Abstract

**Objectives:** The aim of the present work is to predict the value of pressure drop for different inlet-outlet configurations of an air cooled cross flow heat exchanger using artificial neural network. **Methods:** Configuration and mass flow rate are given as inputs. The pressure drop is calculated based on numerical simulations for various mass flow rates and different configurations. The numerical results are validated with experiments. This numerical data obtained for 4 different flow rates for each of the 24 configurations is used in training a back propagation based neural network to predict the pressure drop. **Results:** In the present work Levenberg-Marquardt algorithm is used to train the network. Two inputs are specified in the present study. Mass flow rate and type of configuration are assigned in the input layers and the output is the pressure drop across the heat exchanger. The number of hidden layers is fixed as 10 after a series of trial and error. The data are taken from the simulations and are fed to the network. 80% of data is taken for training and 20% are taken for validation and testing. Using the feed forward perception network the input is propagated and the error in the output is back propagated to modify the weight. Sigmoid transfer function is used as the activation function for the hidden layer and is represented in Equation 3. It can be concluded that the neural network is able to predict the pressure drop for varying input parameters. The neural network gave a mean regression coefficient to be 0.97. The regression plot for the training, validation, testing data has been shown in Figure 6. **Conclusion:** As the regression value approaches 1, it may be concluded that ANN is capable of predicting the results for different set of input parameters within the training range.

**Keywords:** Artificial Neural Network, Flow Maldistribution, Heat Exchangers, Pressure Drop, Radiator

1. Introduction

Heat Exchangers have various applications in the modern world. One of the most commonly found application is in radiators of automobiles, where the pressure required for the coolant to pass through the heat exchanger is supplied by a pump which in turn is driven by the engine itself. Hence, more the pressure drop across heat exchanger, more power is required by the pump. Thus increase in pressure drop has a direct effect on the engine performance. Position of the inlet and outlet ports (configuration) is one of the predominant factors influencing the pressure drop across the heat exchanger. Generally, 3 types of configurations are considered for manufacturing of heat exchanger. They are U-type, Z-type and I-type of which I-type and U-type are said to have the minimum and maximum pressure drops respectively as shown in Figure 1.

Artificial Neural Network (ANN) is a machine learning method that is being used in various predictions and optimisations. Artificial neural networks are capable of predicting the non linear relation ships between the inputs and outputs. A handful of works have been done in the past to analyse the performance of heat exchanger using ANN. Matsumoto, et al. studied the effect of pin arrangement on end wall heat transfer by applying neural network on color-temperature transformation using thermo sensitive liquid crystal film. Mazzola studied the
Artificial Neural Network based Prediction of Pressure Drop in Heat Exchangers

Diaz, et al.3 used ANN to design a dynamic control for a heat exchanger. The authors also tested the performance of the single row, fin tube heat exchanger using ANN4. It is difficult to study the performance of heat exchangers experimentally because of the variety of parameters involved in the physical structure of the heat exchanger. Ding, et al.5 used a hybrid method involving a combination of mathematical model with ANN and arrived at a faster computing algorithm for the study of heat exchangers. Rui, et al.6 used a self adaptive method using ANN and presented a model for accurate simulation of heat exchangers. Baby and Balaji7 used ANN to optimize the thermal performance of phase change material based heat sinks. Xiao, et al.8 studied the parametric dependency of fins in heat exchangers using Artificial Neural Network. They used Levenberg-Marquardt based training on the experimental results. Gharechopogh, et al.9 employed a new approach in ANN algorithms for bloggers classification. Mohanraj, et al.10 applied ANN for thermal analysis of heat exchangers. The heat exchanger performance assessment was done using intelligent decision making tools by Ahilan, et al.11.

It can be seen that ANN has been used widely to study the performance of heat exchangers. The present work is aimed at filling the research gap by predicting the pressure drop in radiators using ANN. The aim of the present work is to predict the pressure drop for a given configuration (inlet-outlet combination) and given mass flow rate for an air cooled cross flow heat exchanger using artificial neural network. Different configurations are obtained by changing the position of the inlet and outlet ports. The results are based on numerical simulations done in ANSYS FLUENT ©12 and validated with the experiments.

