**Indian Journal of Science and Technology**, *Vol 8(S9), 341-346, May 2015*

*ISSN (Print) : 0974-6846*
*ISSN (Online) : 0974-5645*
*DOI: 10.17485/ijst/2015/v8iS9/65585*

# Prediction of Channel Diameter to Reduce Flow Mal Distribution in Radiators using ANN

**M. Ramakanth, C. Balachandar and M. Venkatesan***

School of Mechanical Engineering, SASTRA University, Thanjavur, Tamilnadu, 613401, India;
ramakanth.raman@gmail.com, balachidambaram1993@gmail.com, mvenkat@mech.sastra.edu

## Abstract

**Background/Objectives:** The non-uniform flow of fluid over parallel channels having a common inlet and outlet is called flow mal distribution. The problem of flow mal distribution is predominant in heat exchangers and affects their performances by increasing the pressure drop over the channels and has non-uniform mass flow rate. **Methods/Statistical Analysis:** In the present study a numerical model using commercial code ANSYS FLUENT © of a cross flow heat exchanger is presented and validated with experimental results. The main objective of the study is to optimize the heat exchanger to reduce the mal-distribution of the fluid. A Soft computing technique, Artificial Neural Network (ANN) is used to predict and optimize the size of the heat exchanger. The neural network is trained by results obtained from the numerical simulations for different conditions. **Results:** It has been found that the flow mal distribution is minimum when the individual channel diameter is minimum. Increasing the channel diameter increases the non-uniformity in the mass flow rate. It has been ascertained from the mean standard deviation based on Neural network prediction that reducing the diameter of the channels 11 and 12 plays a major role in reducing the flow mal distribution inside the heat exchanger. **Conclusion/Application:** The trained neural network predicts the mass flow rate. Based on these results the heat exchanger is optimized to minimize the flow mal distribution. This Neural network can further be implemented for any design.

**Keywords:** Artificial Neural Network, Flow Mal-distribution, Heat Exchanger, Mass Flow Rate, Numerical Simulations

## 1. Introduction

Heat exchangers are used to transfer heat from one fluid to other, especially in cooling systems where the generated heat has to be removed from the system for efficient working. The heat exchangers face a problem of mal-distribution of the fluid that flows over parallel channels having a common header. This results in reduction of heat transfer and increased pressure drop which are undesirable. Rao and Das[1] did an experiment on plate heat exchanger and studied the flow mal distribution. Their results emphasized the importance of the port size and the dependence of flow mal distribution on the port size. Jung and Jeong[2] analytically analyzed NTU in multi-channel heat exchanger with flow distribution effect. They have represented combined effects of mal distribution and poor transverse conduction that degrades the multi-channel heat exchanger NTU. Churchill and Chu[3] experimentally and numerically analyzed the flow mal distribution of parallel micro channel. They have studied the effect of different header assembly and its effect in mal distribution. Huang, et al.[4] used combined CFD and NTU based co-simulation approach in micro channel heat exchanger to study the flow mal distribution characteristics. They also have extended their approach to two phase flows in heat exchangers.

Apart from experimental and numerical works, computing techniques such as Fuzzy Logic, Artificial Neural Network, Genetic Algorithm, have played a major role in prediction of the results and optimization of the physi-

*Author for correspondence

cal model. Pacheco-Vega, et al.[5] used ANN to predict the performance of a compact heat exchanger with tube-fins and concluded that the ANN predicted results are better than available correlations. Diaz, et al.[6] predicted the performance of single-row, fin-tube heat exchanger with ANN and compared it with laboratory experimental results. Pacheco-Vega, et al.[7] studied the performance of refrigerating heat exchanger using ANN based on limited experimental results. Jia and Sunden[8] used ANN to optimize the plate fin heat exchanger. They have also found relationship between thermal coefficient and other parameters such as geometry of the model. Tan, et al.[9] made use of ANN model of compact heat exchangers to study the thermal performance. They concluded that the ANN is accurate by comparing experimental results with that of predicted results. Latha, et al.[10] applied the ANN in predicting the thermal resistance of loop heat exchanger and also have stated that ANN results have been very promising with sufficient experimental results.

