PREDICTION OF THE HEAT TRANSFER RATE OF A FIN AND TUBE HEAT EXCHANGER – USING ARTIFICIAL NEURAL NETWORK TRAINED AND TESTED WITH EXPERIMENTAL DATA

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ABSTRACT

Heat exchangers are devices that are widely used to transfer heat between fluids because of their temperature differences. The logarithmic mean temperature difference (LMTD) and effectiveness-number of transfer units (ε-NTU) methods are the commonly used methods of heat exchanger performance prediction and analysis. Besides these methods, in the recent decades Artificial Neural Networks (ANNs) have become a powerful tool used for thermal analysis and performance prediction of heat exchangers. Experimental studies for complex devices like multi-row, multi-column heat exchangers are time consuming, costly and not applicable for large scale devices. Thus, the prediction of target data like heat rate with an acceptable error percentage is gaining importance. This study presents an application of artificial neural networks to predict the heat transfer rate of a fin and tube heat exchanger with air and water as the working fluids. Experimental data are used to train and test the network. It is also studied how the different number of hidden layers and different number of nodes in each layer of the Multilayer Perceptron (MLP) – a feedforward artificial neural network model- affects the accuracy of the heat transfer rate prediction. Thus, an optimized ANN is being suggested for water-air finned tube heat exchangers as a better predicting tool.

INTRODUCTION

For the last two decades, artificial neural networks (ANN) have been used in many engineering fields as well as in many other areas. Heating, cooling and air conditioning is also an industry that is benefiting from the artificial neural networks. Performance tests of heat exchangers are required to test the accuracy of the mathematical models for the calculation of the heat exchanger capacity. In some cases, these tests can be limited to parameters such as capacity, size and problems such as being costly or time consuming are encountered. Therefore, the use of artificial neural networks in the field of heat exchanger performance estimation provides many benefits. Due to their better and reasonable results, artificial neural networks are preferred over traditional methods for the prediction of the heat transfer rates. Studies in this area have helped to develop new models to ensure more accurate and converged results.

An example for the engineering field study of ANN is done by Singh et al. [1] studied on an ANN model for the prediction of the specific heat capacity of working fluid LiBr-H2O used in vapor absorption refrigeration systems. A feed forward back propagation algorithm is used for the ANN model and the results of ANN model and experimental study was achieved by a mean relative error (MRE) 0.00573. Nasr et al. [2] applied four different ANN model for gasoline consumption respectively to past consumption values, to gasoline consumption time series and price, to gasoline consumption and car registration and finally to combine gasoline consumption, price and car registration. First one is univariate, and the others are multivariate model. Results showed that the multivariate models achieved reasonable errors than the univariate model. Datta et al. [3] studied on a Bayesian regulated ANN to model the erosion behavior of Ni base alloys. Two different scenarios; a simple equation-based model and a comprehensive dataset looking at erosion as a function of particle size, velocity, impact angle and temperature have been used and the results showed that the Bayesian regularization algorithm gave much more successful accuracies averaging better than 90% respect to traditional algorithms of multilayer perceptron ANN.

NOMENCLATURE

D	[mm]	Tube diameter
A	[m^2]	Heat transfer surface area
t_f	[mm]	Fin thickness
NC	[-]	Number of circuits
L	[mm]	Tube/ finned length
V_a	[m^3/h]	Air side volumetric flow rate
V_F	[m^3/h]	Fluid side volumetric flow rate
T_{ai}	[C°]	Air inlet temperature
T_{fi}	[C°]	Fluid inlet temperature
Q	[kW]	Heat transfer rate

