



AN EXPERT MODEL FOR THE SHELL AND TUBE HEAT EXCHANGERS ANALYSIS BY ARTIFICIAL NEURAL NETWORKS

A.R. Moghadassi¹, S.M. Hosseini¹, F. Parvizian¹, F. Mohamadiyon¹, A. Behzadi Moghadam¹ and A. Sanaeirad²

¹Department of Chemical Engineering, Faculty of Engineering, Arak University, Arak, Iran

²Department of Civil Engineering, Faculty of Engineering, Arak University, Arak, Iran

E-Mail: a_moghadassi@yahoo.com

ABSTRACT

Due to the importance of heat exchangers in chemical and petrochemical industries, heat exchangers analysis and heat transfer calculations are preceded. The conventional and prevalent methods (such as KERN method and etc) are presented heat transfer calculation for the analysis and selection of shell and tube heat exchanger based on the obtained pressure drop and fouling factor after consecutive calculation. Also there are many properties and parameters in prevalent methods. The current work proposed a new method based on the artificial neural network (ANN) for the analysis of Shell and Tube Heat Exchangers. Special parameters for heat exchangers analysis were obtained by neural network and the required experimental data were collected from Kern's book, TEMA and Perry's handbook. The work used back-propagation learning algorithm incorporating levenberg-marquardt training method. The accuracy and trend stability of the trained networks were verified according to their ability to predict unseen data. MSE error evaluation was used and the error limitation is 10^{-3} - 10^{-6} . Parameters can be obtained without using charts, different tables and complicated equations. During this research, twenty two networks were utilized for all different properties. The results demonstrated the ANN's capability to predict the analysis.

Keywords: model, shell and tube heat exchanger, analysis, KERN method, artificial neural network.

Nomenclature

A	Heat-transfer surface ft ²
B	Baffle spacing in
C _p	Specific heat of fluid Btu/(lb)(°F)
D _e	Equivalent diameter for heat transfer and pressure drop ft
F _c	Caloric Fraction
F _T	Temperature difference factor
f	Friction factor
ID	Inside diameter in
j _H	Factor for heat transfer
K _c	Caloric constant
k	Thermal conductivity Btu/(hr)(ft ²)(°F/ft)
L	Tube length ft
LMTD	Log mean temperature difference °F
N _t	Number of tubes
n	Number of tube passes
P _T	Tube pitch in
P _s Δ	Tube side and return pressure drop,
P _t Δ	respectively psi
Q	Heat flow Btu/hr
R	Temperature group, (T ₁ -T ₂)/(t ₂ -t ₁)
Re	Reynolds number for heat transfer and pressure drop
S	Temperature group, (t ₂ -t ₁)/(T ₁ -t ₁)
s	Specific gravity
t _w	Tube wall temperature °F
φ	The viscosity ratio (μ/μ _w) ^{0.14}
μ	Viscosity lb/(ft)(hr)
μ _w	Viscosity at wall temperature lb/(ft)(hr)

1. INTRODUCTION

Heat exchangers may be classified according to their flow arrangement. Counter current heat exchangers are most efficient because they allow the highest log mean temperature difference between the hot and cold streams. In a cross-flow heat exchanger, the fluids travel roughly perpendicular to one another through the exchanger. For efficiency, heat exchangers are designed to maximize the surface area of the wall between the two fluids, while minimizing resistance to fluid flow through the exchanger. The exchanger's performance can also be affected by the addition of fins or corrugations in one or both directions, which increase surface area and may channel fluid flow or induce turbulence. The driving temperature across the heat transfer surface varies with position, but an appropriate mean temperature can be defined. In most simple systems this is the log mean temperature difference (LMTD). Sometimes direct knowledge of the LMTD is not available and the NTU method is used.

Fouling occurs when a fluid goes through the heat exchanger, and the impurities in the fluid precipitate onto the surface of the tubes. Precipitation of these impurities can be caused by: Frequent use of the heat exchanger, Not cleaning the heat exchanger regularly, Reducing the velocity of the fluids moving through the heat exchanger and Over-sizing of the heat exchanger. Effects of fouling are more abundant in the cold tubes of the heat exchanger than in the hot tubes. This is because impurities are less likely to be dissolved in a cold fluid. This is because, for most substances, solubility increases as temperature increases. A notable exception is hard water where the opposite is true. Fouling reduces the cross sectional area for heat to be transferred and causes an increase in the resistance to heat transfer across the heat



exchanger. This is because the thermal conductivity of the fouling layer is low. This reduces the overall heat transfer coefficient and efficiency of the heat exchanger. This in turn, can lead to an increase in pumping and maintenance costs. The conventional approach to fouling control combines the "blind" application of biocides and anti-scale chemicals with periodic lab testing. This often results in the excessive use of chemicals with the inherent side effects of accelerating system corrosion and increasing toxic waste - not to mention the incremental cost of unnecessary treatments. There are however solutions for continuous fouling monitoring. In liquid environments, such as the Neosens FS sensor, measuring both fouling thickness and temperature, allowing to optimize the use of chemicals and control the efficiency of cleanings.

2. MAINTENANCE

Plate heat exchangers need to be disassembled and cleaned periodically. Tubular heat exchangers can be cleaned by such methods as acid cleaning, sandblasting, high-pressure water jet, bullet cleaning, or drill rods. In large-scale cooling water systems for heat exchangers, water treatment such as purification, addition of chemicals, and testing, is used to minimize fouling of the heat exchange equipment. Other water treatment is also used in steam systems for power plants, etc. to minimize fouling and corrosion of the heat exchange and other equipment. A variety of companies have started using water borne oscillations technology to prevent biofouling. Without the use of chemicals, this type of technology has helped in providing a low-pressure drop in heat exchangers [1, 2].

