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Estimated Outlet Temperatures in Shell-and-Tube Heat Exchanger Using Artificial Neural Network Approach Based on Practical Data

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Abstract

The objective of this study is to apply Artificial Neural Network for heat transfer analysis of shell-and-tube heat exchangers widely used in power plants and refineries. Practical data was obtained by using industrial heat exchanger operating in power generation department of Dura refinery. The commonly used Back Propagation (BP) algorithm was used to train and test networks by divided the data to three samples (training, validation and testing data) to give more approach data with actual case. Inputs of the neural network include inlet water temperature, inlet air temperature and mass flow rate of air. Two outputs (exit water temperature to cooling tower and exit air temperature to second stage of air compressor) were taken in ANN.

150 sets of data were generated in different days by the reference heat exchanger model to training the network. Regression between desired target and prediction ANN output for training , validation, testing and all samples show reasonably values are equal to one (R=1) . 50 sets of data were generated to test the network and compare between desired and predicated exit temperature (water temp. and air temp.) show a good agreement ($\pm 0.3\%$).

Keywords: *Artificial neural network, Shell-and-tube heat exchanger, Outlet temperatures, training, validation and testing.*

1. Introduction

Heat exchangers are devices that facilitate the exchange of heat between two fluids that are at different temperatures while keeping them from mixing with each other. Heat exchangers are commonly used in practice in a wide range of applications, from heating and air conditioning systems in a household, to chemical processing and power production in large plants. Different heat transfer applications require different types of hardware and different configurations of heat transfer equipment. The most common type of heat exchanger in industrial applications is the shell-and-tube heat exchanger.

Analysis of heat exchanger needs some steps like the choice of a method of solution (LMTD or NTU) based on the type of application, consideration fitted with environment of work and determine the fouling factor and correction factor from figures or experimental correlation. All these steps give result with some error whene compared with actual case.

A number of experimental and numerical researches on the heat exchanger characteristics have been conducted for several decades. Jian-Fei Zhang [1] presented 3D numerical simulation of a whole heat exchanger with middle-overlapped helical baffles which is carried out by using commercial codes of GAMBIT 2.3 and FLEUNT 6.3. The validation of the computational model is performed by comparing the total pressure drop and average Nusselt number of the whole heat exchanger with experimental data. Reasonably good agreement is obtained. Yusuf Ali Kara[2] presented The program determines the overall dimensions of the shell, the tube bundle, and optimum heat transfer surface area required to meet the specified heat transfer duty by calculating minimum or allowable shell-side pressure drop. Nasser Ghorbani[3] presented an experimental investigation of the mixed convection heat transfer in a coil-in-shell heat exchanger. The calculations were performed for the steady-state and the experiments were conducted for both laminar and turbulent flow inside coil .The results indicated that the ε−NTU relation of the mixed convection heat exchangers was the same as that of a pure counter-flow heat exchanger.

The Computational Intelligence (CI) techniques, such as Artificial Neural Networks (ANNs), have been successfully applied in many scientific researches and engineering practices. Several investigators have proposed (ANN) modeling with experimental or theoretical work for thermal engineering application. G.N. Xie[4]presented Artificial Neural Network (ANN) for heat transfer analysis of shell-and-tube heat exchangers with segmental baffles or continuous helical baffles. Limited experimental data was obtained for training and testing neural network configurations. The maximum deviation between the predicted results and experimental data was less than 2%. Comparison with correlation for prediction shows superiority of ANN. Dheerendra Vikram Singh[5] compare performances of three training functions (TRAINBR, TRAINCGB and TRAINCGF) used for training neural network for predicting the value of the specific heat capacity of working fluid. The comparison is shown on the basis of percentage relative error, coefficient of multiple determination R-square, root mean square error and sum of the square due to error.

The goal of this study is to built artificial neural network based on actual data to training model of shell and tube heat exchanger by dividing the data to three samples (training , validation and testing data) to give more approach data with actual case. Two outputs (exit water temp. and exit air temp.) were taken in ANN because of importance them for cooling tower and air compressor connected with the heat exchanger.

2. Heat Exchanger Database Modeling

Sufficient data samples are necessary for NN model development. It is almost needed to take more accuracy data from actual cases to represent any model. Shell-and-tube heat exchanger working in Dura refinery used as reference model to result sufficient data for NN training and testing.

