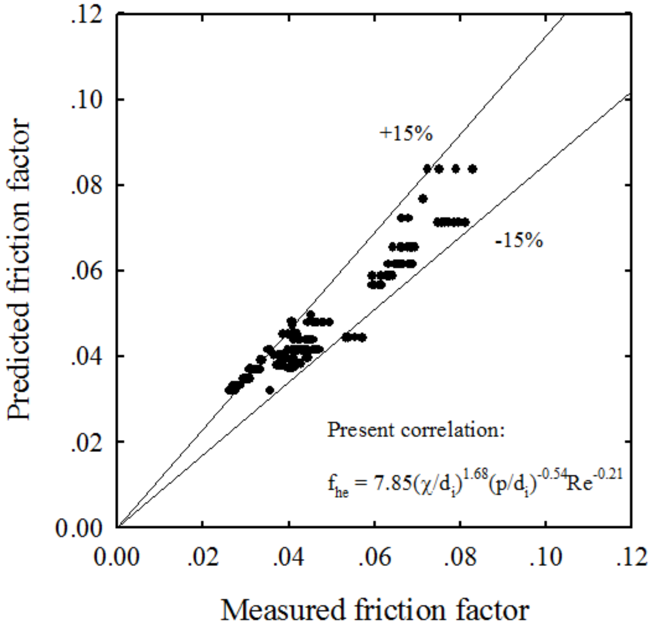

Fig. 9. Comparison between the measured data and predicted friction factor [22].

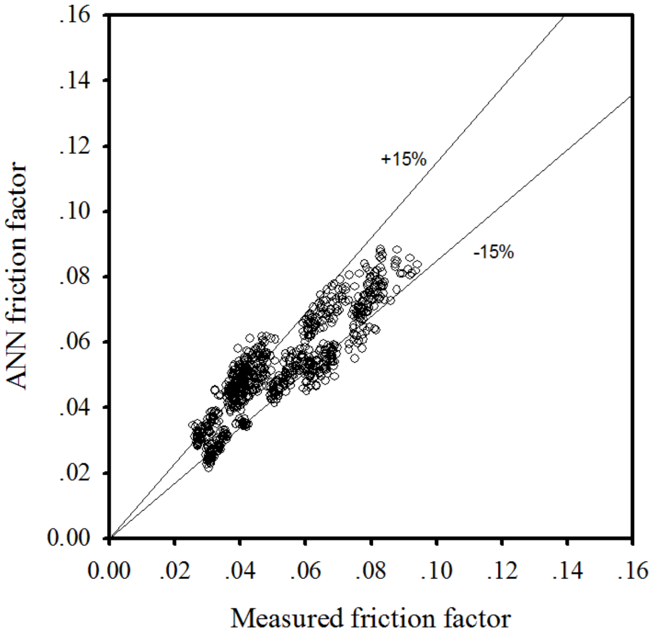

Fig. 10. Comparison between the measured data and ANN results.

3.5 Comparison of optimal ANN model with the published correlations

Figures 9-12 show the comparison between the predicted friction factor results, the predicted Nusselt number results obtained from the published correlation [22] and the predicted friction factor results, the predicted Nusselt number results obtained from the optimal ANN model.

The Nusselt number for the tube with helical ribs is proposed by [22] as the following forms:

$$Nu_{he} = \frac{h_i d_i}{k} = 44.26\left(\frac{\chi}{d_i}\right)^{0.89}\left(\frac{p}{d_i}\right)^{-0.96}\left(Re - 1500\right)^{0.27} Pr^{-0.26} \tag{11}$$

which $5{,}000 \leq Re \geq 25{,}000,\quad Pr > 3,\quad 0.12 \leq \chi / d_i \leq 0.19,\quad 0.63 \leq p / d_i \leq 1.05$

Although the flow characteristic in the tube with helical rib is highly complex, the friction factor results obtained from the measured data are properly correlated in the simple mathematical function. Non-isothermal correlations of the friction factor of tube with helical rib are proposed by [22] as the following form:

$$f_{he} = 7.85\left(\frac{\chi}{d_i}\right)^{1.68}\left(\frac{p}{d_i}\right)^{-0.54} Re^{-0.21} \tag{12}$$

which $5{,}000 \leq Re \geq 25{,}000,\ 0.12 \leq \chi / d_i \leq 0.19,\quad 0.63 \leq p / d_i \leq 1.05$

The results obtained the comparison between the predicted results from the published correlations [22] and the measured data. It can be seen from these figures that the deviation is in the range of ±15% for the friction factor and ±15% for the Nusselt number as comparing with the published correlations [22]. As comparison between the predicted results from the ANN model and the predicted results from the published correlations. It can be found that the results obtained from the optimal ANN model are found to be more accurate than the predicted results obtained from the published correlations [22] especially the Nusselt number.