Subscripts

a	Air side
ai	Air inlet
fi	Fluid inlet
F	Fluid side
f	Fin

Also some studies are listed for the application of ANN to the studies related with the heat exchangers; Yiğit et al. [4] applied ANN to predict the air temperature and humidity at the outlet temperature of a cooling coil. 9 different coil test parameters were measured and two of them were the prediction parameters for ANN model. As the backpropagation algorithm ANN model trained with the test data, results were good as an error less than 1% and 2% respectively for coil outlet temperature and humidity. Islamoglu et al. [5] applied ANN to analyses heat transfer for air flowing in corrugated channels. With the help of the experimental data to train and test the ANN, results were achieved with an MRE less than 4%. Also another study of Islamoglu [6] was for a wire-on-tube type heat exchanger heat transfer rate prediction with an ANN trained with the experimental data of another study. Twelve different inputs of 19 test results was given to backpropagation ANN model for training and then to predict the heat transfer rate as output. 5 of the test results were predicted and results were achieved with 1.30% (training) and 4% (test) MRE. Diaz et al. [7] applied ANN to heat transfer prediction for one-dimensional conduction, then to predict the heat transfer for the convection with one and two heat transfer coefficient. This study gives the best configuration for the ANN model of the heat exchanger heat transfer coefficient. Pacheco-Vega et al [8] study on an ANN to a fin-tube heat exchanger with a number of limited experimental test data to predict the heat rate. Results showed that the accuracy of the estimation error is dependent on the number of the data that is given to the ANN as the training data. All the literature researches show that ANN technology is a valid method for heat transfer predictions. And this study contributes to ANN studies with the combined analysis of the network model.

EXPERIMENTAL DATA

The heat exchangers used for this study are provided by the manufacturer Friterm Inc. and experimentally tested in the laboratory site of Friterm. Tested fin and tube type heat exchangers are schematically shown in Fig. 1. Heat transfer is gained by the temperature difference of two fluids. First one is the air that flows outside the tubes and fins, whereas the second fluid water flows inside the tubes. Fin and tube type heat exchangers are commonly used in refrigeration applications.

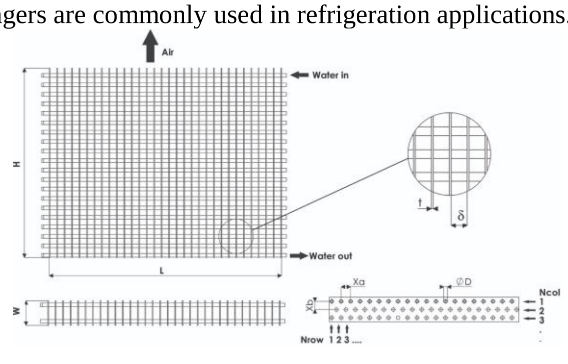

Figure 1. Heat exchanger coil

The heat exchangers at the first test group had nominal sizes; 715 mm length and two different height 576 mm and 684 mm. These sizes were compatible with the size of test chamber. First test group consists of 3 different heat exchangers. Two of them are with the same tube alignment configuration; number of tubes in row and in column differs from each other with the size of the tube diameter and fin thickness, tested for 6 different air inlet volumetric flows. The other one with a different tube alignment configuration but identical with other two heat exchangers for the fin thickness and tube diameter size is also tested for the same six air inlet volumetric flow. Tests are done with the same fluid side volumetric flow rate and air side-fluid side inlet temperatures. For three types of coil, number of circuits was kept unaltered.

Bare coils are tested by the help of the switchboard module installed in the air conditioning chamber. The schematic drawing of the test chamber which is used for testing the coils is given in the Figure 2.

