Coupled Computational Fluid Dynamics (CFD) and Artificial Neural Networks (ANNs) for Prediction of Thermal-hydraulic Performance of Plate-fin-tube Heat Exchangers

W. Yaici[1], E. Entchev[1]

[1]Renewable Energy, Heat and Power Laboratory, CanmetENERGY Research Centre, Natural Resources Canada, Ottawa, ON, Canada

Abstract

Plate fin-tube heat exchangers are used extensively in heating, ventilating, and air conditioning, process engineering, and refrigeration systems. They have a high degree of surface compactness. Substantial heat transfer enhancement is obtained as a result of the periodic starting and development of boundary layers over interrupted channels formed by the fins and their dissipation in the fin wakes. This is however accompanied by an increase in the pressure drop due to increased friction and form-drag contribution from the finite thickness of the interrupted fins.

Despite diverse research efforts made so far, the development of correlations for predicting heat transfer and friction characteristics of heat exchangers requires an extensive experimental database. The proposed correlations are generally within more than 20% accuracy compared to the experimental data.

This study presents a combination of computational fluid dynamics (CFD) and artificial neural networks (ANNs) to propose an alternative method for modelling and predicting the fluid flow and heat transfer characteristics of plate-fin-tube heat exchangers [1-10]. Since the development of accurate correlations for the prediction of the thermal-hydraulic performance of these heat exchangers require extensive testing and expensive equipment in experimental set-ups, Computational Intelligence techniques can be used as alternatives to conventional measurement and prediction methods. Hence, the objective of this work is to investigate the feasibility of using the coupled CFD and ANNs in order to propose precise correlations of heat transfer and friction data for these heat exchangers.

The ANN model was developed on a database generated by 3D-CFD analysis to predict the flow characteristics in a fin-tube heat exchanger [9-12]. Figure 1 illustrates an artificial neuron and a schematic of a multi-layer network. Figure 2 shows the geometric model of the plain-fin-tube staggered heat exchanger considered in the present study. 3D steady flow models of plate-fin-tube heat exchangers with four rows for staggered arrangement were built using the CFD Module of the COMSOL Multiphysics® software[1].

A validated CFD model (Figure 3) was used to generate a database that covered the range of Reynolds numbers from 200 to 2000 [2,3]. Computational assessments of the air-side heat transfer and pressure drop characteristics for a variety of geometrical parameters of

staggered plate fin-tube heat exchangers were undertaken on heat exchangers with different longitudinal tube pitches, transversal tube pitches, and fin pitches. Characteristics of CFD predicted thermal-hydraulic performance were reported in terms of Colburn j−factor, Fanning friction f−factor, and efficiency index j/f as a function of Reynolds (Re) numbers [3]. The results of the CFD data were utilized to train, validate and test the proposed ANN model.

The ANN model was then applied to predict j− and f−factors. The back-propagation learning algorithm with two different variants, the Levenberg-Marquardt algorithm (LM) and scaled conjugate gradient (SCG) algorithm were used in the networks.

Figure 4 presents a comparison of the relative errors between the results predicted by the ANN model and the CFD values. It can be seen that the f− and j−factor predictions agreed well with the CFD values using the training and testing data sets, within less than ±10% errors.

The ANN results have been also compared with the existing experimental data and correlation results of Wang et al. [13-15] and have been used to validate the implementation of the current CFD-ANNs investigation. A good agreement was obtained. The agreement between the ANN results and the data predicted from the correlations was within less than ±15% errors.

In conclusion, this study presented the results of a combination of computational fluid dynamics (CFD) and artificial neural networks (ANNs) to propose an alternative method for modelling and predicting the performance of plate-fin-tube heat exchangers. The results showed that it is possible to model and train certain architectures of ANNs with CFD data to predict the fluid flow and heat transfer characteristics of plate-fin-tube heat exchangers with good accuracy.

The results confirmed that the coupled CFD-ANNs is an effective and robust method for predicting the thermal-hydraulic performance of plate-fin-heat exchangers more accurately than the correlations proposed in the literature. This approach can be easily applied to other types of heat exchangers or energy systems.