The above literature review represents the predicting potential of ANN with greater accuracy and hence this predicting tool can be applied to study the performance and to optimize the geometry of the heat exchanger to reduce the flow mal distribution. In this present work numerical model of cross flow heat exchanger is presented and the simulated results are trained using ANN. The geometry is optimized to reduce the mal distribution of the fluid in channels to enhance the performance.

## 2. Numerical Model

The present problem is analyzed numerically using ANSYS FLUENT 3D. The geometry is created in SOLID WORKS and the model is shown in Figure 1. It includes an inlet and outlet heater connected to an inlet and outlet respectively. The model consists of two parallel rows of channels containing 22 channels in a row. The dimensions are chosen in such a way that the model is similar to that of dimensions of a Maruthi Omni radiator. It has been shown in References [11,12] that among the three configurations (Z, U and I types), I has the least flow mal distribution and further numerical predictions are done only in this configuration.

### 2.1 Grid Independency and Validation of Numerical Model

The geometry is meshed using ICEM CFD. The parameter considered for grid independency is change in pressure drop across the channels. The grid independency test is carried out and is represented in Figure 2. In the present study 2500000 elements is taken as optimal mesh. This mesh is then exported to FLUENT to carry out the analysis. Validation is done by comparing numerical results with that of the experimental results which is conducted on a similar cross flow heat exchanger. The validation is represented in Figure 3 taking the change in pressure drop for different Reynolds number. The model result are closer with that of experimental results and validates the numerical model for the present study.