Air represented one of the important working substance used in many devices in Dura refinery especially in power service department. Multi stage air compressor was used to produce pressurized air. When the air is inter to each stage of air compressor, its pressure and temperature will increase. Therefore should be used heat exchanger to decrease air temperature before the next stage to safe the parts of air compressor.

Fig.(1) show the shell-and-tube Heat exchanger use in practical work. Heat exchanger have the following specification: Mass flow rate of water is (7 kg/s) diameter of shell is (609.6mm), one pass flow of shell (for air flow), two pass flow of tube (for water flow), diameter of tube is (15.9mm), number of tube is (46), the tubes contain aluminum fins with (0.22mm) thickness, the material of shell and tube is carbon steel, and length of tube (2134mm). [6]

The heat exchanger performance data with different state parameters are generated by the validated reference model. In total, 200 sets of data were generated in different days by the reference heat exchanger model. The data range used for neural network training and testing is listed in Table (1).

Table 1,
Data Range of Input and Output Parameters.

Input parameters	**Range**
$T_w)_i$	$28-38\ ^oC$
$T_a)_i$	$155-165\ ^oC$
$m^{\bullet}{}_a$	$2.3-2.4\ Kg/s$
Output parameters	**Range**
$T_w)_e$	$38-48\ ^oC$
$T_a)_e$	$54-64\ ^oC$

Fig. 1. Shell-and-Tube Heat Exchanger use in Practical Work (Power Generation Department in Dura Refinery).

3. Input and Output Parameters

Proper selection of input and output parameters is the first step of NN model development shown in Fig (2). Input parameters for heat exchanger neural network modeling include inlet water temperature $T_w)_i$, inlet air temperature $T_a)_i$, air flow rate $m^{\bullet}_a$. Output parameters include exit water temperature $T_w)_e$ and exit air temperature $T_a)_e$.

$T_w)_e$ and $T_a)_e$ are very important output parameters for two reasons, Firstly because output parameters selection in this study refer to performance level of heat exchanger operation, Secondly because the known $T_w)_e$ necessary to calculate air flow rate needed to cool warm water in cooling tower connected with heat exchanger and the known $T_a)_e$ important for calculate the change in water flow rate of heat exchanger to avoid the danger limits of air temperature exit when the air enter to next stage of air compressor.

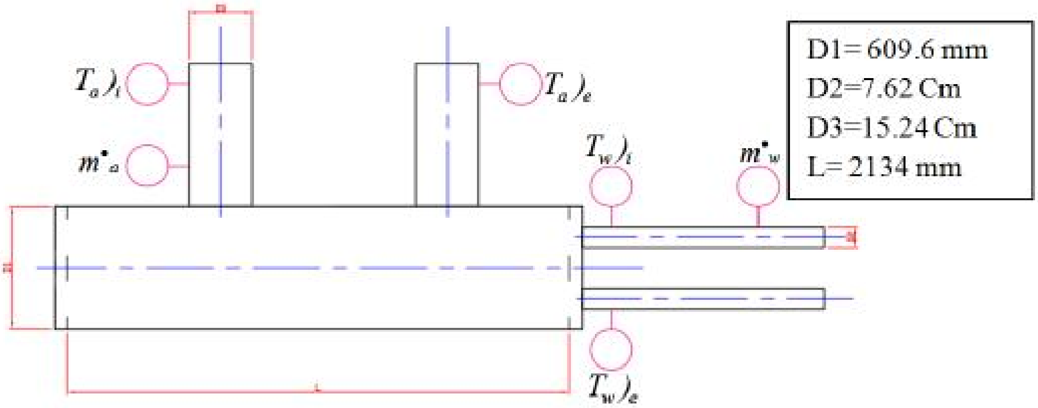

Fig. 2. Input and Outlet Properties of Heat Exchanger use in Practical Work with General Dimension.

4. Neural Network Modeling

The type of neural network used in this study is the multilayer neural network (MLNN) with a feed forward Back propagation learning rule. Input vectors and the corresponding target vectors are used to train a network until it can approximate a function.