3. THE ALGORITHM CALCULATION OF A SHELL AND TUBE EXCHANGER

Process conditions required:

Hot fluid: T_1 , T_2 , W , C , s , μ , k , R_d , ΔP

Cold fluid: t_1 , t_2 , w , c , s , μ , k , R_d , ΔP

For the exchanger the following data must be known:

Shell side: ID, Baffle space, passes

Tube side: Number and length, OD, BWG, and pitch, Passes

(1) From T_1 , T_2 , t_1 , t_2 check the heat balance, Q , using c at T_{mean} and t_{mean} .

$$Q = WC(T_1 - T_2) = wc(t_2 - t_1) \quad (1)$$

$$T_s(t) = W, w \text{ (lb/hr)} \cdot C, c \text{ (Btu/lb. F)} \cdot \text{Btu/hr}(Q)$$

(2) True temperature difference Δt :
(Assuming counter flow)

$$LMED = [(T_1 - t_2) - (T_2 - t_1)] / [\ln(T_1 - t_2) / (T_2 - t_1)] \quad (2)$$

$$R = (T_1 - T_2) / (t_2 - t_1), S = (t_2 - t_1) / (T_1 - t_1) \Rightarrow F_T \Delta$$

$$t = LMTD \times F_T \quad (3)$$

(3) Caloric temperature T_c , t_c :

$$T_c = T_2 + F_c(T_1 - T_2) \quad (4)$$

$$t_c = t_1 + F_c(t_2 - t_1) \quad (5)$$

The coleric fraction F_c can be obtained from experimental results [3] by computing K_c from U_h and U_c and $\Delta t_c / \Delta t_h$ for the process conditions. If neither of the liquids is very viscous at the cold terminal, say not more than 1.0 centipoises, if the temperature ranges do not exceed 50 to 100°F, and if the temperature difference is less than 50°F, the arithmetic means of T_1 and T_2 and t_1 and t_2 may be used in place of T_c and t_c for evaluating the physical properties.

Cold fluid: tube side

(4) Flow area, a_t .

Flow area per tube a_t' (in²) [3].

$$N_t \cdot a_t' / 144n, (\text{ft}^2) = a_t \quad (6)$$

(5) Mass vel, G_t .

$$G_t = w / a_t, (\text{lb/hr.ft}^2) \quad (7)$$

(6) Obtain D from Table (10), ft. Obtain μ at

$$t_c, \text{lb/(ft)(hr)} = cp \times 2.24 \quad (8)$$

$Re_s = D_e \cdot G_s / \mu$

(7) Obtain j_H [3]

(8) At t_c obtain $c, \text{Btu/(lb)}(^{\circ}\text{F})$ and $k, \text{Btu/(hr)(ft}^2)(^{\circ}\text{F/ft)}$.

Compute $(c\mu/k)^{1/3}$

$$(9) h_i = j_H \cdot (k/D) \cdot (c\mu/k)^{1/3} \cdot \Phi_t \quad (9)$$

$$(10) h_{io}/\Phi_t = h_i/\Phi_t \times ID/OD \quad (10)$$

(11) Obtain t_w from (10').

Obtain μ_w and $\Phi_t = (\mu/\mu_w)^{0.14}$.

(12) Corrected coefficient, $h_{io} = (h_{io}/\Phi_t) \times \Phi_t, (\text{Btu/hr.ft}^2.\text{F})$

Hot fluid: shell side

(4') flow area a_s .

$$a_s = ID.C.B/144.P_T, (\text{ft}^2) \quad (11)$$

(5') Mass vel, G_s .

$$(\text{Lb/hr.ft}^2) G_s = w/a_s,$$

(6') compute $D_e = 4 \times \text{free area/wetted perimeter, (ft)}$ (12)

$$d_e = 4 \times (P_T - \pi d_o^2/4) / \pi d_o, (\text{in}) \quad (13)$$

Obtain μ at $T_c, \text{lb/(ft)(hr)} = cp \times 2.24$

$$Re_s = D_e \cdot G_s / \mu$$

(7') Obtain j_H [3]

(8') At T_c obtain $C, \text{Btu/(lb)}(^{\circ}\text{F})$ and $k, \text{Btu/(hr)(ft}^2)(^{\circ}\text{F/ft)}$. (8')

Compute $(c\mu/k)^{1/3}$

$$(9') h_o = j_H \cdot (k/D_e) \cdot (c\mu/k)^{1/3} \cdot \Phi_s$$

(10') Tube wall tem, t_w .

$$t_w = t_c + [(h_o/\Phi_s) / ((h_{io}/\Phi_t) + (h_o/\Phi_s))] \times (T_c - t_c) \quad (14)$$

(11') Obtain μ_w and $\Phi_s = (\mu/\mu_w)^{0.14}$.

(12') Corrected coefficient, $h_o = (h_{io}/\Phi_s) \times \Phi_s$



(13) Clean overall coefficient U_c :

$$U_c = (h_{io}, h_o) / (h_{io} + h_o) \quad (15)$$

(14) Design overall coefficient U_D : obtain external surface/lin ft a'' from Table-10. Heat transfer surface, $A = a''LN_t$, (ft²)

$$U_D = Q/A''\Delta t, (\text{Btu/hr.ft}^2.\text{F}) \quad (16)$$

(15) Dirt factor R_d :

$$R_d = (U_c - U_D)/U_c, U_D, (\text{hr.ft}^2.\text{F/Btu}) \quad (17)$$

If R_d equals or exceeds the required dirt factor, proceed under the pressure drop.

