PREDICTION OF HEAT TRANSFER COEFFICIENTS BY ANN FOR ALUMINUM & STEEL MATERIAL

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Abstract

The engineering properties of the metals are affecting efficiency of heat transfer processes in heat exchangers which mainly used in heating, refrigeration, air conditioning, power plants, chemical plants, petrochemical plants, petroleum refineries, and natural gas processing. Therefore, selection the material types are very important for heat exchangers manufacturing. Heat exchangers can be commonly made of steel, copper, bronze, stainless steel, aluminum, or cast iron. In heat exchangers applications, the heat transfer rate and coefficients plays an critical role while producing and manufacturing. This paper presents the experimental results of heat transfer data for the same rectangular cross-section aluminum and steel plates and heat transfer coefficient predictions of these materials done by using Artificial Neural Network (ANN) based on the experimental data.

Keywords: Forced convection heat transfer, heat exchangers, Artificial Neural Network

1-Introduction

Nowadays, growth of the World Population and industrial development are increased the energy requirement. Hence, effective usage of energy and cost of energy efficiency have an important role to play both in developed and developing countries.

Using less energy to provide the same process can be called energy efficiency in engineering applications. Heat exchangers which commonly used in industrial applications ensure efficient energy use for heating and cooling, in some cases, directly determines the overall energy efficiency of the plant [1]. Especially, to reduce heating and cooling cost, designers have used better energy transfer techniques and particular materials to greatly reduce heat leaks. Choosing thermally conductive materials and proper design of heat exchangers make the process energy efficient and minimize overall heat loss and helping protect the environment. In heat exchanger design, heat transfer coefficient is being considered a one of the essential parameter required choosing the true material [2]. Many researchers touch upon on these phenomena in their studies.

Artificial Neural Network (ANN) has become a modeling tool frequently used in applications and analyzing the complex problems in different disciplines. Particularly, the usage of artificial neural networks (ANNs) has increased in engineering applications such as heat transfer analysis, performance prediction and dynamic control [3-5]. For the heat transfer applications and/or heat exchangers applications, there is not sufficient experiment in the literature. Although, heat transfer systems has complex variables, the ANN is very helpful to determinate the prediction of heat transfer parameters. ANN has been successfully used in the analysis of heat transfer data and the heat transfer coefficient” by Thibault et al.[6], Jambunathan et al. [7] and Nasr et al. [8]. Also; Xie et al., [9] used the experimental data with back propagation (BP) algorithm for training and testing steps of neural network configurations, investigated the in-out temperature differences in each side and overall heat transfer rates for three
heat exchangers experimentally. They revealed that the maximum deviation between the predicted results and the experimental data was less than 2%.

In addition, ANNs have been used by various researchers reported in references listed with Sen and Yang; Diaz, Sen, Yang, McClain; Pacheco-Vega, Sen, Yang and McClain; Pacheco-Vega, Diaz, Sen, Yang and McClain; Ayoubi; Jalili-Kharaajoo and Araabi; Varshney and Panigrahi [10-16].

In this paper, heat coefficients that are obtained from the experimental heat transfer data for the same rectangular cross-section aluminum and steel material plates in forced convection condition, are predicted by a feed-forward two-layer Back Propagation Artificial Neural Network (ANN). Predicted and measured values of heat transfer coefficients are compared for aluminum and steel respectively and given with different graphics. Also prediction errors are compared with stepwise regression analysis results.

2- Experimental Set-Up

Experiments were carried out on the natural and forced convection experiment set, which shown in Figure 1, located at the Heat Transfer Laboratory in the Department of Mechanical Engineering, Erciyes University, TURKEY. In the rig of experiment, aluminum (10.9 x9.9 cm (EN 1050); thermal conductivity 218 W / (mK)) and steel ((AISI 321) (thermal conductivity 15 W / (mK)) flat plates are used as heat exchanger material. In this paper, only a brief description of the experimental setup and procedures will be provided. After aluminum plate is placed into the channel, it was heated by constant heat transfer rate respectively 10–20–25–30 W. For each given value of constant heat flow, as fluid air is applied over the aluminum plate that is vertical condition with velocity of 0.5-1-1.5-2 m/sec respectively. In each case both aluminum plate and ambient temperature are measured. The heat transfer experimental data used in this study, along with a detailed description of the experimental apparatus and procedures used, were reported by Mert [17].

