OPTIMIZATION OF NEURAL NETWORK TOPOLOGY FOR PREDICTION OF OUTLET TEMPERATURE OF SHELL AND TUBE HEAT EXCHANGER

Abdul Rashid Bin Amir Latif, Zalizawati Binti Abdullah

Faculty of Chemical Engineering, Universiti Teknologi Mara

Abstract- Performance of heat exchanger always fluctuating because of non-linearity property of heat transfer rate, Q. Artificial Neural Network (ANN), is applied for nearly a decades in most industries for its ability to project the non-linear property of heat transfer rate. Training algorithms used in this experiment to optimize the heat exchanger are trainlm,trainbr and trainscg. A neural network is constructed to best fit the prediction of outlet temperature of the shell and tube heat exchanger with crossing flow fluids.

keywords- ANN, shell and tube heat exchanger, trainlm,trainbr,trainscg.

1. INTRODUCTION

Since that we are in the technology era equipped with touch screen age, artificial neural networks have been applied in industries of many sectors by simulating the process of learning of human beings. ANN approved worldwide as a promising tool to solve complex engineering problems and have wide application in performance prediction, pattern recognition, system identification, and even dynamic control. ANN have more advantages since it able to simulate nonlinear, limited data and incomplete input-output relationship [1]. Even according to Mohamed et al [2] it is proven that ANN is more efficient tool either to predict or to forecast heat transfer compared to the(Computational Fluid Dynamics) CFD.

For example type of topology used for distillation column is feedforward backpropagation algorithm, made up of one hidden layer and one output layer with hyperbolic tangent function for the hidden layer and linear transfer function for the output layer [3]. For the application to determine new void fraction equations for two-phase flow in helical heat exchangers, the algorithm used was Levenberg-Marquardt with two neuron number in hidden layer, with tansig function for the hidden layer part and purelin function for output layer [4]

2. METHODOLOGY

<u>Relationship between the inputs and output.</u>

For this particular experiment to be conducted, the inputs are T_{set} and V_{set} whereby T_{out} as the output.

Based on the parameters, T_{set} is set temperature for the output stream of heat exchanger which is constant through the sets of experiments at 30°C, V_{set} is the opening valve to control the flow rate of water into the heat exchanger and T_{out} is the observed temperature out of the heat exchanger.

To relate that between the inputs and the output, is the limit opening of valve for the T_{out} to reach T_{set} provided with variety set of $V_{set.}$

<u>Design of the most suitable network topology of ANN.</u>

In order to determine the best network topology for optimization of temperature output, Feed Forward with Back Propagation was chosen and with different sets of training algorithms.

The training algorithms that will be varied for optimization of T_{out} are, Levenberg Marquardt (trainlm), Bayesian Regularization (trainbr), and Scaled Conjugate Gradient (trainscg).

<u>Comparison for the best network topology.</u>

R, known to measure correlation between inputs and outputs. If the R value obtained is close to 1, it means that the topology is accurate and if it close to 0, it is out of range.[5]

MSE, known as Mean Squared Error is used to indicate the degree of error of certain topology possessed. It is the average squared difference between outputs and targets. The lower the value the better the topology is in optimization of T_{out}.

3. RESULTS AND DISCUSSION

a) <u>ANN</u>

To determine the most precise control prediction for heat exchanger temperature output, T_{out}, designation of several topology of neural networks have been constructed. The basis of the topology consists of three layers that are 2 input data (V_{set} and T_{set}) as the input layer, adjustable neuron numbers inside the hidden layer and T_{out} as the output layer. The mapping of the topology of the neural network was shown below;