2. Experimental Setup

2.1 Cycle Thermodynamic Simulation

The line diagram of the experimental setup is shown in Figure 2 and Figure 3. In U and Z-type configurations, the orientations of the inlet/outlet ports are such that the ports are positioned in directions either perpendicular to the flow in the manifold or parallel to it. Therefore by orienting the ports in both directions (parallel to the flow in the manifold and perpendicular to the flow in the manifold) in U and Z-type configurations, more inlet-outlet combinations are obtained. In I-type configuration, the inlet and outlet ports are oriented in parallel direction to the flow in the channels and then in perpendicular direction to the flow in the channels. These orientations result in 4 inlet ports (denoted by alphabets) and 6 (denoted by numbers) outlet ports. Thus in overall, 24 configurations are obtained by selecting one inlet and one outlet port at a time. Each inlet and outlet port is provided with a valve and care is taken such that only one inlet and one outlet
Figure 2. Schematic diagram of experimental setup.

Figure 3. Experimental setup (Line diagram).

For example, consider a flow configuration A6. Here, 'A' represents the inlet port and the '6' represents the outlet port. The valves of ports 'A' and '6' alone are opened in A6 configuration while all other valves are closed.

Working fluid is supplied from a tank to the inlet of heat exchanger through a pump. Volumetric flow rate of the working fluid is calculated with help of a measuring vessel and is controlled by a control valve. Bypass pipes both from inlet and outlet ports are connected to a differential pressure transmitter (BT-DPT-II) which generates a 4-20mA output for measuring the pressure drop across the heat exchanger. This current output is measured online continuously using NI cDAQ 9174 chassis with NI 9203, 8 channel current input analog module with a frequency of 1kHz. The heat exchanger used for the experiments is a Maruti Omni radiator.

3. Numerical Model

The 3D geometric model of heat exchanger used for experimental studies is modelled in Solid works and is imported to ICEM-CFD for grid generation. A compromise between the grid size and the computational time has to be made, for the size of the grid to be minimal with fewer approximations. The computational time is directly proportional to the number of elements. So in order to reduce the computational time, smaller grid size should be used. But smaller grid size gives rise to higher degree of approximations. The grid independent study gives a measure of the sensitivity of the grid. For different grid sizes with the same boundary conditions, the solutions are obtained and optimal grid size is selected. The parameter considered for the grid independent study is the pressure difference across the heat exchanger. From the results of grid independent study an optimum mesh size of around 25,00,000 elements is used to generate mesh and exported to solver. The flow governing equations are mass and momentum equations shown in eqn 1 and eqn 2 and are solved in ANSYS FLUENT.

Continuity equation:

\[
\frac{\partial \rho}{\partial t} + \nabla \cdot (\rho V) = 0
\]  \hspace{1cm} (1)

Momentum equation:

\[
P \frac{\partial V}{\partial t} + \rho (V \cdot \nabla) V = -\nabla p + \rho g + \nabla \cdot \tau
\]  \hspace{1cm} (2)

Here \(P\) is the pressure, \(V\) is the velocity, \(\rho\) is the density, \(g\) is gravitational constant, \(\tau\) is the shear stress. Working fluid is water of density 998.2kg/m\(^3\) and dynamic viscosity 0.001003kg/m-s. The boundary conditions adopted in the present work is detailed in Reference 13. The model is validated with the results of described experimental setup. A detailed description on validation is available in Reference 13. The pressure drop across the heat exchanger is found for 24 configurations for four different Reynolds numbers. This is shown in the Figure 4.
3.1 Pressure Drop Prediction using Artificial Neural Network

In the present work ANN is employed to predict the result for a specific set of inputs. ANN makes use of neural network similar to that of the neurons present in human beings. An activation function and a weight are assigned to every neuron. It has set of layers like input layers, hidden layers and output layers that are employed to train, test and validation of the results. In the present work Levenberg-Marquardt algorithm is used to train the network. Two inputs are specified in the present study. Mass flow rate and type of configuration are assigned in the input layers and the output is the pressure drop across the heat exchanger. The number of hidden layers is fixed as 10 after a series of trial and error. The data are taken from the simulations and are fed to the network. 80% of data is taken for training and 20% are taken for validation and testing. Using the feed forward perception network the input is propagated and the error in the output is back propagated to modify the weight. Sigmoid transfer function is used as the activation function for the hidden layer and is represented in Equation 3. The designed ANN is shown in Figure 5. It can be concluded that the neural network is able to predict the pressure drop for varying input parameters. The neural network gave a mean regression coefficient to be 0.97. The regression plot for the training, validation, testing data has been shown in Figure 6. It can be seen that the regression coefficient is close to 1 which makes it clear that ANN is able to predict the pressure drop precisely. This makes Neural Network an effective tool in designing the heat exchangers. Table 1 shows a comparison of few values between the predicted value of pressure drop by ANN, experimental and numerical simulation by Ansys Fluent ©.