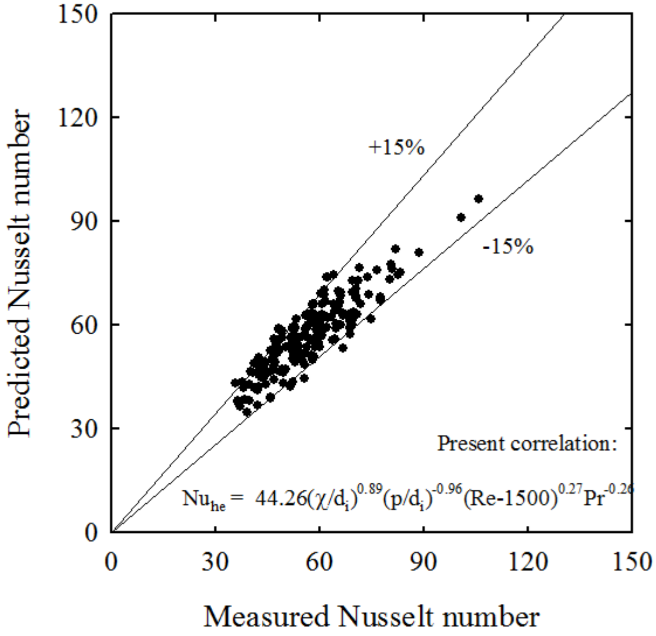

Fig. 11. Comparison between the measured data and predicted Nusselt number [22].

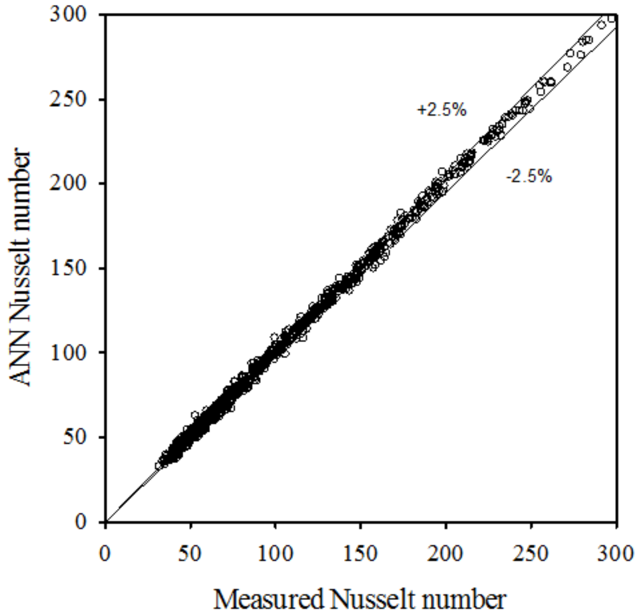

Fig. 12. Comparison between the measured data and ANN results.

5. Conclusion

The main focus of this study is to present the performance of the ANN model to predict the convective heat transfer coefficient and the friction factor of the spirally fluted tube. The optimal ANN model showed a precise and an effective prediction of the experimental data with a satisfactory correlation coefficient value of 1.00 and the mean relative error value of 0.0123. In addition, the optimal ANN model results are found to be more accurate than the predicted results from the published correlations. To conclude, the optimal ANN model can provide a future contribution to develop a better understanding of the heat exchanger dynamic behavior.

6. ACKNOWLEDGEMENT

The authors would like to express their appreciation to the Srinakharinwirot University (SWU) for providing financial support for this study.

NOMENCLATURE

d	diameter, m
f	friction factor
h	heat transfer coefficient, kW/(m^2 ^{o}C)
k	thermal conductivity, kW/(m ^{o}C)
m	mass flow rate, kg/s
Nu	Nusselt number
p	helical rib pitch, m
Pr	Prandtl number
Q	heat transfer rate, kW
Re	Reynolds number
χ	helical rib depth, m

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