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Neural Network-Based Prediction of Adiabatic Capillary Tube Characteristics With Alternative Refrigerant

Amer Nordin Darus[1*], Shodiya Sulaimon[1,2], Azhar Abdul Aziz[1], Henry Nasution[2,3]

[1]Department of Thermofluids, Faculty of Mechanical Engineering, Universiti Teknologi Malaysia (UTM),Skudai, Johor, Malaysia.
[2]Department of Mechanical Engineering, Faculty of Engineering, University of Maiduguri (UNIMAID), Maiduguri, Borno, Nigeria.
[3]Department of Mechanical Engineering, Bung Hatta University
E-mail: amer@fkm.utm.my

Abstract

Capillary tubes are expansion device which are commonly used in small vapour compression refrigeration systems. An artificial neural network (ANN), a feed-forward network with back propagation algorithm was developed using alternative refrigerant. The feed-forward ANN with three-layers is used as a universal approximator for the multiple-input and single-output non-linear function. For the ANN training and testing, experimental data for refrigerant HC290/HC600a/HFC407C mixture from open literature was used. The most appropriate number of neurons in the hidden layer was found to be fifteen with average error between the predicted mass flow rate from ANN and experimental data is less than 1.6%. This paper shows the suitability of ANN for the predictions of mass flow rate of alternative refrigerant flowing through adiabatic capillary tube.

***Keywords**: Capillary tube, Refrigeration system, ANN, Alternative refrigerant*

1. Introduction

Capillary tubes are predetermined lengths of small diameter pipe that is located between the condenser and evaporator of the refrigeration system. It helps in reducing the high pressure condenser to the low pressure evaporator and also controls the refrigerant flow into the evaporator. Figure 1 shows refrigeration system with capillary tube as expansion device and the p-h diagram. Capillary tubes are widely used in refrigerators, freezers and small air-conditioners because of their simplicity, reliability and low cost. Though, it configuration is simple, the refrigerant is a complex two-phase flow under a given operating condition.

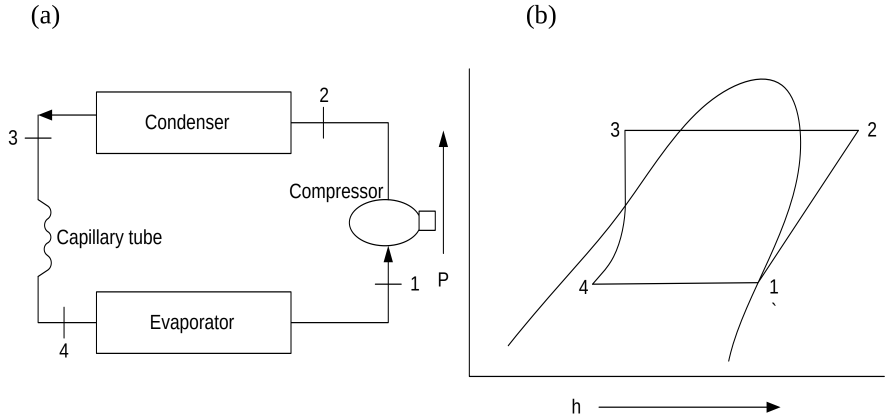

Figure 1: (a) Refrigeration system with capillary tube as expansion device (b) the p-h diagram

The mass flow rate of the refrigerant through the capillary tube has a strong influence on the performance of the system. Due to the Montreal Protocol that was signed world wide, the halogenated refrigerants must be substituted with environmentally friendly refrigerants (Lorentzen, 1994). As a result, all potential refrigerants must be assessed with the refrigeration system components and capillary tube, being the heart of the system, needs special attention.

For cost effectiveness, numerical models are developed to study the refrigerant flow characteristics in the capillary tube. To generate theoretical models, some researchers used mathematical approach that is based on numerical simulations of refrigerant flow in capillary tube. The models used by Wong and Ooi (1995), Wong and Ooi (1996), Bansal and Rupasinghe (1998), Sami and Tribes (1998), Wonwises et al. (2000b), Gu et al. (2003) and Bansal and Yang (2005) divided the capillary tube length into two regions: single-phase subcooled liquid and two-phase vapor liquid regions. The two-phase flow has been generally simplify to be homogeneous two-phase where it is assumed that no slip occurs between the phases. For example, Bansal and Rupasinghe (1998) developed a two-phase homogeneous model which they termed 'CAPIL'. The mass, energy and momentum conservation equations were solved simultaneously using iterative procedure and Simpson's rule.