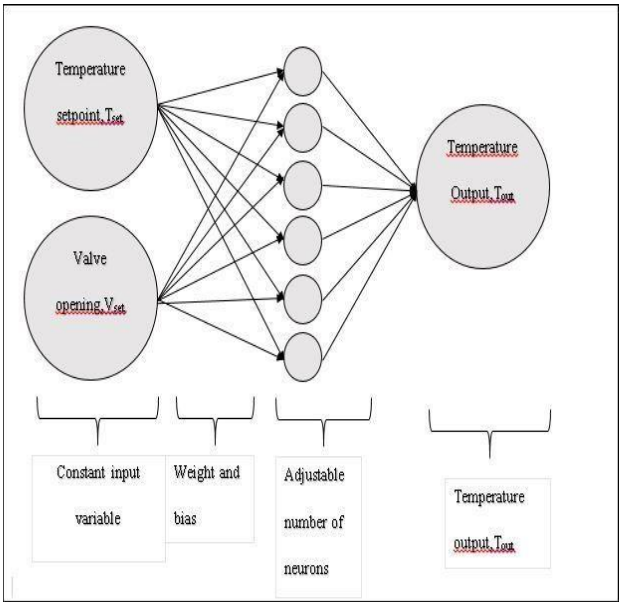

Figure 1: Topology of neural network model

b) <u>DETERMINATION OF NUMBER OF NEURONS INSIDE HIDDEN LAYER.</u>

In order to determine the best model, variety of neuron numbers have been tested ranging from 2 as the minimum and 20 at maximum. The neurons were tested using different training algorithm. The results for all the three training algorithms which are trainlm, trainbr, and trainscg were shown in table 1.

Table 1: Data of MSE and R for different set of training algorithms.

NO		LM		BR		SCG	
		MSE	R	MSE	R	MSE	R
2	training	1.99E-01	9.87E-01	1.38E-01	9.92E-01	2.00E-01	9.88E-01
	validation	1.41E-01	9.94E-01	0.00E+00	0.00E+00	1.07E-01	9.95E-01
4	training	7.24E-03	1.00E+00	7.00E-03	1.00E+00	1.89E-01	9.87E-01
	validation	7.73E-03	9.99E-01	0.00E+00	0.00E+00	1.50E-01	9.94E+00
6	training	7.24E-03	1.00E+00	8.81E-04	1.00E+00	1.87E-01	9.88E-01
	validation	7.73E-03	9.99E-01	0.00E+00	0.00E+00	2.34E-01	9.85E-01

8	training	6.59E-04	1.00E+00	1.62E-04	1.00E+00	9.58E-02	9.94E-01
	validation	6.02E-04	1.00E+00	0.00E+00	0.00E+00	1.08E-01	9.95E-01
10	training	6.03E-04	1.00E+00	1.18E-04	1.00E+00	1.34E-01	9.91E-01
	validation	5.88E-04	1.00E+00	0.00E+00	0.00E+00	8.01E-02	9.96E-01
12	training	8.43E-04	1.00E+00	1.23E-04	1.00E+00	4.71E-02	9.98E-01
	validation	8.48E-04	1.00E+00	0.00E+00	0.00E+00	2.63E-02	9.95E-01
14	training	1.33E-04	1.00E+00	1.17E-04	1.00E+00	9.13E-03	9.99E-01
	validation	1.47E-04	1.00E+00	0.00E+00	0.00E+00	1.25E-02	9.99E-01
16	training	1.07E-04	1.00E+00	1.22E-04	1.00E+00	1.59E-01	9.88E-01
	validation	1.59E-04	1.00E+00	0.00E+00	0.00E+00	3.27E-01	9.86E-01
18	training	1.19E-04	1.00E+00	1.14E-04	1.00E+00	2.18E-03	1.00E+00
	validation	1.94E-04	1.00E+00	0.00E+00	0.00E+00	3.01E-03	1.00E+00
20	training	1.21E-04	1.00E+00	1.22E-04	1.00E+00	3.15E-04	1.00E+00
	validation	9.51E-05	1.00E+00	0.00E+00	0.00E+00	2.90E-04	1.00E+00

Through execution between different training algorithms that are, trainlm, trainbr and trainscg, the properties of each individual training algorithm have been constructed using a graph that are shown below in figure 2. The transfer functions used for all the three training algorithms, are tansig for the input layer and purelin for the output layer. The network type is feed forward with back propagation, because that this type of propagation is the best tool to optimize operating condition of heat exchanger during the heat exchange process.