Pressure drop

(1) For Re_i in (6) obtain f , ft²/in².

$$(2) \Delta P_i = (f.G_i^2.L_n) / (5.22 \times 10^{10}.D.s.\Phi_i), (\text{psi}) \quad (18)$$

$$(3) \Delta P_r = (4.n/s) \times (V^2/2g), (\text{psi}) \quad (19)$$

$$P_T = \Delta P_i + \Delta P_r, (\text{psi})\Delta$$

(1') For Re_s in (6') obtain f , ft²/in².

$$(2') \text{No. of crosses, } N+1=12L/B \quad (20)$$

$$(3') \Delta P_s = (f.G_s^2.D_s.(N+1)) / (5.22 \times 10^{10}.D_e.s.\Phi_s) [3], (\text{psi})$$

4. ARTIFICIAL NEURAL NETWORKS

In order to find relationship between the input and output data derived from experimental work, a more powerful method than the traditional ones are necessary. ANN is an especially efficient algorithm to approximate any function with finite number of discontinuities by learning the relationships between input and output vectors. These algorithms can learn from the experiments, and also are fault tolerant in the sense that they are able to handle noisy and incomplete data. The ANNs are able to deal with non-linear problems, and once trained can perform estimation and generalization rapidly.

They have been used to solve complex problems that are difficult to be solved if not impossible by the conventional approaches, such as control, optimization, pattern recognition, classification, and so on, specially it is desired to have the minimum difference between the predicted and observed (actual) outputs. Artificial neural networks are biological inspirations based on the various brain functionality characteristics. They are composed of many simple elements called neurons that are interconnected by links and act like axons to determine an empirical relationship between the inputs and outputs of a given system. Multiple layers arrangement of a typical interconnected neural network is shown in Figure-1. It consists of an input layer, an output layer, and one hidden layer with different roles. Each connecting line has an associated weight. Artificial neural networks are trained by adjusting these input weights (connection weights), so that the calculated outputs may be approximated by the desired values. The output from a given neuron is calculated by applying a transfer function to a weighted

summation of its input to give an output, which can serve as input to other neurons, as follows.

$$\alpha_{jk} = F_k \left(\sum_{i=1}^{N_{k-1}} w_{ijk} \alpha_{i(k-1)} + \beta_{jk} \right) \quad (21)$$

Where α_{jk} is neuron j 's output from k 's layer β_{jk} is the bias weight for neuron j in layer k . The model fitting parameters w_{ijk} are the connection weights. The nonlinear activation transfer functions F_k may have many different forms. The classical ones are threshold, sigmoid, Gaussian and linear function, etc... [4], for more details of various activation functions see Bulsari.

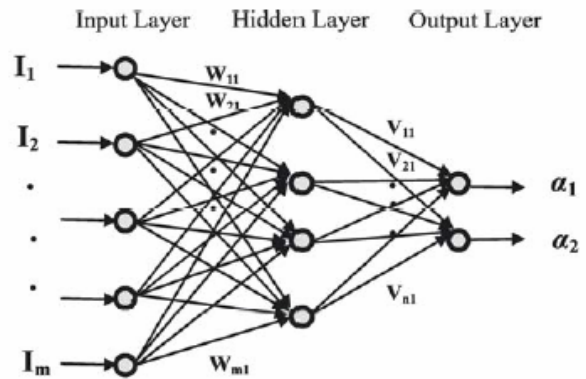


Figure-1. Schematic of typical multi-layer neural network model.

The training process requires a proper set of data i.e., input (I_i) and target output (t_i). During training the weights and biases of the network are iteratively adjusted to minimize the network performance function. The typical performance function that is used for training feed forward neural networks is the network Mean Squares Errors (MSE) Eq. (22).

$$MSE = \frac{1}{N} \sum_{i=1}^N (e_i)^2 = \frac{1}{N} \sum_{i=1}^N (t_i - \alpha_i)^2 \quad (22)$$

There are many different types of neural networks, differing by their network topology and/or learning algorithm. In this paper the back propagation learning algorithm, which is one of the most commonly used algorithms is designed to predict the PVT properties. Back propagation is a multilayer feed-forward network with hidden layers between the input and output. The simplest implementation of back propagation learning is the network weights and biases updates in the direction of the negative gradient that the performance function decreases most rapidly. An iteration of this algorithm can be written as follows.

$$x_{k+1} = x_k - l_k g_k \quad (23)$$

There are various back propagation algorithms such as Scaled Conjugate Gradient (SCG), Levenberg-Marquardt (LM) and Resilient back Propagation (RP). LM



is the fastest training algorithm for networks of moderate size and it has the memory reduction feature to be used when the training set is large. One of the most important general purpose back propagation training algorithms is SCG.

The neural nets learn to recognize the patterns of the data sets during the training process. Neural nets teach themselves the patterns of the data set letting the analyst to perform more interesting flexible work in a changing environment. Although neural network may take some time to learn a sudden drastic change, but it is excellent to adapt constantly changing information. However the programmed systems are constrained by the designed situation and they are not valid otherwise. Neural networks build informative models whereas the more conventional models fail to do so. Because of handling very complex interactions, the neural networks can easily model data, which are too difficult to model traditionally (inferential statistics or programming logic). Performance of neural networks is at least as good as classical statistical modeling, and even better in most cases. The neural networks built models are more reflective of the data structure and are significantly faster.

Neural networks now operate well with modest computer hardware. Although neural networks are computationally intensive, the routines have been optimized to the point that they can now run in reasonable time on personal computers. They do not require

supercomputers as they did in the early days of neural network research [5, 6].

5. NEURAL NETWORK MODEL DEVELOPMENT

Due to shell and tube heat exchanger analysis method, all physical and chemical properties and parameters have been trained by artificial neural network. That all of the physical and chemical properties and parameters of 30 non- petroleum and 6 petroleum samples. Experimental data is collected Kern's book [3] and TEMA [7] and Perry's handbooks [2]. 70 percent of experimental data randomly is selected for training and the remaining 30 percent used for testing by matlab2009. 22 networks are obtained containing different properties such as viscosity, specific gravity, specific heat and special parameters of heat exchangers. Error back- propagation method and levenberg-marquardt training algorithm at the feed forward network were used in this networks. Hidden layer function is tangent-sigmoid and output layer function is linear. In all of these networks mean square errors (MSE) and regression factor has been used as criteria for models. Most of networks have one hidden layer function and only in LMTD correct factor (F_T) networks have two hidden layers. Hidden layer numbers, type of hidden layer, type of out put layer function and number of neurons of hidden layer specified by trial and error and experience. Error limitation is 10^{-3} - 10^{-6} and the result is corresponding with experimental numbers. The data of these networks are presented in Table-1.