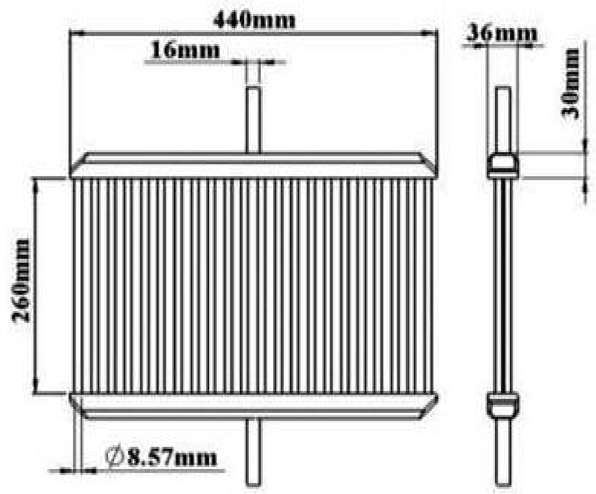


**Figure 1.** Geometry of the numerical model.

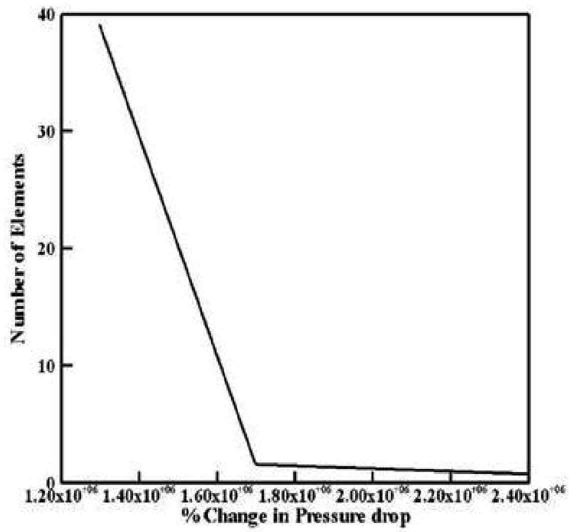


**Figure 2.** Grid independency study[12].

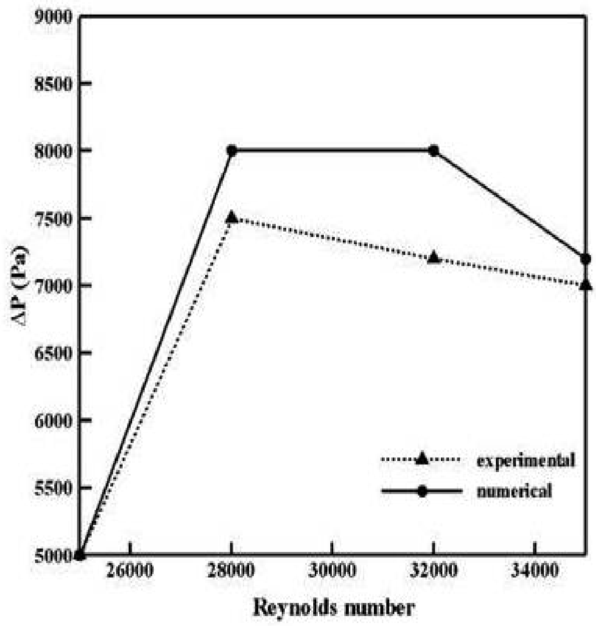


**Figure 3.** Numerical model validation[12].

## 3. Results and Discussion

In the present numerical analysis parametric dependency of the flow mal distribution on the channel diameter is studied. The analysis starts with varying the diameters of the channels. The diameter of all the channels are taken as constant and is varied from 2 – 10 mm and the mass flow rate is measured. It is observed from the analysis that mass flow rate is very high on channels 11 and 12 and very low on 10 and 13. In the rest of the channels mass flow rate is found to be steady and uniform. Further analysis is carried to reduce the flow mal distribution by varying the diameters of channels 10,11,12,13 through which the flow is not uniform. The diameters are varied from 3-9 mm and the mass flow rate of all the channels is calculated. The mean standard deviation of mass flow rate is calculated as per the relation shown in Equation 1. Smaller the deviation in mass flow rate, uniform the flow of fluids in the channels.

$$\sigma = \sqrt{\frac{1}{N}\sum_{i=1}^{N}(\dot{m}_i - \dot{m})^2} \quad (1)$$

Here σ is the mean standard deviation, $\dot{m}$ is the mass flow rate and N is the total number of observations.

### 3.1 Mass Flow Rate Prediction using Artificial Neural Network (ANN)

Artificial neural network is soft computing technique that was created analogues to the neuron network of human body. Neural Network toolbox of MATLAB is used to model the ANN. It makes use of group of neurons that forms layer which are classified as hidden, input and output layers. An activation function and a weight are assigned to every neuron. The Levenberg-Marquardt back propagation algorithm is used to train the network. The input given is the diameters of the channels and the output is the mean standard deviation. The data are taken from the simulations and are fed to the network. 70% of data is taken for training and 30% of taken for validation and testing. Using the feed forward perception network the input is propagated and the output error is back propagated to modify the weight. Initially the number of hidden layers is taken as 5 and the network is trained. The number of hidden layers is increased to make the regression coefficient approach 1. After series of trial and error approach the number of hidden layers is taken as 10. The activation function used is Sigmoid transfer function for the hidden layer and is represented in equation 2. The designed ANN is shown in Figure 4.