Another approach employed is the separated flow model where the slip that existed between the liquid and vapor is considered and a mixture variable called void fraction is introduced to the conservation equations. For instance, Wongwises et al. (2000a), used separated flow model to compare various two-phase friction correlations and slip ratio correlations. They applied the conservation of mass, momentum and energy equations to obtain sets of partial differential equations which were solved using fourth order Runge-Kutta method. The last model that is often used is the drift flux model where the entire two-phase liquid-vapor mixture is considered when formulating the conservation equations. Liang and Wong (2001) in their study, developed a model based on drift flux formulation to predict the R-134a behavior in adiabatic capillary tube. Their model has been validated with experimental data of previous researches.

From the numerical studies reviewed, most of the researchers developed mathematical models to determine the performance characteristics of refrigerant flow in the capillary tube. In this approach, computer program are developed to solve large set of partial differential equations, especially the separated flow and drift flux models, which are not only complicated but also time consuming. In addition, some geometric correlations are required in the modelling which may not be readily available, hence, affecting the accuracy of the model. An alternative way of determining performance characteristics of adiabatic capillary tube is by applying artificial neural network (ANN) which requires less effort. This technique is based on the mechanism of human brain by imitation. It has been applied in so many engineering practice especially where traditional approach could not be used or too complex as reviewed by Mohanraj et al. (2012). ANN has a functional capability of transforming its input data to a precise defined output when adequate experimental data are provided.

Many investigators have used ANN in modelling performance characteristics of adiabatic capillary tube in refrigeration and air-conditioning system. For example, Islamoglu at al. (2005) used ANN to predict the performance of non-adiabatic capillary tube using back propagation (BP) algorithm. Zhang and Zhao (2007), using ANN developed a correlation for refrigerant mass flow rate in adiabatic capillary tube using refrigerant R600a and R407C. A network 5-6-1 was used to train the simulated data obtained from homogenous equilibrium model (HEM). Also, Vins and Vaceks (2009), presented experimental investigation on two-phase flow in capillary tube using R-218 refrigerant. Two correlations were developed using two approaches: conventional Buckingham pi theorem and artificial neural network (ANN) approach. Comparing the two approaches, the average and standard deviation for Buckingham pi theorem correlation gives -0.41% and 4.85% respectively while the ANN correlation gives -0.12% and 3.45% respectively.

Most of the previous studies on this issue used conventional refrigerants, which are not ecologically friendly, in their investigations. The main objective of this study is to use ANN approach to simulate alternative refrigerants (ecologically friendly) using experimental data of Jabaraj et al.,(2006).

2. ARTIFICIAL NEURAL NETWORK MODEL

ANN is an attempt at modeling the information processing capabilities of the brain and nervous systems. The brain consist of large number (approximately 10^{11}) of highly connected elements (approximately 10^{4} connections per element) called neuron. Each neuron consists of three components – dendrite, cell body and axon. The dendrite (input unit) receive electric signal and pass it to cell body (processing unit) that process the signal and pass the processed signal to other neuron through the axon (output unit). The ANN is analogous to the biological neural network whereby the network is trained by some set of input and the associated output data. After the training, another set of input data are used to predict the output with the hope that during the training, the neurons has learned the relationship between the input and output data (error between the output and target is minimal). A typical example of an architectural neural network that consists of three layers is shown in Figure 2. As shown in the Figure, there are R inputs, S^1 neurons in the first layer; S^2 neurons in the second layer etc. Different layers can have different number of neurons. The number of hidden layer may be varied which can improve the predictive capability of the network. The number of input parameter must be equal to the number of input layer. Likewise, the number of output parameter must also be equal to the number of output layer.