Table-1. The data of networks.

Parameter	No. of data	No. of hidden layer	No. of neurons	MSE (training)	MSE (test)	Regration (training)	Regration (test)
Cp (non oil component)	348	1	15	0.00037	0.0013	0.99	0.97
f (tube)	25	1	7	1.01×10^{-9}	8×10^{-8}	1	0.99
f (shell)	35	1	11	4.7×10^{-9}	3.7×10^{-6}	1	0.97
$\Phi_t [(\mu/\mu_w)^{14}]$	25	1	4	0.00016	0.0004	1	1
k(oil component)	91	1	7	7.11×10^{-9}	1.8×10^{-6}	1	0.99
K_c	62	1	5	0.00035	0.0002	1	1
s (oil component)	218	1	11	0.00002	0.0002	1	1
Viscosity (oil component)	91	1	9	0.0044	0.02	0.99	1
Cp (oil component)	435	1	7	4×10^{-5}	2×10^{-5}	1	1
$V^2/2g$	17	1	4	3.9×10^{-9}	0.0008	1	1
μ (non oil component)	576	1	16	0.0018	0.0015	1	1
F_c	112	1	4	.00003	.00003	1	0.99
j_H (tube)	159	1	7	0.5	1	1	1
j_H (shell)	37	1	7	2.16	1.77	1	1
k(non oil component)	213	1	15	.00005	.0004	0.99	0.96
F_T (1-2 heat exchanger)	469	1	11	.00043	.00054	0.99	0.99



F _T (2-4 heat exchanger)	480	2	7,9	.0008	.0005	1	0.97
F _T (3-6 heat exchanger)	493	2	9,9	.00036	.00063	0.98	0.98
F _T (4-8 heat exchanger)	473	2	7,7	.00006	.0032	0.99	0.9
F _T (5-10 heat exchanger)	257	2	7,5	.00029	.00012	1	1
F _T (6-12 heat exchanger)	290	2	7,5	.00014	.00021	0.99	0.99
F _T (1-3 heat exchanger)	245	1	9	.00008	.00009	1	1

6. RESULTS

The optimum performance of networks is empirically obtained by changing the number of neurons in the hidden layer using the trial-and-error method. The minimal number of neurons is sufficient for prediction performance without leading to over-fitting or an unreasonably long computational time. If too few neurons exist in the hidden layer, the performance of the network will not be satisfactory. Conversely, if too many neurons exist in the hidden layer, the convergence will be very slow and may be compromised by local minima or over-fitting. The LM training algorithm was found to have a superior performance among all the best networks. There

fore, the LM method containing 14 hidden neurons with minimum error is selected as the optimum structure. The trained ANN models were also tested and evaluated against the new data. Figures 2-45 shows the scatter diagrams that compare the experimental data versus the computed neural network data in both training and testing networks in many aspects. As evident in the Figures, a tight cluster of points around the 45° line occurs for the data points, indicating excellent agreement between the experimental and calculated data. Almost all data fall along this line, which confirms the accuracy of the ANN model.

Friction coefficient (tube)

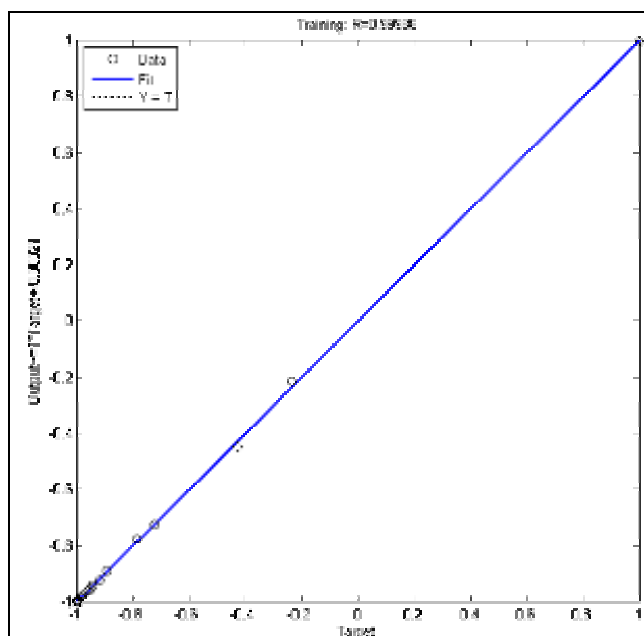


Figure-2. A Comparison between ANN and experimental data for training the network.

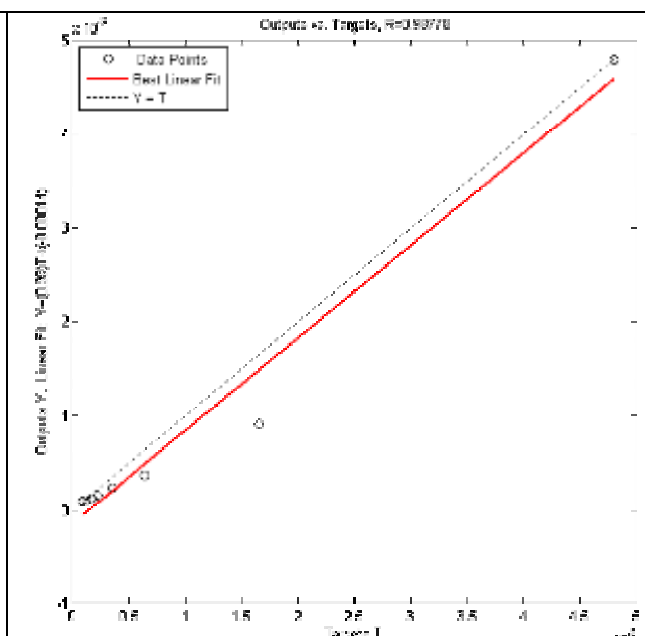


Figure-3. A Comparison between ANN and experimental data for testing the network.