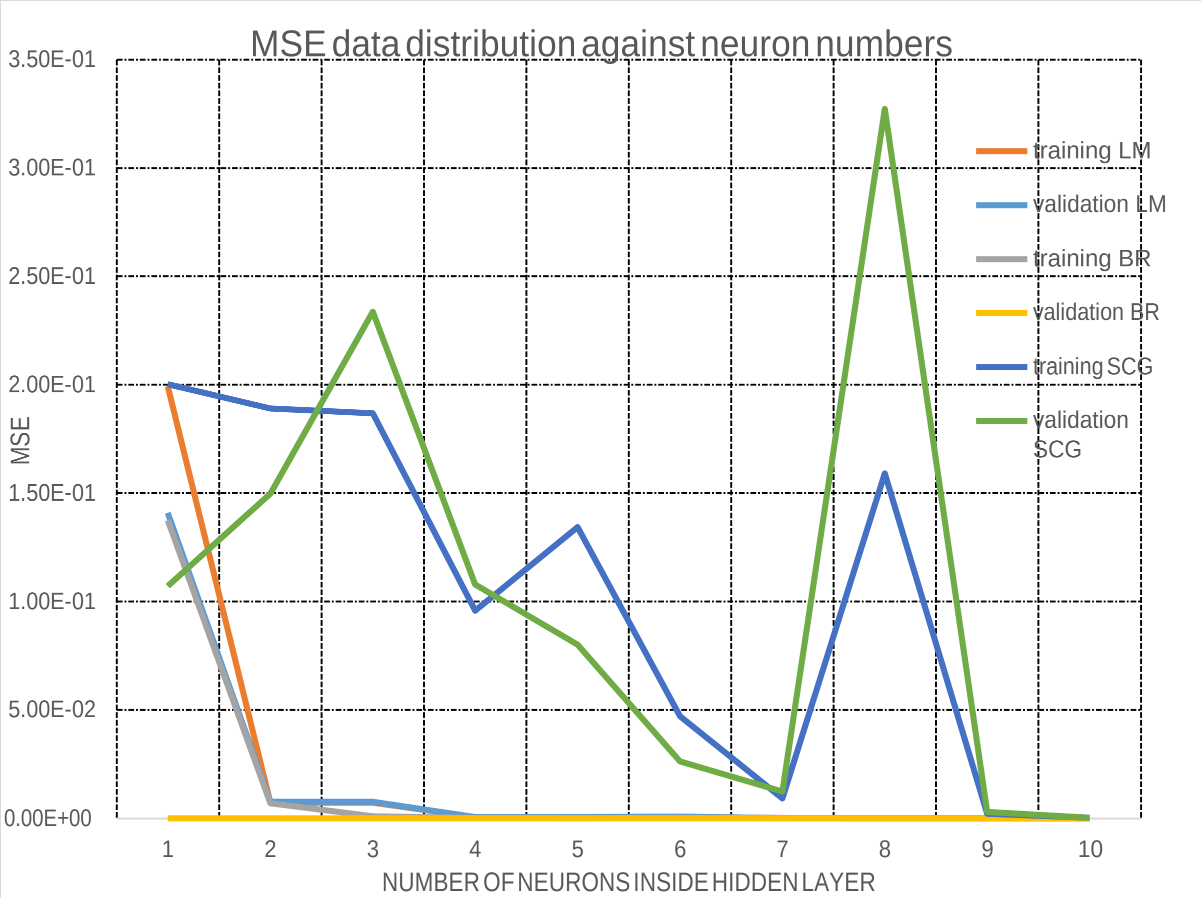

Figure 2: MSE data distribution for trainlm, trainbr and trainscg for both validation and training.