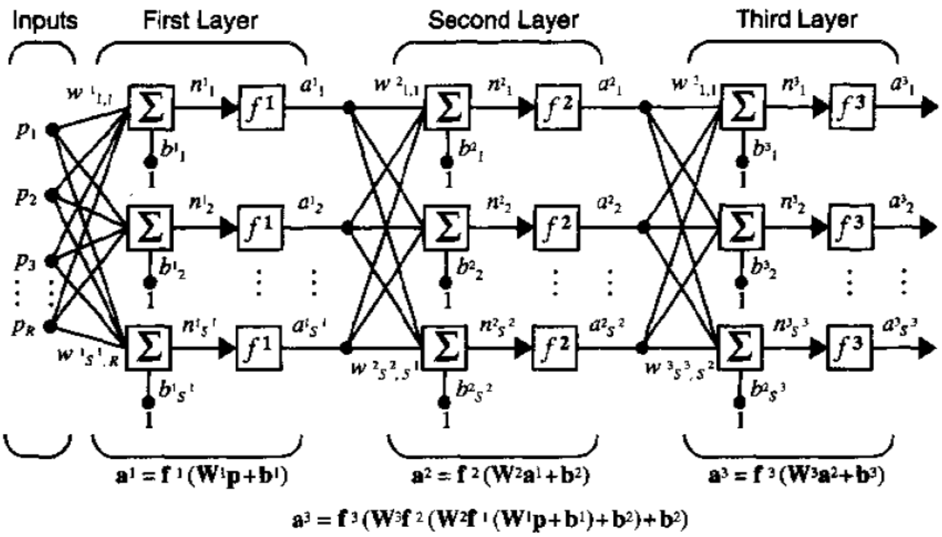

Figure 2: Three layers Network (Martin et al., 1996)

In this present study, the mass flow rate (output parameter) is a function of four input parameters, namely, condenser temperature, Capillary tube length, capillary tube inner diameter and subcooling. The architectural structure is shown in Figure 3 which comprises of input layer with four neurons, hidden layer with six and four neurons and output layer with one neuron. 70% of the experimental data was used for training, 15% for validation and the remaining 15% was used for testing.

A back propagation (BP) algorithm was used to train the network because it has been proven that BP with appropriate number of hidden layer, can successfully model any nonlinear relation to high level of accuracy. The purpose of BP is to reduce the error between the output (o) and the target (t) as much as possible. The ANN neuron activation for unit j is formed from the weighted (w_{ji}) linear sum of the inputs to unit j with the bias $(bias_i^p)$, given in equation (1):

$$o_j^p = \sum_i w_{ji}\, i_i^p + bias_i^p \qquad (1)$$

i_i is the ith input to j, o_j is the output and the function “f” that is chosen is sigmoid function, i.e

$$f(o_j) = \frac{1}{1 + e^{-o_j}} \qquad (2)$$

The mean square error (MSE) during the learning process is given in equation (3)

$$MSE = \frac{1}{n}\sum_j (t_j - o_j)^2 \qquad (3)$$

Where “t” is the measured data and “o” is the ANN result.