A feed-forward network has a layered (l) structure as shown in Fig.(3) . Each layer consists of units which receive their input from units from a layer directly below and send their output to units in a layer directly above the unit. There are no connections within a layer. The N_i inputs are fed into the first layer of $N_{h,1}$ hidden units. The input units are merely 'fan-out' units; no processing takes place in these units. The activation of a hidden unit is a function f_i of the weighted inputs plus a bias. The output of the hidden units is distributed over the next layer of $N_{h,2}$ hidden units, until the last layer of hidden units, of which the outputs are fed into a layer of N_o output units. [7]

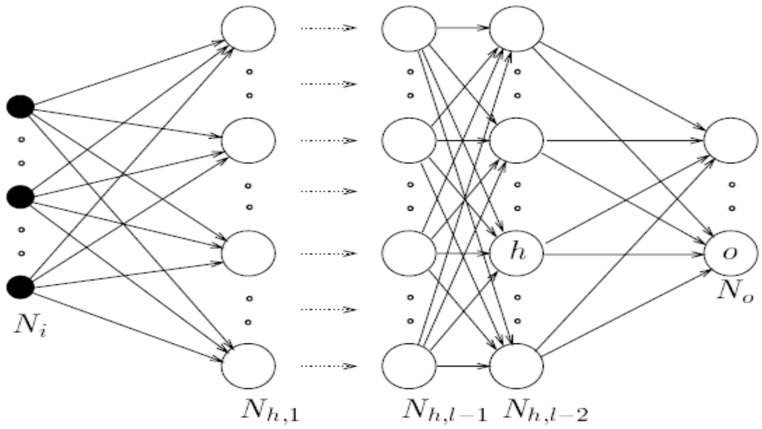

Fig. 3. A Multi-Layer Network with l Layers of Units.

Depending on delta rule, the activation is a differentiable function of the total input, given by: [8].

$$y_k^p = f(s_k^p) \qquad \ldots(1)$$

In which $s_k^p = \sum_j w_{jk} y_j^p + q_k$ …(2)

Where:

$j =$ Number of element (neuron) $j = 1,\ldots\ldots,J$

$k =$ Number of element (neuron) $k = 1,\ldots\ldots,K$

$p =$ Input pattern vector

$y_k^p =$ The activation values of the network when input pattern vector p was input to the network.

$s_k^p =$ The input to a set of neurons when input pattern vector p is clamped.

$y_j^p =$ The activation values of element j of the network when input pattern vector p was input to the network;

$w_{jk} =$ The weight of the connection from unit j to unit k

$q_k =$ The biases to the units.

$f =$ The activation function.

To get the correct generalization of the delta rule we must set

$$\Delta_p w_{jk} = -g \frac{\partial E^p}{\partial w_{jk}} \qquad \ldots(3)$$

The error measure E^P is defined as the total quadratic error for pattern (p) at the output units:

$$E^P = \frac{1}{2}\sum_{0=1}^{N_o}(d_o^p - y_o^p)^2 \qquad \ldots(4)$$

Where

$o =$ An output unit.

$g =$ Constant of proportionality.

$\Delta_p =$ Modified of pattern p.

$d_o^p =$ The desired output of the network when input pattern vector p was input to the network.

$y_o^p =$ The activation values of the network when input pattern vector p was input to the network.

$$\Delta_p w_{jk} = g\, d_k^p y_j^p \qquad \ldots(5)$$

where

$d_k^p =$ Product of two factors. One factor reflects the change in error as a function of the output of the unit and one reflecting the change in the output as a function of changes in the input. assume firstly.

$$d_o^p = (d_o^p - y_o^p) f(s_o^p) \qquad \ldots(6)$$

and secondly assume $k = h$
Where
$h =$a hidden unit

$$d_h^p = f(s_h^p)\sum_{o=1}^{N_o} d_o^p w_{ho} \qquad ..(7)$$

Equations (6) and (7) give a recursive procedure for computing the d 's for all units in the network, which are then used to compute the weight changes according to Equation (5). This procedure constitutes the generalized delta rule for a feed-forward network.

Working in back-propagation should by used the all above equations and the steps of solution are clarified in the following. When a learning pattern is clamped, the activation values are propagated to the output units, and the actual network output is compared with the desired output values, we usually end up with an error in each of the output units. We have to bring the error to zero.

The application of the generalized delta rule thus involves two phases: During the first phase the input x is presented and propagated forward through the network to compute the output values y_o^p for each output unit. This output is compared with its desired value d_o, resulting in an error signal d_o^p for each output unit. The second phase involves a backward pass through the network during which the error signal is passed to each unit in the network and appropriate weight changes are calculated.