$$S(t) = \frac{1}{1+e^{-t}} \quad (2)$$

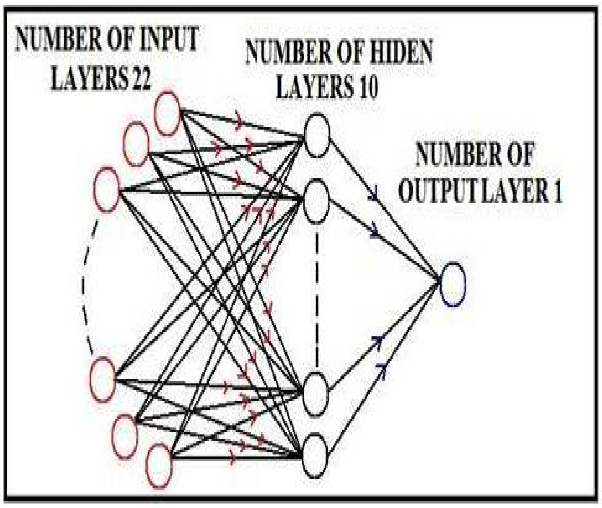


**Figure 4.** Neural network comprising of different layers.

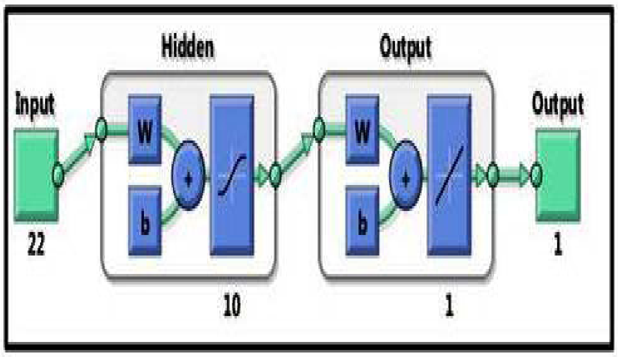


**Figure 5.** Neural Network[13].

Figure 5 shows the Simulink result of the ANN designed using Matlab toolbox[13] which could be further used to predict the mass flow data when the channel diameters are given as input to the toolbox. The neural network gave a mean regression coefficient to be 0.99. The regression plot for the validation, training and testing data is shown in Figure 6.

The contour comprising of channel number, channel diameter and mean standard deviation of the mass flow rate is represented in Figure 7. From this graph it can be concluded that the parameters for uniform mass flow rate having a reduced mal distribution of fluid is found to minimum for a low diameter tube (2 mm). The minimum mean standard deviation is indicated by blue color. The encircled portion indicates the region in which the other tube diameters are kept constant at 8.57 mm and the tube diameters of channel 11 and 12 alone is varied. This also indicates that to reduce the mal distribution the diameter of the channels 11 and 12 has to be reduced.

## 4. Conclusion

In this present study cross flow heat exchanger is numerically investigated and Artificial Neural Network is used to predict the mean standard deviation of the mass flow rate for different channel diameters. The result from the numerical simulation is fed to the neural network to train