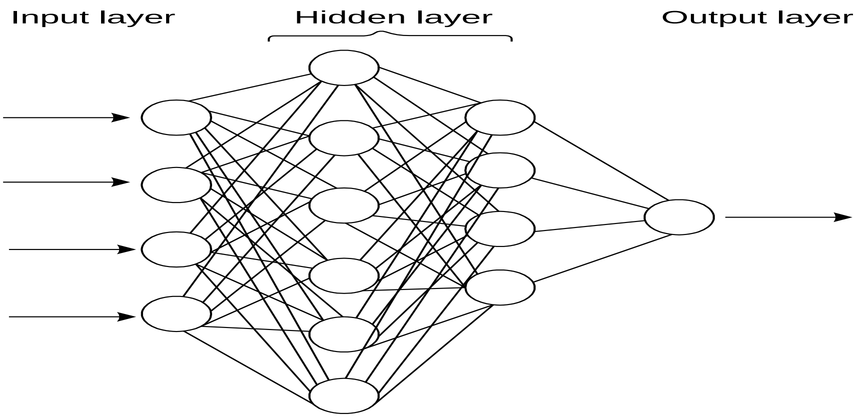

Figure 3: schematic diagram of multilayered ANN

3.0 RESULTS AND DISCUSION

A trial and error method was used for the selection of number of neurons in the hidden layer starting from 5, 10, 15 and 20. Also 70% data that was used for the training was randomly selected from experimental data of Jabaraj et al.,(2006) to ensure homogeneity and better training of the network for better prediction. Figure 4 – 7 depicts the effect of number of neurons (n) in the hidden layer on the output of the network for training, validating, testing and the combination of these three. The most important in these figures are the training and testing results, as a result, only these two will be in the discussion. In the figures, the target (measured results) mass flow rate is in the abscissa and the output (predicted from ANN) is on the ordinate.

In Figure 4, with hidden neuron n = 5, it can be seen from the testing result that the target mass flow rate between about 4kg/s to 12.2 kg/s has a very wide different with the output. Also, there is an outlier of the experimental data at 10.2kg/s. Consequently, the testing result has a very high mean square error (MSE) of 1.5856kg/s and R^2 of 0.94477. This high error could also be attributed to inappropriate selection of initial condition of the network for the training.

Figure 5 compares the mass flow rate prediction from ANN (output) and sample result (target) for n = 10. In this figure, n has been increased from 5 to 10 and there is an improvement in the prediction of mass flow rate due to better training of the network. It is observed that in the training, the predictions are highly improved at higher mass flow rate between about 8 – 15 kg/s. However, at the lower mass flow rate, the prediction is still highly inaccurate. As a result, in the testing section, the prediction improves at relatively higher mass flow rate with MSE of 0.4500kg/s and R^2 of 0.97634.

Similarly, Figure 6 compares the mass flow rate prediction from ANN (output) and sample result (target) for n =15. It could be observed that the prediction has improved considerably compared to Figure 5. The mass flow rate prediction in the training section almost equal to the target mass flow rate at the two extremes, that is lower and higher mass flow rate. Conversely, at the middle (between 10 – 12 kg/s) the mass flow rate prediction is still quite inaccurate with MSE of 0.1452 kg/s and R^2 of 0.99511. This could be attributed to the outlier of the experimental data.

Also, Figure 7 compares the mass flow rate prediction from ANN (output) and sample result (target) for n = 20. From this Figure, it can be seen that the prediction has reduced when compared with Figure 6 with n = 15. The inaccurate prediction starts again from about 6 kg/s to the highest mass flow rate. Even though the value of n was increased when compared with Fig. 6, this increase does not improve predicting capability of the network with increase MSE of 1.3188 kg/s and decrease in R^2, 0.94188.

Figure 8 shows the relation of mean square error during the training with the Epochs for n = 15. It is seen in the figure that MSE is less than 0.15 kg/s. It can also be observed that the validation and testing lines almost follow the training line which suggests a good network.

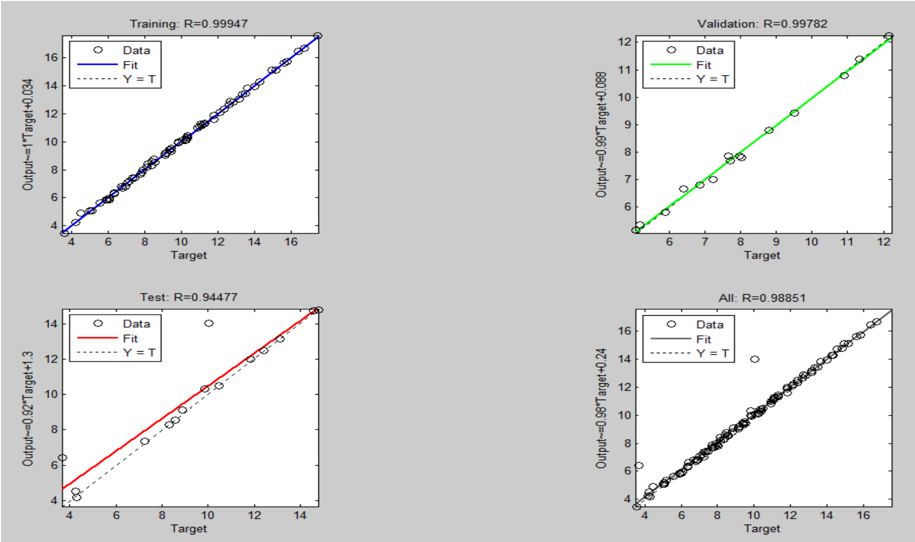

Figure 4: comparison of mass flow rate prediction for training, testing, validating and the combination with n=5.