There are generally seven steps in the training process working in back propagation: [9]

1. Start with random weights for the connections
2. Select an input vector x from the set of training samples
3. The weight of a connection is adjusted by an amount proportional to the product of an error signal d , in the unit k the input and the output of the unit j are received sending this signal along the connection.
4. Calculate the error signal after choice the activation function.
5. The error signal for a hidden unit is determined recursively in terms of error signals of the units to which it directly connects and the weights of those connections.
6. The learning procedure requires that the change in weight is proportional to $\frac{\partial E^p}{\partial w}$. True gradient descent requires that infinitesimal steps are taken. The constant of proportionality is the learning rate g .
7. Make the change in weight dependent of the past weight change by adding a momentum term:

$$\Delta w_{jk}(t+1) = g d_k^p y_j^p + a\Delta w_{jk}(t) \qquad ...(8)$$

Where
a =Modified weight connection.
t =Time.

5. Neural Network Training

In artificial neural network all data are divided to three kinds of samples. The first kind (training) presented to the network during training, and the network is adjusted according to its error. The second kind (validation) used to measure network generalization, and to halt training when generalization stops improving. The third kind (testing) has no effect on training and so provides an independent measure of network performance during and after training. [10]

Agood network should includ small mean square error (MSE) for training data performance and validation data performance. 150 sets of data were generated by the reference heat exchanger model use to train the network.

Here, the neural network with 1-3 layers (hidden layer), 2-16 neurons is studied and results mean square error for training and validation are provided in Table (2). It 'is clear that 3 layers with 3 neuron ($(T_w)_i$, $(T_a)_i$ and $m^\bullet{}_a$) in input layer , 16 neurons in hidden layers ,and 2 neuron ($(T_w)_e$ and $(T_a)_e$) in output layer have less error approach to zero.

Table 2,
Results of Neural Networks.

No. of neuron	**No. of layer** / **Type of (MSE)**	**1**	**2**	**3**
2	Performance training	5.9*10^-8	8.1*10^-9	5.6*10^-12
	Validation training	9.1*10^-8	5.5*10^-9	5.4*10^-13
3	Performance training	1.5*10^-9	3.2*10^10	6.2*10^-12
	Validation training	8.3*10^-10	2.1*10^10	5.8*10^-13
4	Performance training	5*10^-10	2.4*10^-11	7.1*10^13
	Validation training	9.5*10^-10	1.65*10^-11	8.2*10^14
6	Performance training	4.3*10^-11	1.34*10^-11	9.2*10^-15
	Validation training	1.4*10^-11	1.24*10^-12	6.6*10^-16
8	Performance training	8*10^-11	6.2*10^-11	7.3*10^-16
	Validation training	2*10^-11	2.3*10^12	9.2*10^-17
10	Performance training	9.8*10^-11	3.8*10^-12	8.5*10^-17
	Validation training	2.4*10^-11	1.2*10^-12	1.2*10^-18
12	Performance training	3.5*10^-11	4.1*10^-14	3.5*10^-19
	Validation training	1.2*10^-11	8.1*10^-13	1.8*10^-19
14	Performance training	2*10^-12	8.2*10^-14	7.4*10^-20
	Validation training	4*10^-11	3.2*10^-14	4.9*10^-19
16	Performance training	9.6*10^-12	6.1*10^-16	2.33*10^-21
	Validation training	5.2*10^-11	8.2*10^-15	5.23*10^-19

The goal of training is to find an optimum answer of network. Fig. (4) show the training, validation and testing graph of developed network with 3 layers and 16 neurons. The graph resulted show a very good performance (very small mean square error) after 472 attempts. Fig. (5) illustrate regression between desired target and prediction ANN output for training , validation, testing and all samples. All outputs seem to track the targets reasonably well and regression values are equal to one (R=1).