For trainlm, in term of Regression (R) comparison, trainlm only reach the target and stability starting at 8th neuron. In term of MSE, trainlm achieve the best condition at 4th neuron. Trainbr, the algorithm already reach both stability and target at the second neuron (R comparison) and MSE at the 4th neuron. , the best condition for trainscg for MSE is at 8th neuron, however for regression is already out of range.

For regression between these training functions, the stability and precision of neuron number in hidden layer, give the upper hand value for the trainbr than trainlm. Trainscg is out of choice because based on the properties presented in figure 2, trainscg is already away from the target that are apart from value 1 for regression comparison. Hence it is not suitable to perform the neural network training.

In term of MSE comparison, back to the concept, the lower the value of MSE the better it would be for optimizing the $T_{out.}$ Based on the figure 2, for trainlm, both training and validation are not in balance up until count 7. For trainbr, the decline in term of error are steady for both training and validation until reach a stable count at 4. Trainscg, both validation and training reach stability is quite late at count 8.

Therefore, in term of arrangement order, from least to the best for stability, trainscg is the least followed by trainlm and trainbr as the best training algorithm for neural network topology.

c) <u>REGRESSION OF THE TRAINING ALGORITHM.</u>

Since that there are two candidates for best fit the neural network training, a regression plot to simulate the relationship between the target and the output data are shown in figures below;

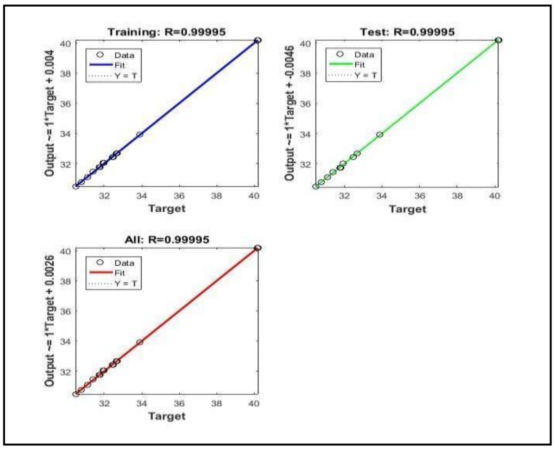

Figure 2: Regression plot for trainbr with 6 neuron numbers inside the hidden layer.

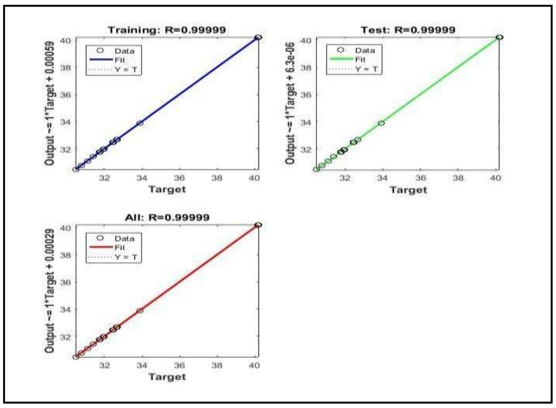

Figure 3: Regression plot for trainbr with 12 neuron numbers inside the hidden layer

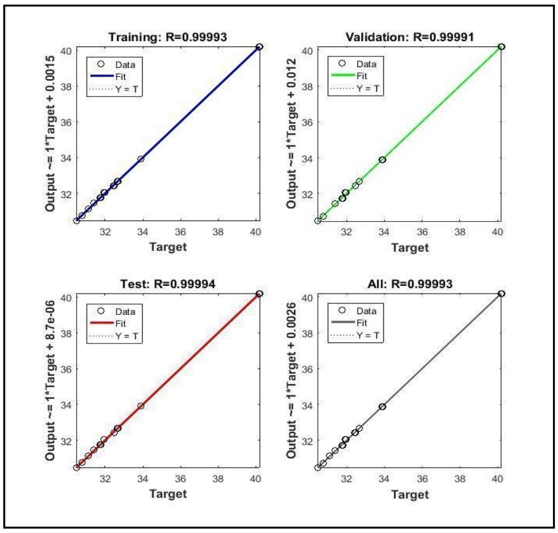

Figure 4: Regression plot for trainlm with 6 neuron numbers in hidden layer.