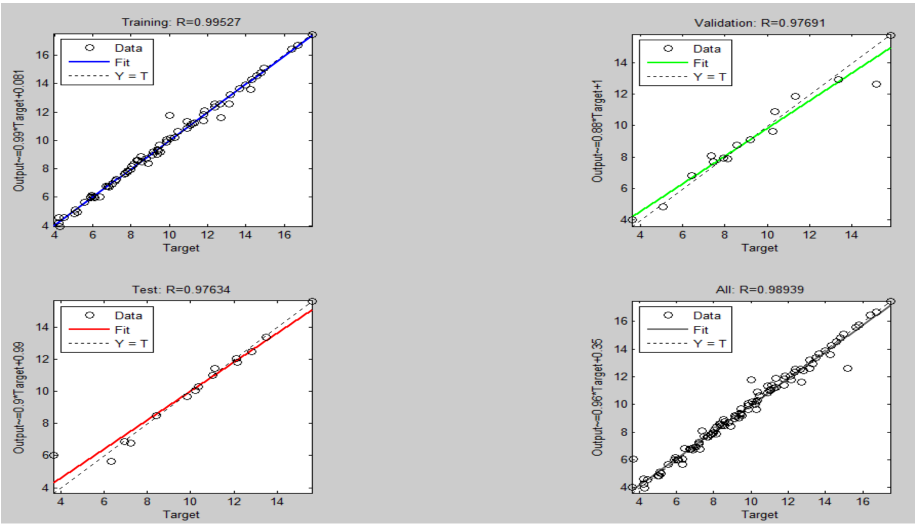

Figure 5: comparison of mass flow rate prediction for training, testing, validating and the combination with n=10.

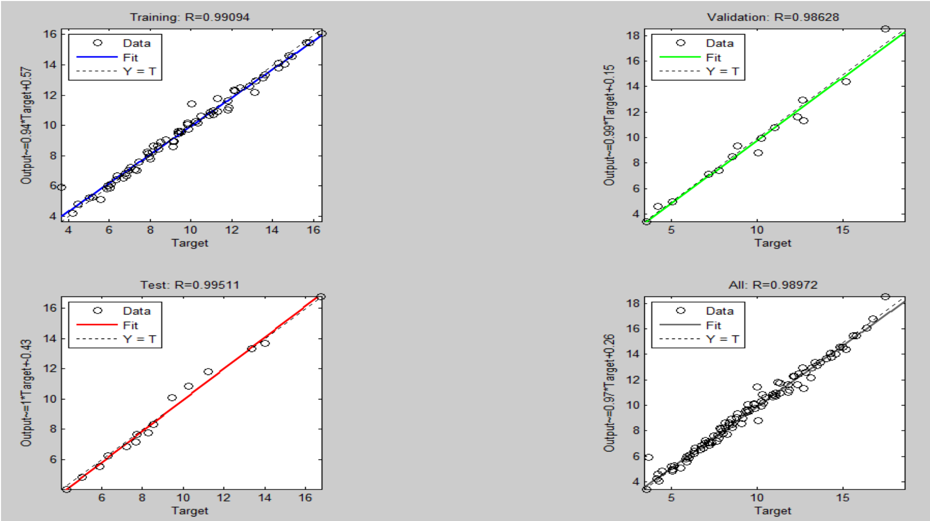

Figure 6: comparison of mass flow rate prediction for training, testing, validating and the combination with n=15.