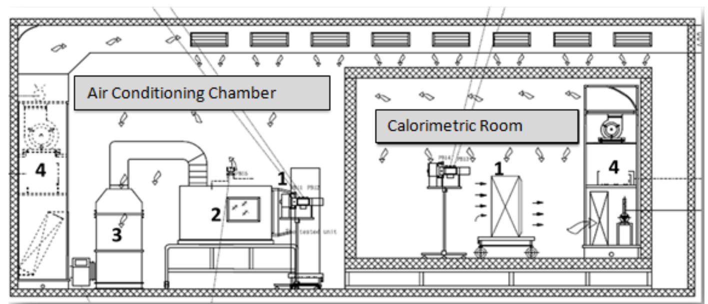

Figure 2. Experimental Test Room

Tests are done according to the measurements of the inlet and outlet properties for the inside and outside fluids; water and air, respectively. Air enthalpy method was used to evaluate heat transfer rates of the coils. The air enthalpy method (psychrometric method) measures capacity by accurately measuring the psychrometric air properties at the inlet and outlet of the bare coil. The air conditioning chamber maintains proper indoor and outdoor test conditions. Typically, this method requires to measure dry bulb temperature, wet bulb temperature/, relative humidity/, dew point temperature, barometric pressure, pressure drops both in the inlet and outlet. An airflow measuring device (3) is attached to the air discharge equipment. This device discharges air directly into the test room AHU or space, which is provided with suitable means for maintaining the air entering the unit at the desired dew point and dry-bulb temperatures. The experimental setup and procedure are explained in more detail in study of Okbaz et al.[9].

ARTIFICIAL NEURAL NETWORK STRUCTURE

Artificial neural networks are computational methods for the information processing. The inspiration is come from the biological brain neuron system. It consists of a large number of highly interconnected processing elements called as neurons Piuri et al. [10]. When there is not a clear relationship between the inputs and outputs, it is not easy to formulate the mathematical model for such systems. Or even a mathematical model can be built, to prove the accuracy of the mathematical model, some tests must be done. If there is a limitation for the test conditions, then there must be another way to prove the model. Besides, experimental studies for complex devices like multi-row, multi-column heat exchangers are time consuming, costly and not applicable for large scale devices. Even if the working principle of finned tube heat exchangers is quite simple, it is difficult to perform performance analysis due to the large number of parameters affecting heat transfer. Therefore, artificial neural networks (ANNs) have been considered as a powerful tool used for thermal analysis of heat exchangers. Among the various kinds of ANNs that exist, the feedforward configuration has become the most popular in engineering applications [8] Multilayer Perceptron, or MLPs for short, are the classical type of feed forward artificial neural network, which is used in this study. They are comprising one or more layers of neurons. A typical feed forward structure is schematically given in Fig. 3. This model has one input layer, one hidden layer and one output layer. The model is called feedforward because the data is fed to the input nodes at the input layer and the information is transferred through the network to the nodes at the output layer. There may be one or more hidden layers and predictions are made on the output layer, also called the visible layer. The nodes perform non-linear input-output transformations by means of sigmoid activation function. The mathematical background, the procedures for training and testing the ANNs, and account of its history can be found in the book of S. Haykin [11]

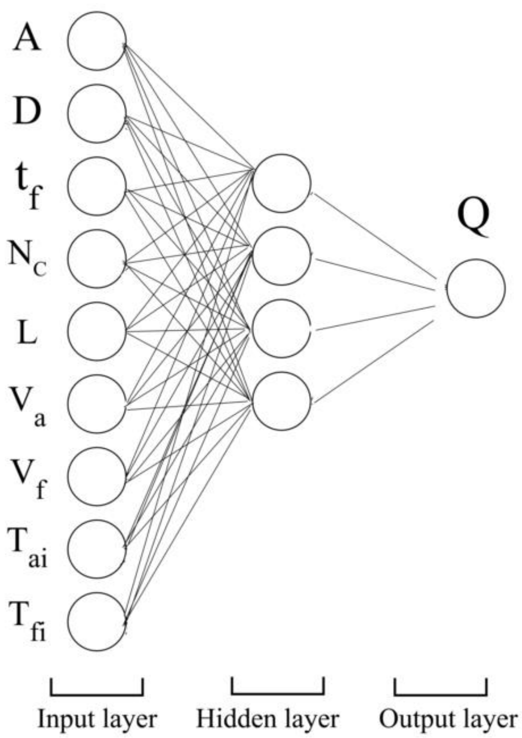

Figure 3. Artificial Neural Network Model

To train and test the neural networks, input data set is divided into two sets. First part is used for training the ANN (generally 75- 80 % of total) while the remaining part (generally 25- 20 %) is used for testing the network to evaluate the accuracy of the results by neural network.

In this study, an open source program KNIME is used to optimize an ANN model for the prediction of heat transfer rate. The inputs were total heat transfer surface area (A), tube diameter (D), fin thickness (t_f), number of circuits (NC), length of finned tube (L), air side volumetric flow rate (V_a), fluid side volumetric flow rate (V_F), air inlet temperature (T_{ai}), fluid inlet temperature (T_{fi}) and output was heat transfer rate (Q).