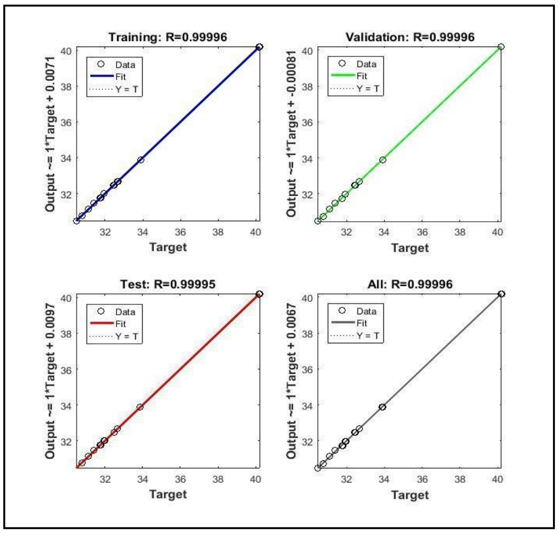

Figure 5: Regression plot for trainlm with 12 neuron numbers in hidden layer.

As the regression plot for all training algorithm known as trainlm and trainbr have been plotted for both 6 and 12 neuron numbers inside the hidden layer applied, the most accurate plot of output with respect of target is trainbr with 12 neuron numbers counted. This can be explained that the neuron number to be implemented inside the hidden layer have already optimized.

4) CONCLUSION

Heat exchanger is an equipment which can function either as heater or cooler and the heat exchanger chosen for this experiment is crossed flow with tube and shell heat exchanger type. This is because, the rate of heat transfer is maximized only when the flow between two moving fluid is crossed. Yet, one main problem with performance of heat exchanger is the rate of heat transfer between the fluids since that the heat transfer rate, Q always exhibit non-linear behaviour. So, ANN is used as the solution to suit the non-linearity properties of heat transfer rate.

Denote the potential of BR as the training algorithm that can best fit the temperature output, T_{out}. Any changes of temperature behavior of the heat exchanger, surely that able to be detected earlier. The best topology configuration for this experiment is 2-12-1 by using BR as the training algorithm.

To improve the research on rate of heat exchange more accurate, additional sets of output should be considered such as pressure drop across the heat exchanger and heat transfer coefficient.

5) REFERENCES

[1] G. Xie, B. Sunden, Q. Wang, and L. Tang, "Performance predictions of laminar and turbulent heat transfer and fluid flow of heat exchangers having large tube-diameter and large tube-row by artificial neural networks," *Int. J. Heat Mass Transf.*, vol. 52, no. 11–12, pp. 2484–2497, 2009.

[2] M. Hemmat Esfe, "Designing a neural network for predicting the heat transfer and pressure drop characteristics of Ag/water nanofluids in a heat exchanger," *Appl. Therm. Eng.*, vol. 126, pp. 559–565, 2017.

[3] L. M. Ochoa-Estopier, M. Jobson, and R. Smith, "Operational optimization of crude oil distillation systems using artificial neural networks," *Comput. Chem. Eng.*, vol. 59, pp. 178–185, 2013.

[4] A. Parrales, D. Colorado, J. A. Díaz-Gómez, A. Huicochea, A. Álvarez, and J. A. Hernández, "New void fraction equations for two-phase flow in helical heat exchangers using artificial neural networks," *Appl. Therm. Eng.*, vol. 130, pp. 149–160, 2018.

[5] S. Ledesma and S. M. Aceves, "Prediction of heat transfer coefficients for forced convective boiling of N 2 -Hydrocarbon mixtures at cryogenic conditions using artificial neural networks," *Cryogenics (Guildf).*, 2018.