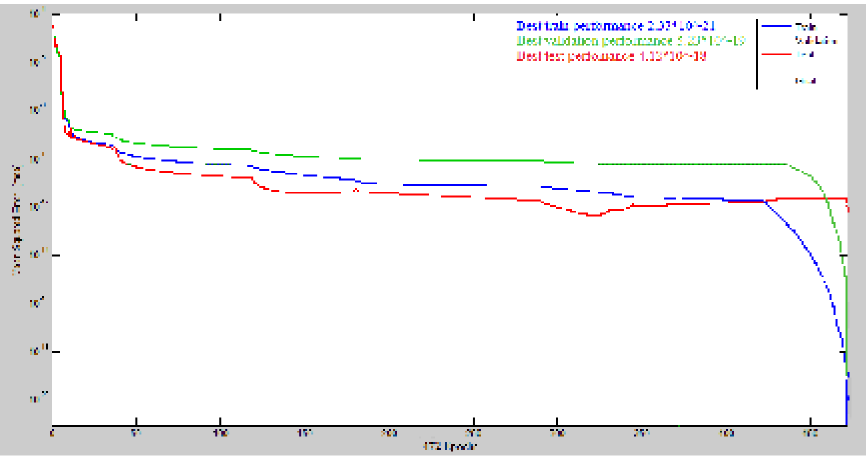

Fig. 4. The Best Training

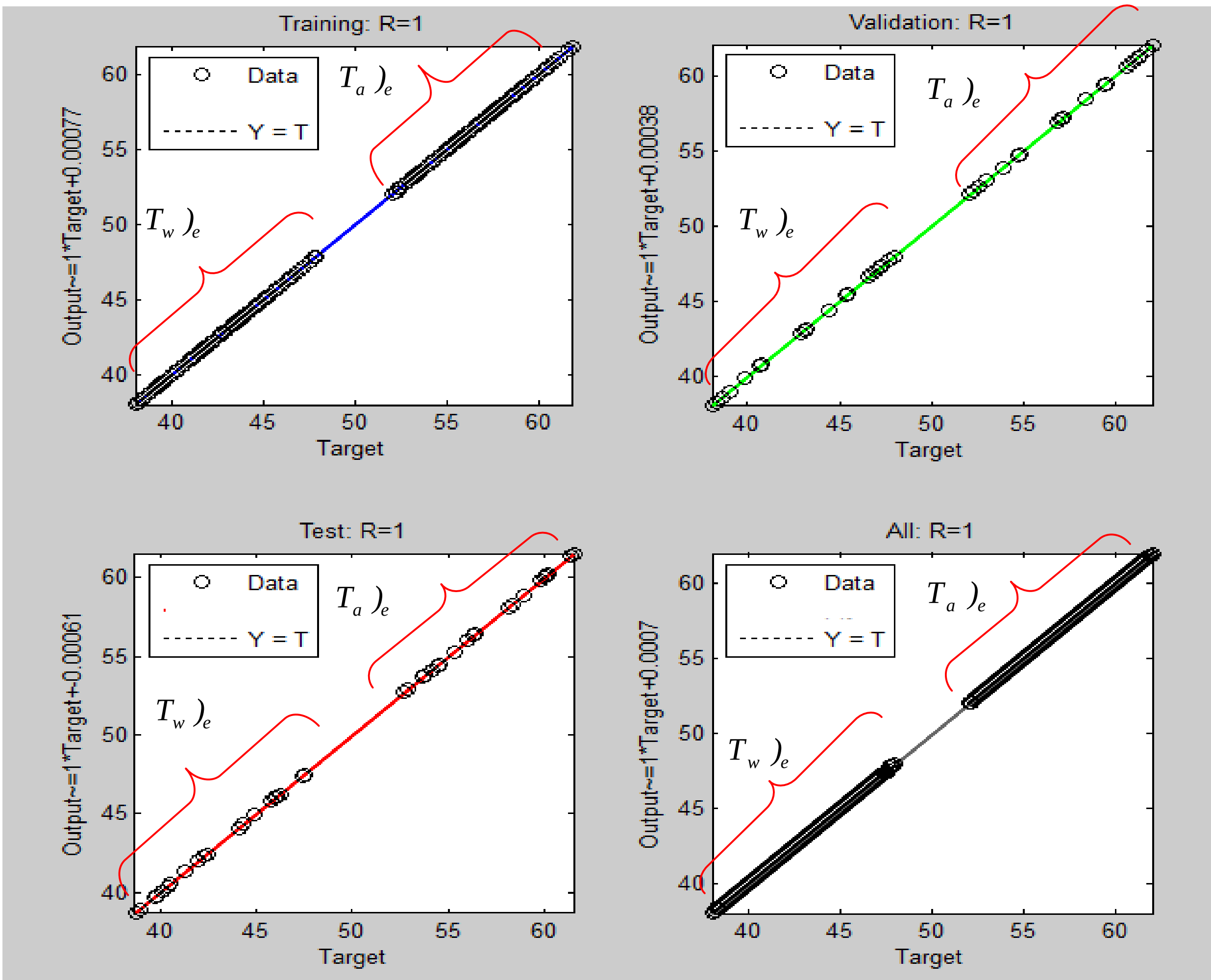

Fig. 5. Regression between Desired Target and Prediction ANN Output for Training, Validation, Testing and all Samples.