Input values are presented to the ANN with the configuration file. Neural network requires that the range of the both input and output values should be between 0 and 1. All the data used in this study as training or test data are normalized in order to have the values. Normalization is done due to the range difference of the different inputs in an ANN model. A change of 0.5 is 100% change for an input where as a change by 0.5 is only a change of 0.05% for another input. With the normalization of all the inputs are at a comparable range. Normalization (or scaling) is one of the main parts of ANN learning process. If the inputs are not normalized between (0,1) then equally distribution importance of each input cannot be done, thus naturally large values become dominant according to less values during ANN training. Normalization is done with the following formula;

$$\frac{Actualvalue - Minimum}{Maximum - Minimum} * (Highest - Lowest) + Lowest \qquad (1)$$

Here minimum and maximum values are real tested data, highest and lowest values are normalized data for minimum and maximum tested values, respectively. After the ANN model is applied and the prediction is done, to take back the normalization and find the actual prediction heat transfer rate, following formula is used;

$$\frac{\Pr edictionvalue - Minimum}{Maximum - Minimum} * (Highest - Lowest) + Lowest \qquad (2)$$

Various ANN models with various numbers of hidden layers, validations, number of hidden neurons per layer and two different type of partitioning are tried to develop the best model of ANN for the prediction of the heat transfer rate with minimum error.

Table 1. Inputs and output of first experimental data set used for training and testing ANN

Test No	A	D	tf	NC	L	Va	Vf	Tai	Tfi	Q
	m2	mm	mm	-	mm	m3/h	m3/h	C°	C°	kW
Test0	16.62	12	0.15	6	715	1765.25	4	20	40	7.46
Test1	16.62	12	0.15	6	715	2647.87	4	20	40	9.42
Test2	16.62	12	0.15	6	715	3089.19	4	20	40	10.19
Test3	16.62	12	0.15	6	715	3530.5	4	20	40	10.98
Test4	16.62	12	0.15	6	715	3971.81	4	20	40	11.7
Test5	16.62	12	0.15	6	715	4413.12	4	20	40	12.37
Test6	17.28	9.525	0.15	6	715	1765.25	4	20	40	7.26
Test7	17.28	9.525	0.15	6	715	2647.87	4	20	40	9.08
Test8	17.28	9.525	0.15	6	715	3089.19	4	20	40	9.96
Test9	17.28	9.525	0.15	6	715	3530.5	4	20	40	10.69
Test10	17.28	9.525	0.15	6	715	3971.81	4	20	40	11.37
Test11	17.28	9.525	0.15	6	715	4413.12	4	20	40	11.92
Test12	24.53	12	0.12	6	715	1765.25	4	20	40	7.7
Test13	24.53	12	0.12	6	715	2647.87	4	20	40	9.54
Test14	24.53	12	0.12	6	715	3089.19	4	20	40	10.39
Test15	24.53	12	0.12	6	715	3530.5	4	20	40	11.09
Test16	24.53	12	0.12	6	715	3971.81	4	20	40	11.77
Test17	24.53	12	0.12	6	715	4413.12	4	20	40	12.35