Friction coefficient (shell)

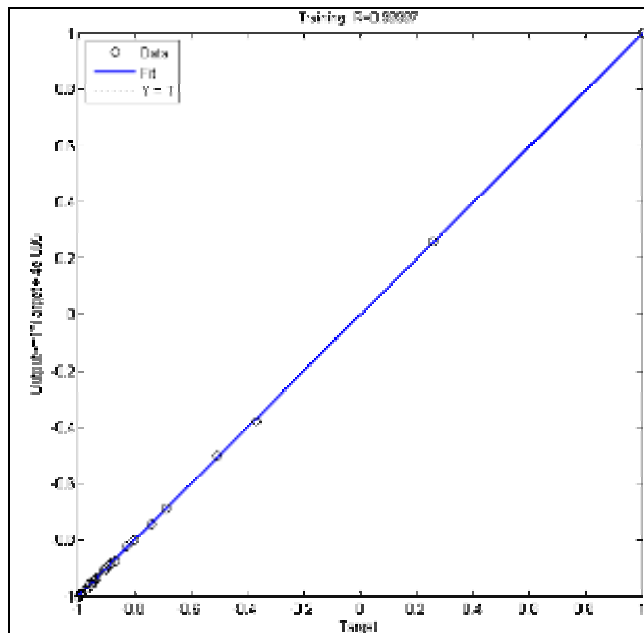


Figure-4. A Comparison between ANN and experimental data for training the network.

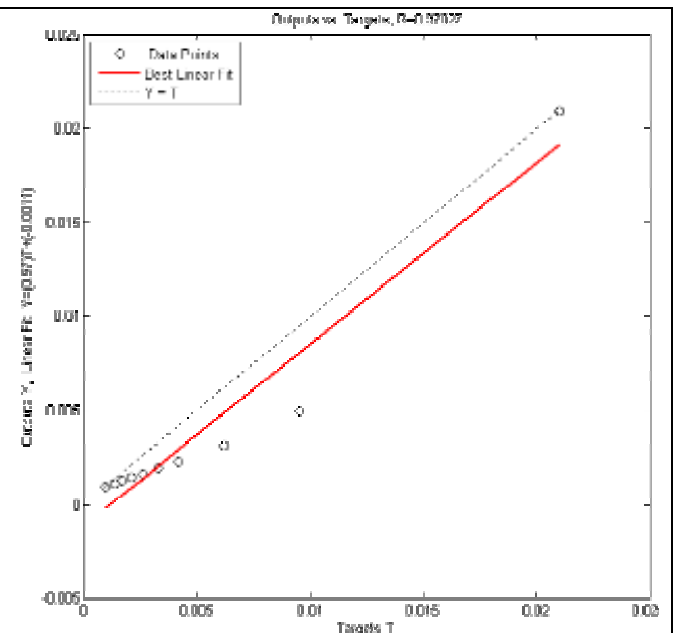


Figure-5. A Comparison between ANN and experimental data for testing the network.

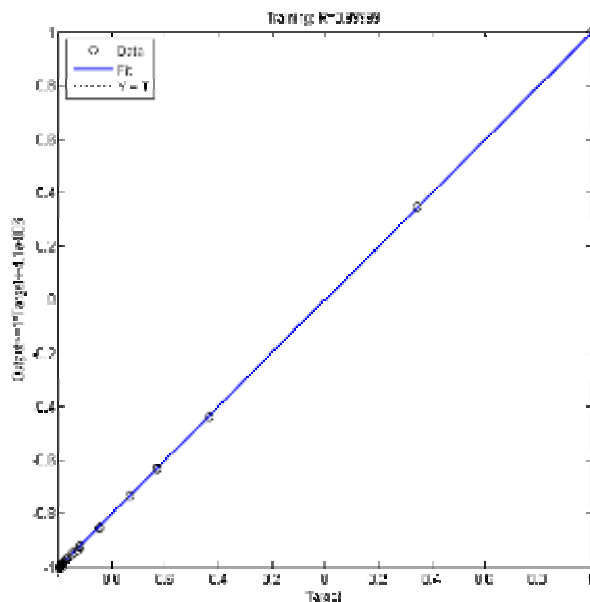
 j_H (tube)

Figure-6. A Comparison between ANN and experimental data for training the network.

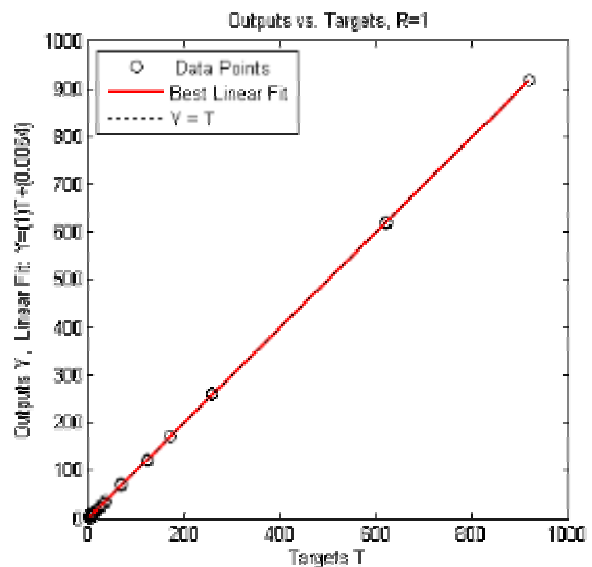


Figure-7. A Comparison between ANN and experimental data for testing the network.