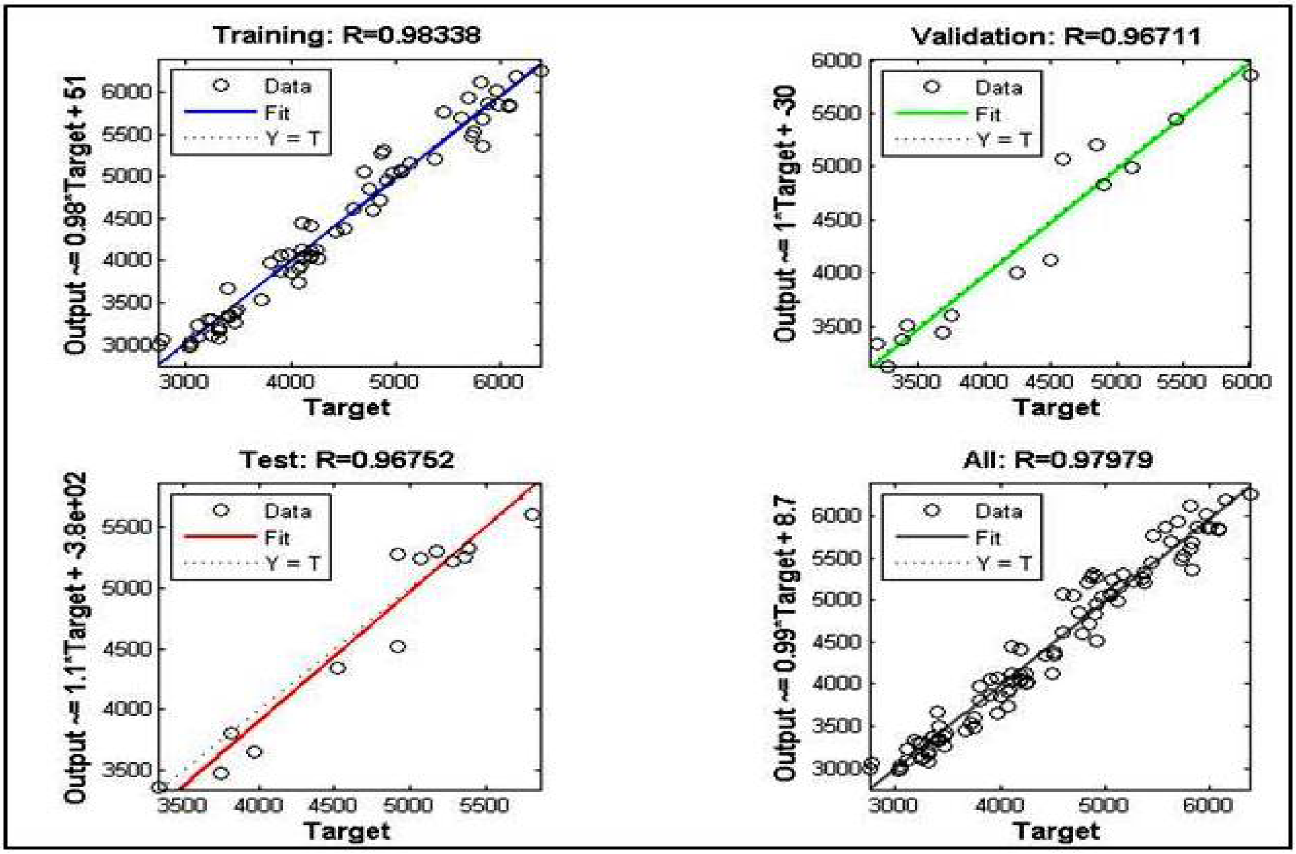


**Figure 6.** Regression plot.

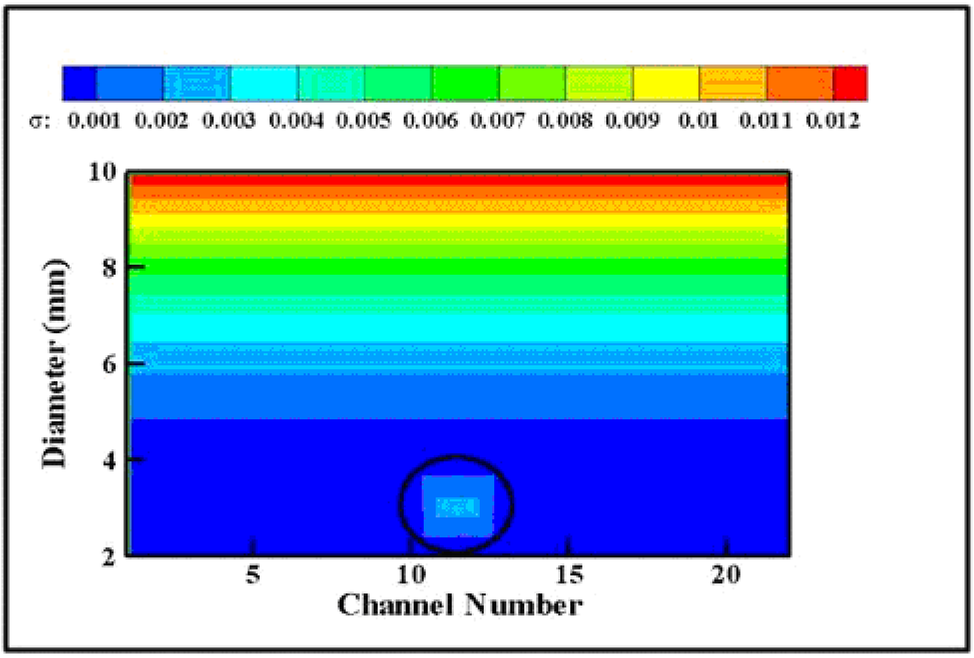


**Figure 7.** Contour graph based on ANN prediction.

it and the predictions are made to obtain the optimal parameters to reduce the flow mal distribution. It has been found that the flow mal distribution is minimum when the individual channel diameter is minimum. Increasing the channel diameter increases the non-uniformity in the mass flow rate. It has been ascertained from the mean standard deviation based on Neural network prediction that reducing the diameter of the channels 11 and 12 plays a major role in reducing the flow mal distribution inside the heat exchanger. Hence it can be concluded that ANN can be a handy tool in the effective design of heat exchanger.

## 5. References


1. Rao BP, Das SK. An experimental study on the influence of flow maldistribution on the pressure drop across a plate heat exchanger. J Fluid Eng. 2004; 126:680–91.
2. Jung J, Jeong S. Effect of flow mal-distribution on effective NTU in multi-channel counter-flow heat exchanger of single body. Cryogenics. 2007; 47:232–42.
3. Churchill SW, Chu HH. Correlating equations for laminar and turbulent free convection from a vertical plate. Int J Heat Mass Tran. 1975; 18:1323–9.
4. Huang L, Lee MS, Saleh K, Aute V, Radermacher R. A computational fluid dynamics and effectiveness-NTU based co-simulation approach for flow mal-distribution analysis in microchannel heat exchanger headers. Appl Therm Eng. 2014; 65:447–57.