Table 2. Inputs and output of second calculated data set used for testing ANN

Test No	A	D	tf	NC	L	Va	Vf	Tai	Tfi	Q
	m2	mm	mm	-	mm	m3/h	m3/h	C°	C°	kW
Test 18	27.45	12	0.12	6	800	1765.25	4	20	40	7.9
Test 19	30.88	12	0.12	6	900	1765.25	4	20	40	8.2
Test 20	34.31	12	0.12	6	1000	1765.25	4	20	40	8.4
Test 21	37.74	12	0.12	6	1100	1765.25	4	20	40	8.6
Test 22	41.17	12	0.12	6	1200	1765.25	4	20	40	8.7
Test 23	44.6	12	0.12	6	1300	1765.25	4	20	40	8.9
Test 24	48.03	12	0.12	6	1400	1765.25	4	20	40	9
Test 25	51.47	12	0.12	6	1500	1765.25	4	20	40	9.1
Test 26	54.9	12	0.12	6	1600	1765.25	4	20	40	9.3
Test 27	58.33	12	0.12	6	1700	1765.25	4	20	40	9.4
Test 28	61.76	12	0.12	6	1800	1765.25	4	20	40	9.5
Test 29	65.19	12	0.12	6	1900	1765.25	4	20	40	9.5
Test 30	68.62	12	0.12	6	2000	1765.25	4	20	40	9.6
Test 31	72.05	12	0.12	6	2100	1765.25	4	20	40	9.7
Test 32	75.48	12	0.12	6	2200	1765.25	4	20	40	9.8
Test 33	78.91	12	0.12	6	2300	1765.25	4	20	40	9.8
Test 34	82.34	12	0.12	6	2400	1765.25	4	20	40	9.9
Test 35	85.78	12	0.12	6	2500	1765.25	4	20	40	9.9

Table 3. Inputs and output of third calculated data set used for testing ANN

Test No	A m2	D mm	tf mm	NC -	L mm	Va m3/h	Vf m3/h	Tai C°	Tfi C°	Q kW
Test 36	24.53	12	0.12	6	715	4900	4	20	40	14
Test 37	24.53	12	0.12	6	715	5300	4	20	40	14.5
Test 38	24.53	12	0.12	6	715	5700	4	20	40	15.1
Test 39	24.53	12	0.12	6	715	6100	4	20	40	15.6
Test 40	24.53	12	0.12	6	715	6500	4	20	40	16

RESULTS

In this study heat transfer rate is predicted by the help of the developed multilayer perceptron ANNs model. To analyse which configuration has the lowest deviation, different types of configurations were tried for the first data set by changing the number of hidden layers and the number of hidden neurons per layer.

Table 4. ANN deviations of different configurations

Configuration	Mean Absolute Error	Mean Squared Error	Root Mean Squared Deviation
9-2-1	0.0421	0.0033	0.0572
9-3-1	0.0676	0.0073	0.0856
9-4-1	0.0294	0.0014	0.0371
9-5-1	0.0835	0.0177	0.1330
9-6-1	0.0467	0.0031	0.0555
9-7-1	0.0680	0.0084	0.0915
9-8-1	0.0574	0.0066	0.0810
9-2-2-1	0.0298	0.0015	0.0390
9-3-3-1	0.0576	0.0083	0.0914
9-4-4-1	0.0778	0.0200	0.1414
9-5-5-1	0.0489	0.0044	0.0666
9-6-6-1	0.0367	0.0025	0.0501
9-7-7-1	0.0296	0.0014	0.0375
9-2-2-2-1	0.1053	0.0192	0.1386
9-3-3-3-1	0.0520	0.0050	0.0706
9-4-4-4-1	0.0691	0.0126	0.1123
9-5-5-5-1	0.0855	0.0214	0.1462
9-6-6-6-1	0.0432	0.0029	0.0539
9-7-7-7-1	0.0334	0.0019	0.0433
9-8-8-8-1	0.0321	0.0014	0.0370

As can be seen in Table 4, the most reasonable error is taken with the configuration 9-4-1 (one hidden layer and 4 nodes at the hidden layer). Therefore, next predictions are done with this configuration.

First group is consisting of 18 heat exchanger production and test parameters. Data set separated into two groups and 14 data are used for training the ANN model and the rest 4 data are used for testing the model. (Table 1)

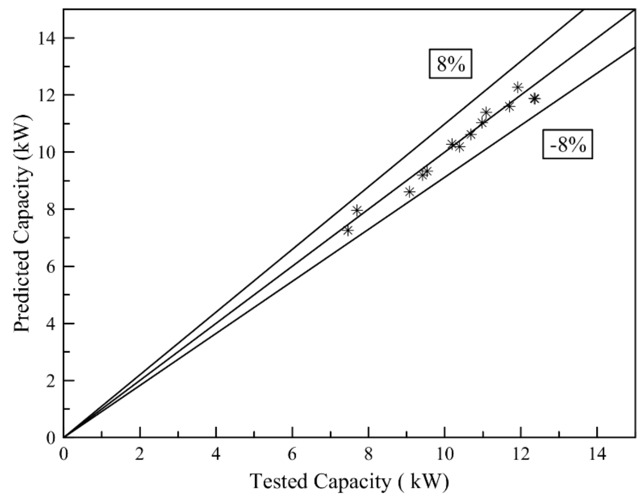

Figure 4. Heat transfer rate of training results evaluated experimentally and using ANNs model for the first data set