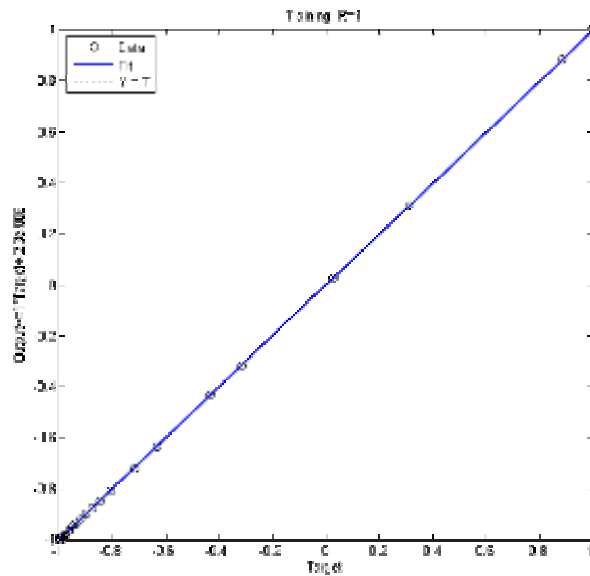
**j_H (shell)**

Figure-8. A Comparison between ANN and experimental data for training the network.

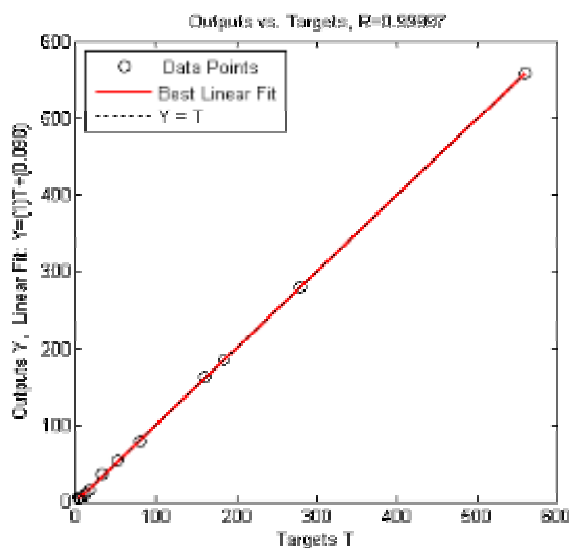


Figure-9. A Comparison between ANN and experimental data for testing the network.

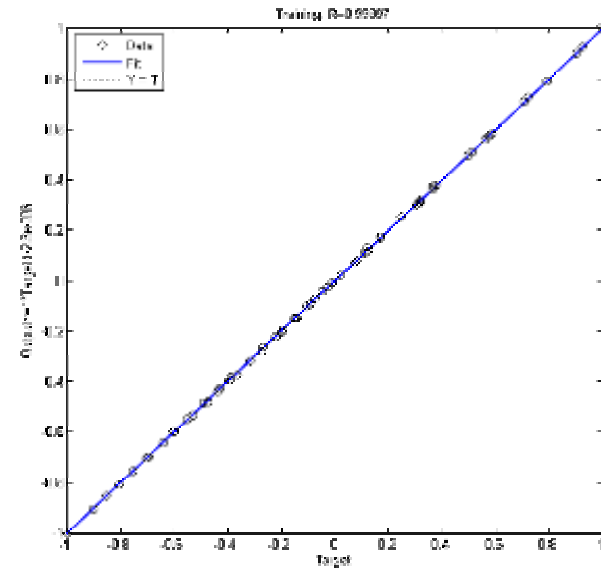
k (petroleum)

Figure-10. A Comparison between ANN and experimental data for training the network.

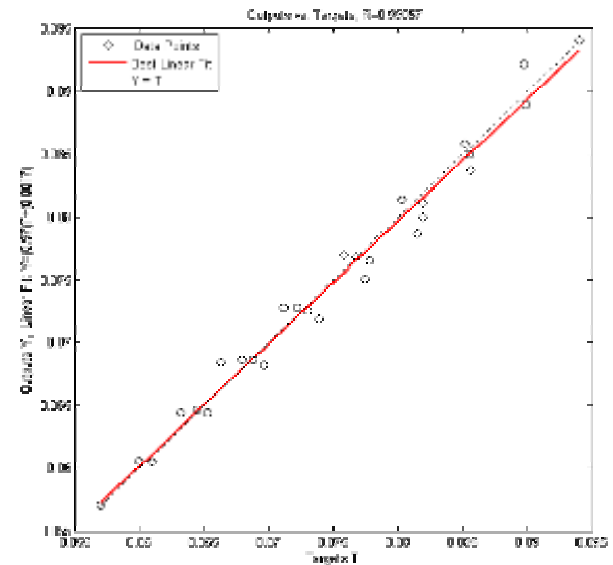


Figure-11. A Comparison between ANN and experimental data for testing the network.

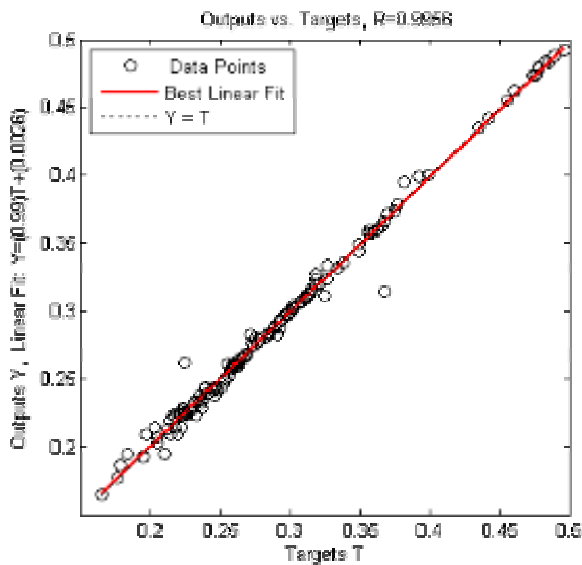
**k (non-petroleum)**

Figure-12. A Comparison between ANN and experimental data for training the network.