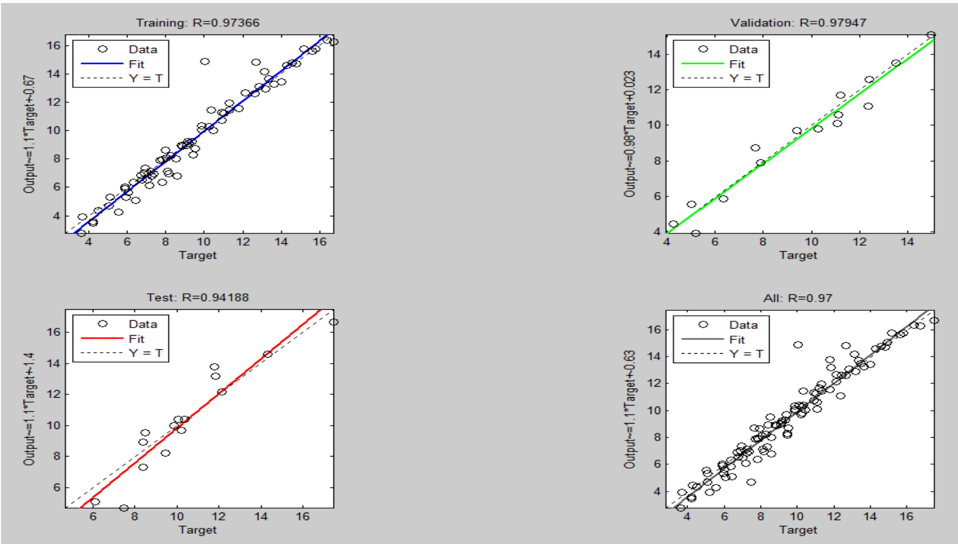

Figure 7: comparison of mass flow rate prediction for training, testing, validating and the combination with n=20.

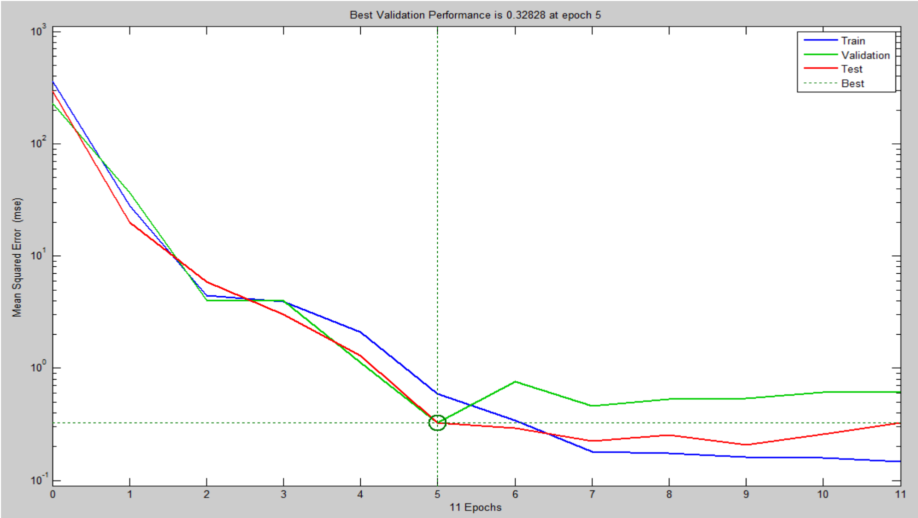

Figure 8: Relations of MSE with Epochs

5. CONCLUSION

Researches on the application of refrigerant substitutes to replace the non-eco-friendly refrigerants due to global warming are ongoing. Performance of refrigeration system depends on appropriate selection of capillary tube size for given condition so that desired mass flow rate can be achieved. This paper, in predicting the mass flow rate of refrigerant in adiabatic capillary tube, employs ANN using alternative refrigerants (HC290/HC600a/HFC407C) from open literature. These experimental data was used to train the BP network model. In developing the ANN, though, increasing the number of neurons from five to fifteen improves the accuracy of the mass flow rate prediction, however, when the number of neuron was further increased to twenty, the accuracy deteriorates. The average error between the ANN and the experimental data was less than 1.6%. From this result, it can be concluded that ANN is suitable for capillary tube engineering designers to use with alternative refrigerants for their design.

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