Figure 4 shows the results of training data for the first data set. Mean relative error is 2.4% and maximum relative error is 5.2% for first training data set.

Table 5 shows the heat transfer rate comparison of experimental and ANN model results for the first data set ANN testing group. Mean relative error is 0.7% for first data set and maximum relative error is 1.2% for the ANN testing data in first data set.

Table 5. Heat transfer rate of ANN testing results comparison evaluated experimentally and using ANNs model for the first data set

Test No	Q (kW) (Experimental Results)	Q (kW) (ANN Model Results)	% RE (Relative Error)
Test6	7.26	7.35	1.19
Test8	9.96	9.95	-0.06
Test10	11.37	11.33	-0.35
Test16	11.77	11.64	-1.09

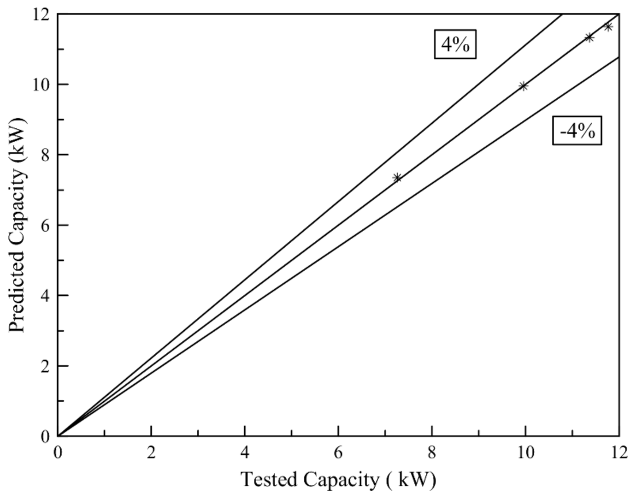

Figure 5. Heat transfer rate of ANN testing results evaluated experimentally and using ANNs model for the first data set

Another data set is used to see what the accuracy of the ANN model will be if the new data inputs, which are out of the range of the first data set inputs, are introduced to the ANN model.
Second and third data set were generated by the help of a mathematical model which's performance were proved by an accredited institution. Every new data added to the first data set one by one. The coil fin lengths are changed from 800 mm to 2500 mm and correspondingly the heat transfer surface area is changing. (Table 2)

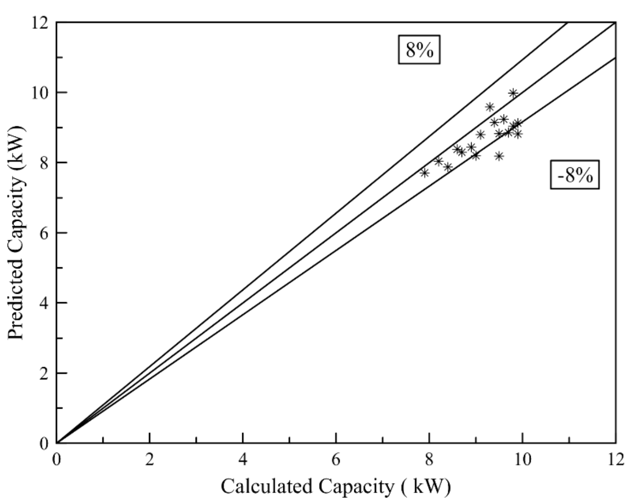

Figure 6. Heat transfer rate of results calculated with mathematical model and using ANNs model for the second data set

Figure 6 shows the results of test data for the second data set. Mean relative error for 18 data is 5.7% and maximum relative error is 13.8% for the second data set. Thus, it can be said that the developed ANN model is valid even if the fin length is changed out of the range of training data.