In figure 1 the natural and forced convection experiment set contains with illustrated number of pieces apparatus. In this figure, number 1 is the test apparatus mounting section; 2 is the temperature sensor; 3 is the anemometer; 4 is the thermistor probe; 5 is the experiment console; 6 is the power cable socket and the 7 is the apparatus for test plate. In the experiments; the temperature

values measured from both plate’s surfaces temperature and duct ambient temperatures. In this way, the physical properties of the fluid are determined. The same procedure is repeated for steel plate too. In this experiment, applied constant heat flux can be read from the test rig. In this way, experimental heat coefficients are calculated by heat flux value that read from experiment rig. And then the experimental heat transfer coefficient is compared with calculated as an empiric heat transfer coefficient. However, in accordance with the experimental work, it has been applied the experimentally calculated heat transfers coefficient to artificial neural network.

3- Calculation Of Heat Transfer Coefficient

In this experimental study; the general law of heat transfer formula is used for determined the heat transfer coefficient (Eq. (1)).

\[ Q = hA \Delta T \]  

(1)

where “Q” is the heat transfer rate, “A” is the area of the aluminum and steel plates, “\( \Delta T \)” is the temperature change of the system (Eq. (2)) and the “h” is the heat transfer coefficient (Eq. (3)).

\[ \Delta T = (T_s - T_{at}) \]  

(2)

where “\( T_s \)” is the surface temperature of the plates and “\( T_{at} \)” is the ambient temperature on the experimental set duct.

\[ h = \frac{Q}{A\Delta T} \]  

(3)

In eq. (1) the heat transfer rate “Q”, is read by the display of the experiment set. The areas of plates is calculated and donated with “A” and from eq. (2), “\( \Delta T \)” is calculated with the differences between “\( T_s \)” and “\( T_{at} \)”. And lastly Eq. (3) is the result of heat transfer coefficient for the metal plates. Therefore; the “h” values which calculated from eq. (3), has been using in ANN for output parameters.

4- Artificial Neural Networks

ANNs are computational model, which is based on the information processing system of the human brain. In general, it is composed of three layers, which are an input layer, some hidden layers and an output layer. This network structure is called MLP with either by Isleri & Karlik [18]. Each layer has a certain number of small individual and highly interconnected processing elements called neurons or nodes. The neurons are connected to
each other by communication links that are associated with connection weights. Signals are passed through neurons over the connection weights. Each neuron receives multiple inputs from other neurons in proportion to their connection weights and generates a single output signals which may be propagated to other neurons, referred by Kurt et al. [19].

To develop an ANN, it have to use three stages for processed the network that reported by Karlik [18] too, mentioned that “with no hidden layer, the perceptron can only perform linear tasks”. With these suggestions, in ANN applications multi-layer perceptron is the widely used type. Input variables are processed through mainly layers of “neurons”. This content an input layer, which be equivalent with neurons and problem variable numbers, and an output layer, with a number of neurons equal to the desired number of quantities computed from the inputs. Also “hidden layers” are between input and output layers. In this study we choose one hidden layer for solved the perceptron.

In this paper, the ANN model is achieved by using Matlab Neural Network Module. 70% of the available data is used for training, 15% is used for cross validation and 15% is used for testing. A randomly chosen is used for the data with data set.