5. Pacheco-Vega A, Sen M, Yang KT, McClain RL. Prediction of humid air heat exchanger performance using artificial neural networks. American Society of Mechanical Engineers, Heat Transfer Division, (Publication) HTD; 1999. p. 307–14.
6. Diaz G, Sen M, Yang KT, McClain RL. Simulation of heat exchanger performance by artificial neural networks. Build Eng. 2000.
7. Pacheco-Vega A, Sen M, Yang KT, McClain RL. Neural network analysis of fin-tube refrigerating heat exchanger with limited experimental data. International Journal of Heat and Mass Transfer. 2001; 44:763–70.
8. Jia R, Sundén B. Optimal design of compact heat exchangers by an artificial neural network method. ASME 2003 Heat Transfer Summer Conference; 2003. p. 655–64.
9. Tan C, Ward J, Wilcox S, Payne R. Artificial neural network modelling of the thermal performance of a compact heat exchanger. Appl Therm Eng. 2009; 29:3609–17.
10. Latha A, Reddy KVK, Rao JCS, Raju ASR. Performance analysis on modeling of loop heat pipes using artificial neural networks. Indian Journal of Science and Technology. 2010; 3:463–7.
11. Mohan KP, Santosh SM, Ramakanth M, Thansekhar M, Venkatesan M. Analysis of flow mal-distribution in a cross-flow heat exchanger. Appl Mech Mater. 2014; 1428–32.

12. Santosh Shekar MRM, Mohan Krishna P, Venkatesan M. Flow mal-distribution in a cross-flow heat exchanger. Fortieth National Conference on Fluid Mechanics and Fluid Power, FMFP2013; India: NIT Hamirpur; 2013.
13. Demuth HB, Beale MH. Neural network toolbox for use with MATLAB: Computation, Visualization, Programming-User's Guide: MathWorks, Incorporated, 2000.