Outlet Temperature Prediction of Boiling Heat Transfer in Helical Coils through Artificial Neural Network †

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Abstract: In the present study, deep learning neural network model has been employed in many engineering problems including heat transfer prediction. The main consideration of this document is to predict the performance of the boiling heat transfer in helical coils under terrestrial gravity conditions and compare with actual experimental data. Total of 877 data sample has been used in the present neural model. Artificial new Neural Network (ANN) model developed in Python environment with Multi-layer Perceptron (MLP) using four parameters (helical coils dimensions, mass flow rate, heating power, inlet temperature) and one parameter (outlet temperature) has been used in the input layer and output layer in order. Levenberg-Marquardt (LM) algorithm using L2 Regularization to find out the optimal model. A typical feed-forward neural network model composed of three layers, with 30 numbers of neurons in each hidden layer, has been found as optimal based on statistical error analysis. The 4-30-30-1 neural model predicts the characteristics of the helical coil with the accuracy of 98.16 percent in the training stage and 96.68 percent in the testing stage. The result indicated that the proposed ANN model successfully predicts the heat transfer performance in helical coils and can be applied for others operation concerned with heat transfer prediction for future works.

Keywords: boiling heat transfer; helical coils; neural network; terrestrial gravity

1. Introduction

Helical coils are very widespread and have been used in many applications. From many works, they indicated that the helical coil has a high heat transfer efficiency, compact design, convenient to produce, and free from thermal deformation. In the helical coils, the centrifugal force acts on the fluid and causes the formation of vortex secondary flow in both single and two-phase flow [1]. This paper considers the boiling heat transfer, which is the most efficient process. Many related works study about the characteristic of substances in many processes of heat transfer in devices [2–9].

Artificial Neural Networks (ANNs) have been used widely and successfully for modeling and in predicting various engineering problems, including heat transfer. Many works apply ANN of the prediction of heat transfer parameters. The works in [10–12] demonstrate the prediction of heat transfer but are not in helical coils. However, the implementations can be good examples of ANN architecture.
construction in this experiment. Some works are related to the performance of heat transfer in a helical coil. In [13], the method is to construct the ANN model to predict heat transfer performance in helical coils. They consider many input variables and output parameters. Ref. [14] used the machine learning method on the heat transfer performance of CNT/water nanofluid through a helical coil. In [15], the researchers developed ANN models to predict the heat transfer and friction factor in helically coiled tubes. Ref. [16] developed the model on ANN to predict the new void fraction forming in a two-phase flow of water inside vertical helical coils. Moreover, the approach in [17] constructed both dimensionless correlation and ANN model to predict the mass flow rate in the vapor compression refrigerant system through straight and helical coils. The approach in [18] constructs the model of ANN and adaptive neuro-fuzzy inference system (ANFIS) to evaluate micro-mixing in micro-helical coil tube, result that ANN model has more accuracy than the ANFIS model. From all of the related works, they demonstrate many methods and models for the prediction of heat transfer parameters. From most of the works, the ANN model is the most efficient type of prediction. This paper considers the input as helical coils dimension, mass flow rate, heating power, and inlet temperature to predict the output of outlet temperature through the ANN model.

2. Methods

2.1. Dataset Preparation

The data were generated from the helical coils, heat transfer test equipment [13]. All the signals measured by the temperature and pressure transducers were made by utilizing a digital interface and recorded by a computer. The author runs the experiment on this test equipment and collects the 877 data samples from the record of the PC data Acquisition system. The data samples are separated into two sets for 80 percent of samples are training data, and another 20 percent as testing data.

2.2. Artificial Neural Networks Model Construction

Artificial neural networks construct non-linear correlation by the training rules in which the weight of connections between neurons depends on learning data. In other words, the artificial neural networks learn from the data and find the relation between inputs and outputs. The prediction of ANN will result in close to the actual considered output. From many types of ANN, the feed-forward network is highly widespread in engineering problem applications. It is a convenient method to construct the model with Python for a feed-forward back-propagation (FFBP) multi-layer perceptron (MLP) ANNs and els. The number of neurons in the input and output layers layer is the same as the number of input and output parameters, respectively. The number of hidden layers and neurons in each hidden layer can be changed depending on the complexity of the problem and the dataset. The ANN model is in the construction of 4-30-30-1, in which the digits indicated the number of neurons in each layer from the input layer, two hidden layers, and the output layer, respectively.

In this experiment, the model has been trained using the Levenberg-Marquardt (LM) algorithm using L2 Regularization with 6–35 neurons has been used to find out the optimal model. The experiment employs a Rectified Linear Unit (ReLU) The activation function in between the layers. The model has been training and testing through 1000 epochs. The error of the model has been minimized by Adam optimizer using the loss calculation as the mean squared error between predicted outlet temperature and actual outlet temperature in the dataset.
2.3. Model Accuracy Testing

In the experiment, the author employ means squared error to represent the error of predicted data to the actual data. The author measures the MSE and accuracy during training and testing during 1000 epochs. The accuracy has been calculated from mean squared error in each epoch to the percentage accuracy.

3. Results and Discussion

3.1. MSE and Accuracy

From the experiment, The final MSE is 3.3938% at the training stage and 11.0517 at the testing stage. The final accuracy is 98.16% at the training stage and 96.69% at the testing stage. The accuracy of the model indicated that this model has a high superior performance in the prediction of outlet temperature of boiling heat transfer in helical coils.

3.2. Predicted Data

In Figure 1, the blue line represents the line of 0 percent error, and the region between the orange line and the green line is the region of 10 percent error that is acceptable. As shown in the plot, some predicted values have an error of more than 10 percent. However, most of the predicted values have high accuracy and lie on the blue line in the region of 10 percent error. Thus, the overall result is highly acceptable. Furthermore, the developed model successfully predicts the heat transfer in the helical coils.

![Figure 1. The plot of the predicted outlet temperature compared to the actual outlet temperature.](image)

4. Conclusions

This paper aims to construct the artificial neural networks model in order to predict the outlet temperature of boiling heat transfer in helical coils. The author conducts 877 sets of data samples for heat transfer parameters. The model is constructed by the architecture of a feed-forward back-propagation (FFBP) multi-layer perceptron (MLP) ANNs and els. The results above show that this model has a superior performance in the prediction of the outlet temperature in the process of heat transfer in helical coils devices. And this model can be applied for other processes of heat transfer for the future works.

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