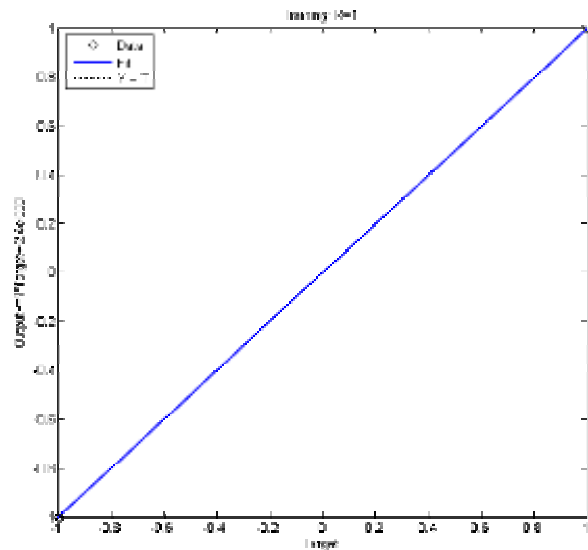
s (petroleum)

Figure-14. A Comparison between ANN and experimental data for training the network.

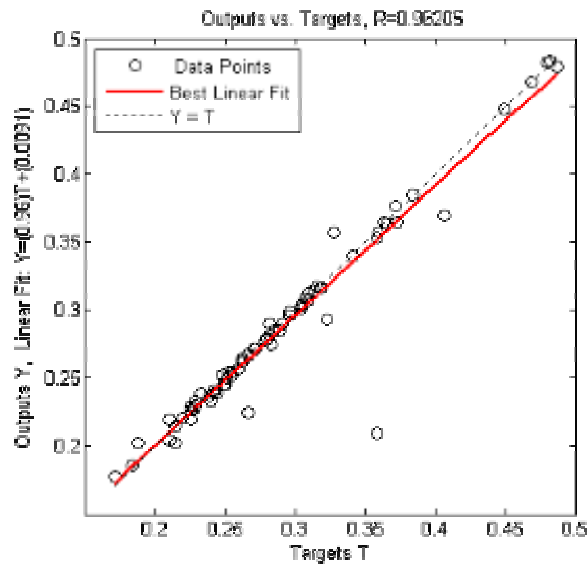


Figure-13. A Comparison between ANN and experimental data for testing the network.

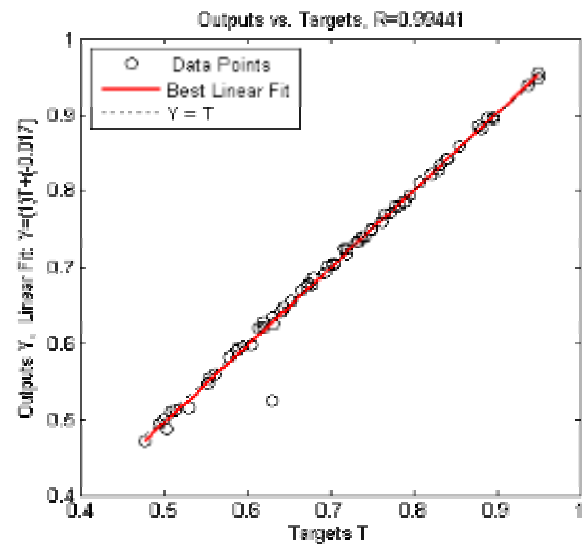


Figure-15. A Comparison between ANN and experimental data for testing the network.

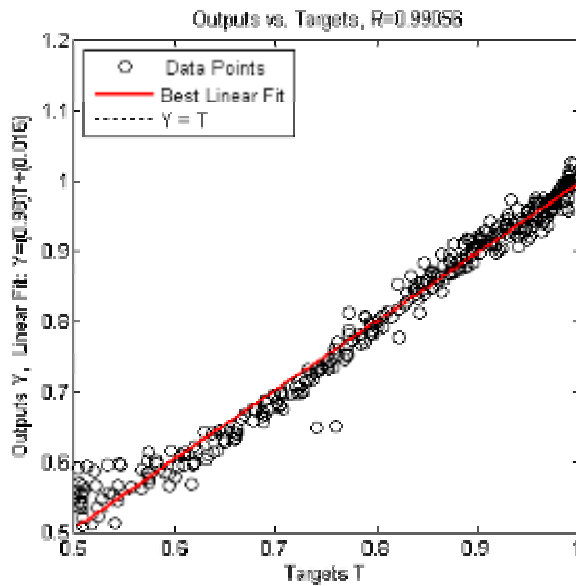
**F_T (1-2 Heat exchanger)**

Figure-16. A Comparison between ANN and experimental data for training the network.

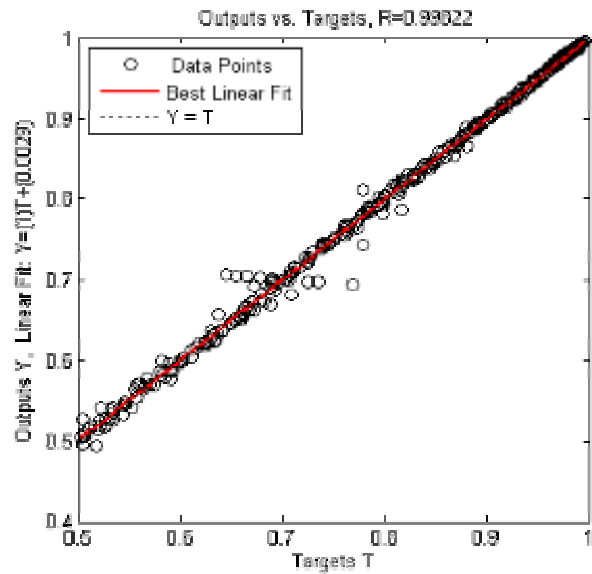
F_T (2-4 Heat exchanger)

Figure-18. A Comparison between ANN and experimental data for training the network.