\[ S(t) = \frac{1}{1 + e^{-t}} \]  

(3)

4. Conclusion

In the present study cross flow heat exchanger is numerically analyzed. Artificial Neural Network is employed to predict the pressure drop across the channels. Set of data for training are taken from numerical simulations and are fed to the neural network. As the regression value approaches 1, it may be concluded that ANN is capable of predicting the results for different set of input parameters within the training range. This makes Artificial Neural Network an effective tool in predicting the pressure drop. Since minimal pressure drop is a criteria for an effective design of heat exchangers ANN can be effectively used as
Figure 5. Neural network.

Figure 6. Regression coefficient.
Table 1. Comparison between ANN predicted, experimental and numerical

| Configuration | Reynolds number | Pressure Drop (Pa) |
|---------------|----------------|--------------------|
| D4            | 25000          | ANN predicted: 4958 | Experimental: 5000 | Numerical: 4900 |
| D4            | 28000          | ANN predicted: 7520 | Experimental: 8000 | Numerical: 7500 |
| D4            | 32000          | ANN predicted: 7224 | Experimental: 8000 | Numerical: 7200 |

a tool for thermal designing of heat exchangers. Further, the efforts are being made to predict the flow maldistribution for each of the 24 configurations.

5. References

1. Matsumoto R, Kikkawa S, Senda M. Effect of pin fin arrangement on endwall heat transfer. Nippon Kikai Gakkai Ronbunshu, B Hen/Transactions of the Japan Society of Mechanical Engineers, Part B. 1996; 62:1953–61.
2. Mazzola A. On the evaluation of two-phase density in heated channels via artificial neural networks. Kerntechnik. 1997; 62:166–71.
3. Diaz G, Sen M, Yang KT, McClain RL. Artificial neural network control of an experimental heat exchanger facility. American Society of Mechanical Engineers, Heat Transfer Division, (Publication) HTD; 1999. p. 325–30.
4. Diaz G, Sen M, Yang KT, McClain RL. Simulation of heat exchanger performance by artificial neural networks. ASHRAE Transactions. 2000. p. PA/.
5. Ding GL, Zhang CL, Liu H. A fast simulation model combining with artificial neural networks for fin-and-tube condenser. Heat Tran Asian Res, 2002; 31:551–7.
6. Rui YB, Ding GL, Wu ZG. Accuracy self-adaptive method of fin and tube heat exchanger simulation software. Shanghai Jiaotong Daxue Xuebao/Journal of Shanghai Jiaotong University. 2006; 40:1360–4.
7. Baby R, Balaji C. A neural network-based optimization of thermal performance of phase change material-based finned heat sinks—an experimental study. Exp Heat Tran. 2013; 26:431–52.
8. Xiao BL, Yu XL, Han S, Lu GD, Xia LF. Parameter sensitivity analysis of fin based on neural network in heat exchanger. Zhejiang Daxue Xuebao (Gongxue Ban)/Journal of Zhejiang University (Engineering Science). 2011; 45:122–5+145.
9. Gharehchopogh FS, Khaze SR, Maleki I. A new approach in bloggers classification with hybrid of K-nearest neighbor and artificial neural network algorithms. Indian Journal of Science and Technology. 2015; 8(3):237–46.
10. Mohanraj M, Jayaraj S, Muraleedharan C. Application of artificial neural network for thermal analysis of heat exchangers. Int J Therm Sci. 2015; 90:150–72.
11. Ahilan C, Dhas JER, Somasundaram K, Sivakumaran N. Performance assement of heat exchangers using intelligent decision making tools. Applied Soft Computing. 2015; 26:474–82.
12. Fluent A. 12.0 User's guide. User Inputs for Porous Media; 2009. p. 6.
13. Mohan KP, Santosh SM, Ramakanth M, Thansekhar MR, Venkatesan M. Analysis of flow maldistribution in cross flow heat exchanger. Appl Mech Mater. 2014; 592-594:1428–1432.
14. Shekar MS, Ramakanth M, Krishna PM, Venkatesan M. Flow mal-distribution in a cross-flow heat exchanger. Fortieth National Conference on Fluid Mechanics and Fluid Power, FMFP2013; NIT Hamirpur, India: 2013. paper No. 220.