Table 6. Heat transfer rate of results comparison evaluated with mathematical model and using ANNs model with added second data set

Test No	Q (kW) (Mathematic Model Results)	Q (kW) (ANN Model Results)	% RE (Relative Error)
Test 18	7.9	7.7	-2.4%
Test 19	8.2	8.0	-2.0%
Test 20	8.4	7.9	-6.3%
Test 21	8.6	8.4	-2.5%
Test 22	8.7	8.3	-4.6%
Test 23	8.9	8.4	-5.2%
Test 24	9	8.2	-8.9%
Test 25	9.1	8.8	-3.3%
Test 26	9.3	9.6	3.1%
Test 27	9.4	9.1	-2.7%
Test 28	9.5	8.8	-7.1%
Test 29	9.5	8.2	-13.8%
Test 30	9.6	9.2	-3.8%
Test 31	9.7	8.9	-8.7%
Test 32	9.8	9.0	-7.7%
Test 33	9.8	10.0	1.9%
Test 34	9.9	9.1	-7.8%
Test 35	9.9	8.8	-10.9%

Finally, another new data set is introduced to the ANN model with the first data set. (Table 3) Again every data added to the first data set one by one. Changing data for this group was air side volumetric flow rate from 4900 m^3/h to 6500 m^3/ h. 5 different air side volumetric flow rate is added to the first 18 data and examined how the accuracy of the ANN model is changing.

Figure 7 shows the results of test data for the third data set. Mean relative error for 5 data is 12.7% and maximum relative error is 17.3% for the third data set. Results shows developed ANN model is valid even if the air volumetric flow rate is changed out of the range of training data.

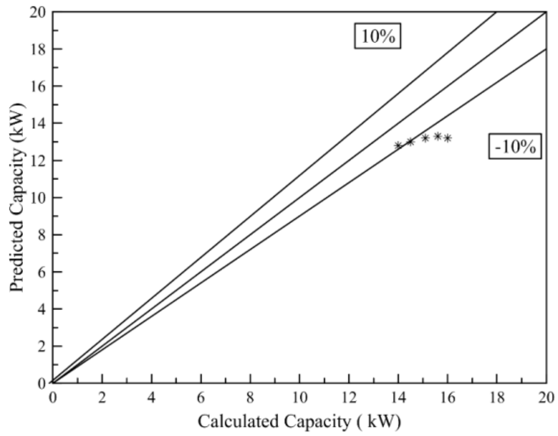

Figure 7. Heat transfer rate of results calculated with mathematical model and using ANNs model for the third data set

Table 7. Heat transfer rate of results comparison evaluated with mathematical model and using ANNs model with third data set

Test No	(kW) (Mathematic Model Results)	q (kW) (ANN Model Results)	% RE (Relative Error)
Test 36	14.0	12.8	-8.9%
Test 37	14.5	13.0	-10.3%
Test 38	15.1	13.2	-12.3%
Test 39	15.6	13.3	-14.7%
Test 40	16.0	13.2	-17.3%

CONCLUSION

In the present study, multilayer perceptron artificial neural network approach is applied to predict the heat transfer rate for fin and tube type heat exchangers that has been widely used in refrigeration systems. First part of the study was focused on the optimum configuration for the ANN model. After the decision of the configuration, ANN model trained and tested for three other data sets. First group data inputs were experimentally tested 18 coil parameters and the results of the neural network agree with the experimental results. Second and third data set inputs were calculated by the help of a mathematical model. For the second data set which the fin lengths are changed, results were achieved with an MRE 5.7% and for the third data set which the air volumetric flows are changed, results were achieved with a MRE 12.7%. It can be said that the predicted values with ANN models are admissible when the training data and the tested data are in a limited range.

If the estimation is made with an input other than the limit of the inputs of the training set, the error rates of the results were increased. Error rates are changing according to the effect of the input to the predicted data. Although further study is required it could also be concluded that the variations in geometrical characteristics results with less deviations when compared with the variation in flow characteristics case.

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