The artificial neural network (ANN) was trained with Levenberg-Marquardt BP algorithm for proposed ANN. This function is a network training function that updates weight and bias values according to Levenberg- Marquardt optimization method which was used by Iseri & Karlik [18] and Yuhong & Wenxin [20]. The aim of training process is to reduce the global error (F). “F” defined as

\[ F = (1/P) \sum_{P=1}^{P} F_p \]  

Where “P” is the total number of training values; and “F_p” is the error for training value p. F_p is calculated by the following equation:

\[ F_p = (1/2) \sum_{n=1}^{N} (OP_n - TG_n)^2 \]

Where “N” is the total number of output nodes, “OP_n” is the network output at the n^{th} output node, and “TG_n” is the target output at the n^{th} output node. In training algorithm, an attempt is carried out to reduce global error by adjusting the weights and biases. Levenberg-Marquardt BP training algorithm was designed to approach second- order training speed without having to compute the Hessian matrix [21]. As the performance function has the form of sum of squares, the hessian matrix can be approximated as shown in eq. (3).

\[ H = Z^T Z \]

And the error gradient can be calculated as

\[ G = Z^T F_n \]

Where

\[ Z \]”, the Jacobian matrix, which contains first derivatives of the network errors with respect to the weights and biases; “F_n” is a vector of network errors.

The Jacobian matrix can be computed through a standard back-propagation method. This computing form is much less complex than computing the Hessian matrix. Levenberg-Marquardt algorithm uses this approximation to the Hessian matrix in the following Newton-like computational mechanism is as follows [22]:

\[ W_{k+1} = W_k - [Z^T Z + \lambda I]^{-1} Z^T F_k (W_k) \]

Where

W_k is weight vector of the previous iteration; 
W_{k+1} is weight vector of the actual iterations; 
Z, the mnx Jacobian matrix with the dimensionality (m is the number of learning values for each iteration, n is total number of weights); 
\lambda is learning ratio; 
I is identical mxm matrix;

F_k(W_k) is vector of n elements, which contains estimation errors for each learning value.

The optimal ANN structure with a flow chart of the Levenberg- Marquardt BP algorithm is illustrated in Figure 2. The layers are shown separately. The activation function is chosen as the tangent sigmoid function in the hidden layer and the linear transfer function in the output layer. In input layer, 4 variable inputs are used for prediction. A/B is symbolized as width/length ratio of the test plate; V is describes the air velocity; Q is the heat transfer rate and T_f represents film temperature. And one output variable is heat transfer coefficient (h). And the hidden layer occurs 20 neurons are obtained via trial and error. Because of the nf-tool hyperbolic tangent transfer function which shown eq. (8), is performed for the hidden layer. So the linear transfer function (purelin), which shown in Figure 2., is used in the output layer.

\[ f(x) = \frac{e^x - e^{-x}}{e^x + e^{-x}} \]

On the other hand the MLP is carried out with layers 4:20:1, which are 4 neurons of input layer, 20 neurons of hidden layer and only one neuron of the output layer.
In the analysis of errors these two parameter is very important for the understanding the error phenomena. Mean Absolute Error (MAE) and Root Mean Square Error (RMSE) commonly used in error analysis. MAE is mentioned that “Absolute error is the absolute value of the difference between target values and outputs” by Karlık, 2009 [18]. The MAE can be computed as follows

\[
MAE = \frac{1}{n} \sum_{i=1}^{n} |A_i - P_i| \quad (9)
\]

Where “\( A_i \)” is the actual data and “\( P_i \)” represents the predicted data.

The RMSE is computed with Eq. (10). In Eq. (10) \( Y_i \) is donated as observation value and \( F_i \) is donated as Forecast value. Therefore the error analysis results are given in Table 2. In Figure 7, the histogram of the errors is given with graphics. As it seen from Figure 7, over 77% of the errors accumulate across 0. That shows our network works very well.

\[
RMSE = \left( \frac{1}{T} \sum_{t=1}^{T} (Y_t - F_t)^2 \right)^{1/2} \quad (10)
\]

5-Result And Discussions

In neural network applications, training parameters have should be select carefully. This selection of artificial neural network affects the successfully prediction positively [23]. Training data which has an important role in the learning process, used by trainlm algorithm are shown below with their values:

- Epochs between displays: 25
- Maximum validation failures: 4
- Maximum number of epochs to train: 1000
- Maximum time to train in seconds: Inf
- Performance goal: 0
- Factor to use for memory/speed Tradeoff: 1
- Minimum gradient error: \( 1 \times 10^{-10} \)
- Initial \( \lambda \): 0.001
- \( \lambda \) decrease factor: 0.1
- \( \lambda \) increase factor: 10
- Maximum \( \lambda \): \( 1 \times 10^{10} \)

The network was trained for twelve epochs and five epochs for aluminum and steel material, respectively. The following error results (Mean Square Error) and correlation coefficients (R) are given in Table 1, with Levenberg-Marquardt BP training algorithm. It can be seen clearly from Table 1, the MSE of training phase is 0.000292 for aluminum plate and 3.60e^{-0.000292} for steel plate.