Reference

[1] COMSOL Multiphysics, CFD, Heat Transfer Modules, Version 5.0, COMSOL, Inc., October 2014.
[2] W. Yaïci, M. Ghorab, E. Entchev, 3D CFD analysis of the effect of inlet air flow maldistribution on the fluid flow and heat transfer performances of plate-fin-and-tube laminar heat exchangers, International Journal of Heat and Mass Transfer 74 (2014) 490–500.
[3] W. Yaïci, M. Ghorab, E. Entchev, 3D CFD study of the effect of inlet air flow maldistribution on plate-fin-tube heat exchanger design and thermal–hydraulic performance, International Journal of Heat and Mass Transfer 101 (2016) 527–541.
[4] S. Haykin, Neural Networks: A Comprehensive Foundation, 2nd Edition, Prentice-Hall, New Jersey, 1999.
[5] L.V. Fausett, Fundamentals of Neural Networks: Architectures, Algorithms, and Applications, Prentice-Hall, Englewood Cliffs, New Jersey, 1994.
[6] L.M. Fu, Neural networks in Computer Intelligence, McGraw-Hill International Editions, New York, 1994, p. 460.
[7] M.T. Hagan, H.B. Demuth, M. Beale, Neural Network Design, PWS Publishing Company, Boston, 1995.
[8] S. Haykin, Neural Networks and Learning Machines (3rd Edition), Prentice Hall, New Jersey, 2009.
[9] W. Yaïci, E. Entchev, Performance prediction of a solar thermal energy system using artificial neural networks, Applied Thermal Engineering 73 (2014) 1346–57.
[10] W. Yaïci, E. Entchev, Adaptive Neuro-Fuzzy Inference System modelling for performance prediction of solar thermal energy system, Renewable Energy 86 (2016) 302-315.
[11] Mathworks, MATLAB, the Language of Technical Computing, Version 8.1 (Release R2013b), The MathWorks Inc., 2013.
[12] M.H. Beale, M.T. Hagan, H.B. Demuth, MATLAB Neural Network Toolbox™ User's Guide, MathWorks, Version 8.0.1 (Release 2013a), The Math-Works Inc., 2013.
[13] C.C. Wang, Y.C. Hsieh, Y.J. Chang, Y.T. Lin, Sensible heat and friction characteristics of plate fin-and-tube heat exchangers having plane fins, International Journal of Refrigeration 19 (1996) 223–230.
[14] C.C. Wang, K.Y. Chi, Heat transfer and friction characteristics of plain fin-and-tube heat exchangers, part I: new experimental data, International Journal of Heat and Mass Transfer 43 (2000) 2681–2691.
[15] C.C. Wang, K.Y. Chi, C.Y. Chang, Heat transfer and friction characteristics of plain fin-and-tube heat exchangers, part II: Heat transfer and friction characteristics of plain fin-and-tube heat exchangers, part II: correlation, International Journal of Heat and Mass Transfer 43 (2000) 2693–2700.

Figures used in the abstract

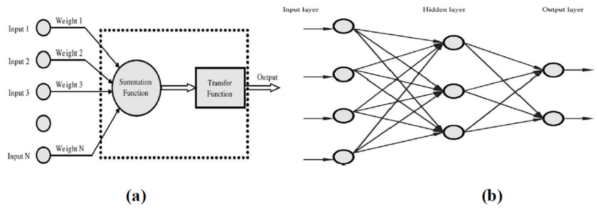

Figure 1: (a) Artificial neuron; (b) Schematic diagram of a multi-layer neural network.

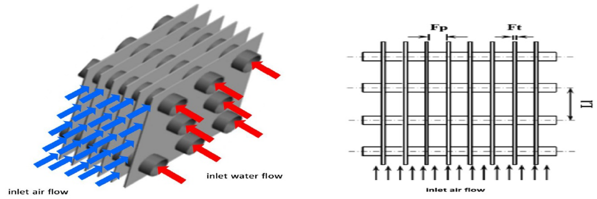

Figure 2: Schematic of typical staggered plain fin-tube compact heat exchanger [2,3].

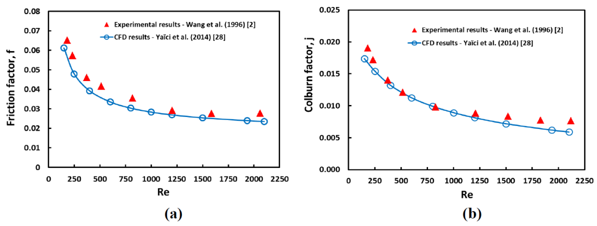

Figure 3: Comparison of CFD results of Yaïci et al. [2.3] with experimental results of Wang et al. [13] in the heat exchanger for validation study: (a) friction factor f; (b) Colburn factor j.

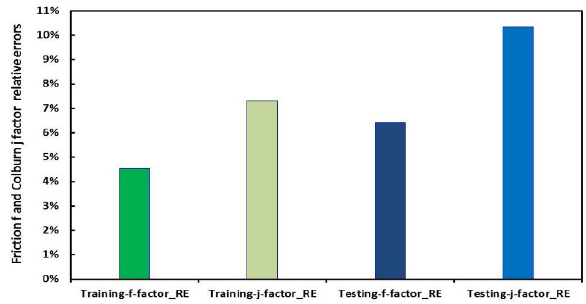

Figure 4: Comparison between CFD and ANN predicted friction f and Colburn j factor relative errors for ANN model using training and testing data.