6. Neural Network Testing

This study used 50 sets of data were that generated by the reference heat exchanger model to test the network .The results shown in Fig. (6) illustrate the good agreement ($\pm 0.3\%$) between desired and predicated exit temperature (water temp. and air temp.) from heat exchanger.

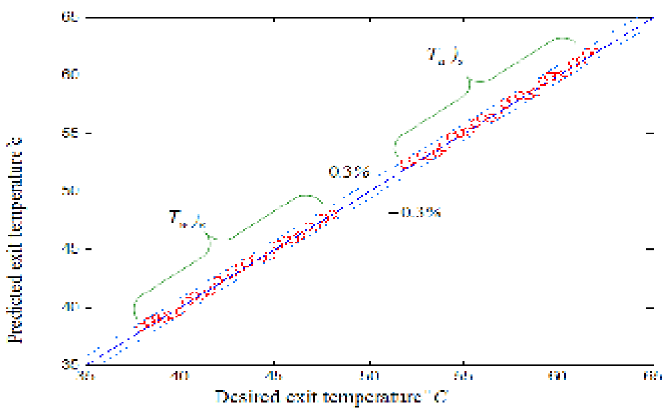

Fig. 6. Desired and Predicated Output Data for Testing Neural Network

7. Conclusion

This paper presents (ANN) modeling approach to the steam condenser performance. Experiment were carried out to validate the ANN model. Practical data was obtained from Heat exchanger operation in Dura refinery and the data was divided to three samples (training, validation and testing data). Two outputs (exit water temp. and exit air temp.) were taken in ANN.

After study 1-3 layers with 2-16 neuron, with back propagation algorithm, the training and testing of the results were carried out and the output of network is created. Three layers with 16 neurons had the best answer and used in this paper.

Comparing target data with experiment results of exit water temperature and exit air temperature showed the all outputs seem to track the targets reasonably well and regression values are equal to one (R=1) .

Compared with experiment results the exit temperatures for water and air drops predicted by the testing ANN is $\pm 0.35\%$ of data. All deviation falls into $\pm 1\%$.
With artificial NN exit temperatures for water and air can be found without need to thermal heat exchanger analysis.

The result of this study helps researchers to study the thermal performance of devices (cooling tower and air compressor) connected with heat exchanger.

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تخمين درجات الحرارة الخارجة من مبادل حراري نوع قشرة – انبوب باستخدام الشبكة العصبية الصناعية اعتمادا على معلومات تطبيقية

هشام حسن جاسم
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الخلاصة

هدف الدراسة هو تطبيق الشبكة العصبية لتحليل انتقال الحرارة لمبادل حراري وهو من الأجهزة واسعة الاستخدام في محطات توليد القدرة والمصافي.النتائج العملية تم الحصول عليها من مبادل حراري يعمل في قسم توليد الطاقة داخل مصفى الدورة.اعتمدنا أشهر طريقة للتدريب وتعليم الخوارزمية وهي Back propagation algorithm من خلال تقسيم النتائج العملية الى ثلاثة أقسام (تدريب، تصديق، اختبار) للحصول على أفضل تقارب مع الحالة الحقيقية. قيم الإدخال للشبكة العصبية هي درجة حرارة الماء الداخل و درجة حرارة الهواء الداخل ومعدل تدفق الهواء أما قيم الإخراج فهي درجة حرارة الماء الخارج لبرج التبريد ودرجة حرارة الهواء الخارج لضاغط الهواء. ١٥٠ قراءة تم أخذها من الموديل في أيام عمل مختلفة لتدريب الشبكة العصبية . مقارنة نتائج الشبكة مع القيم العملية وبأقسامها التدريب والتصديق والاختبار بينة تقارب عالي جدا، ٥٠ قراءة تم أخذها لاختبار مدى دقة الشبكة العصبية في هذه الدراسة من خلال مقارنة درجات حرارة الخروج للماء ودرجة حرارة الخروج للهواء الناتجة من الشبكة والموديل العملي بينة تقارب ودقة معقولة حيث بلغت نسبة الخطأ بحدود ($\pm 0.3\%$).