In Figure 3, the dashed line is the perfect fit line where outputs and targets are equal to each other. The circles are the data points and colored line represents the best fit between outputs and targets. Here it is important to note that circles gather across the dashed line, so our outputs are not far from their targets. According to these results we can notice that used MLP structure of ANN is favorable to predict heat transfer performance of the aluminum and steel test plates.

The variation of the gradient error, \( \lambda \) and validation error for both aluminum and steel plates values are represented in Figure 4. For aluminum plate 12 epochs and also steel plate 5 epochs are reached to desired parameters.

The comparison between actual and estimated heat transfer coefficients are shown in the Figure 5, with separately graphics. And also the individual errors are illustrated in a bar chart in Figure 6. Dark bars refer to aluminum plate and light bars refer to steel plate.

Figures 3, 4, and 5 imply that the heat transfer coefficients within a wide flow range (2994 \( \leq Re \leq 10566 \)) have been estimated with an MAE of less than 1%, an RMSE of less than 1% by means of the ANN method for both plates.

6-Conclusions

In this study, an experimental system for investigation on thermal performance on forced convection of aluminum and steel plates is set up, and the experimental data is obtained via heat transfer rate parameters for 10–20–25–30 W and velocity of air as fluid for 0.5–1–1.5–2 m/sec. The ANN is also proposed with layers 4:20:1, which are 4 neurons of input layer, 20 neurons of hidden layer and only one neuron of the output layer for comparing the experimental heat transfer coefficient values of aluminum and steel plates and predicted by proposed ANN. The ANN is improved by Levenberg-Marquardt BP algorithm as train process. The results pointed out that the ANN approach is able to learn the training heat transfer coefficient data in order to predict the output of unseen validation heat transfer coefficient data accurately. Also, performance of the proposed ANN showed clearly its transcendence over the numerical models formed with assumptions. It is recommended to utilize the ANN used Levenberg-Marquardt training algorithm for simulation of processes of the heat exchanger applications due to ability to establish an accurate relationship between information within a multidimensional cases by ANN.
REFERENCES


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Table 1 Values of MSE and R according to both metal plates

<table>
<thead>
<tr>
<th></th>
<th>Aluminum Test Plate</th>
<th>Steel Test Plate</th>
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<tbody>
<tr>
<td>Samples %</td>
<td>MSE</td>
<td>R</td>
</tr>
<tr>
<td>Training 70%</td>
<td>0.000292</td>
<td>0.999</td>
</tr>
<tr>
<td>Validation 15%</td>
<td>0.058</td>
<td>1</td>
</tr>
<tr>
<td>Testing 15%</td>
<td>0.37</td>
<td>1</td>
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Table 2 Comparison of Al and St plates error analysis results.

<table>
<thead>
<tr>
<th></th>
<th>MAE</th>
<th>R²</th>
<th>RMSE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Al</td>
<td>0.191931</td>
<td>0.991725547</td>
<td>0.219311005</td>
</tr>
<tr>
<td>St</td>
<td>0.157458</td>
<td>0.999991774</td>
<td>0.095807787</td>
</tr>
</tbody>
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Figure 1 P. A. HILTON H920 model of natural and forced convection experiment set [21], and test plates.

Figure 2 Optimal ANN structure with a flow chart of the Levenberg- Marquardt BP algorithm.

Figure 3 Regression analyses for aluminum and steel test plate.

Figure 4 Variation of the gradient error, µ and validation error for both aluminum and steel plates.

Figure 5 Comparison between experimental and estimated “h” values for each metal plates.

Figure 6 Bar chart of individual errors for aluminum and steel plates.

Figure 7 Histogram of errors for each plate.
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