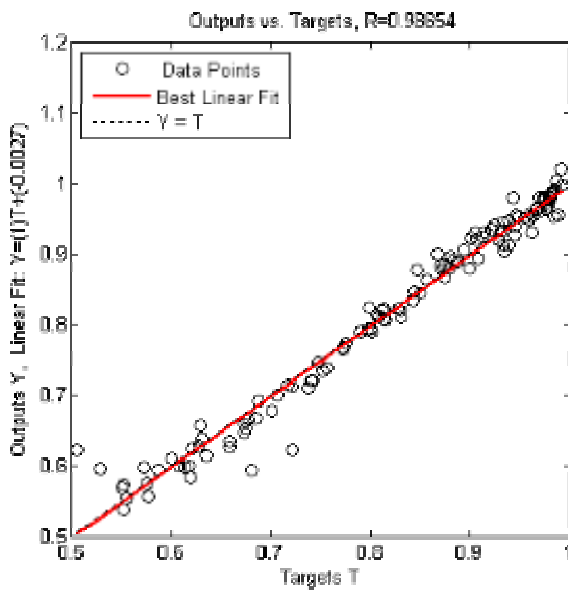


Figure-17. A Comparison between ANN and experimental data for testing the network.

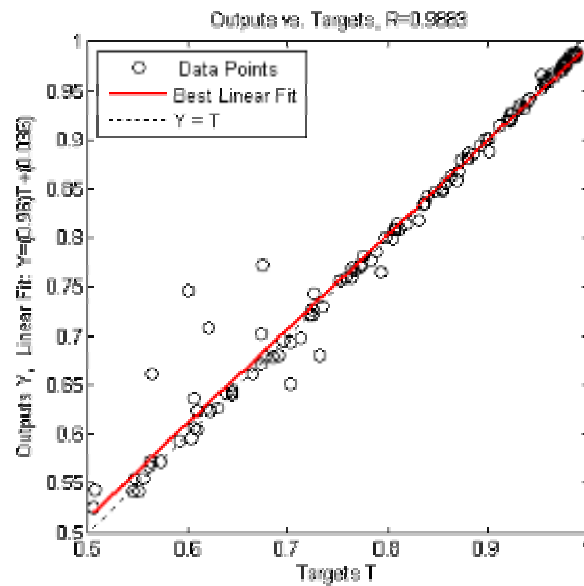


Figure-19. A Comparison between ANN and experimental data for testing the network.

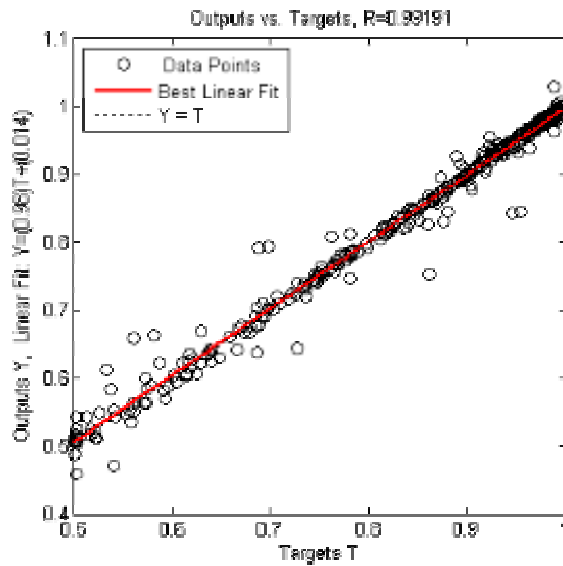
**F_T (3-6 Heat exchanger)**

Figure-20. A Comparison between ANN and experimental data for training the network.

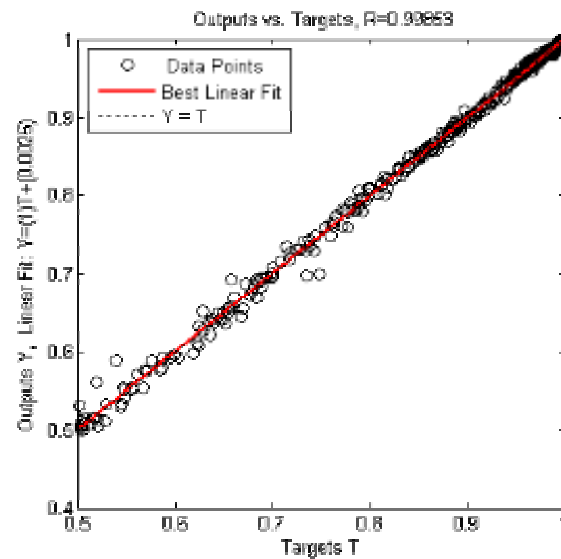
F_T (4-8 Heat exchanger)

Figure-22. A Comparison between ANN and experimental data for training the network.

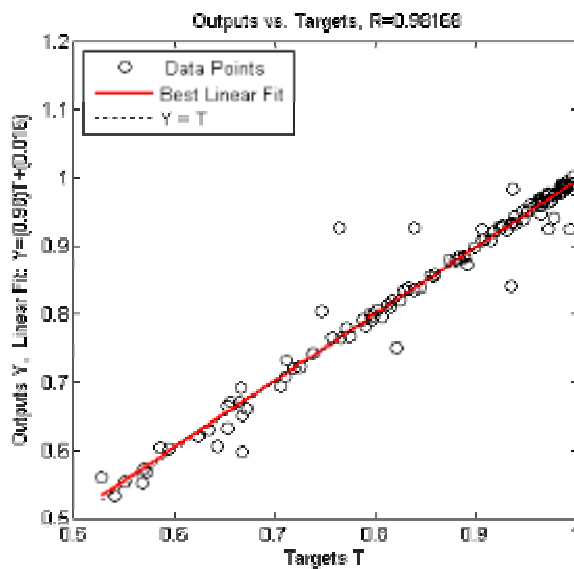


Figure-21. A Comparison between ANN and experimental data for testing the network

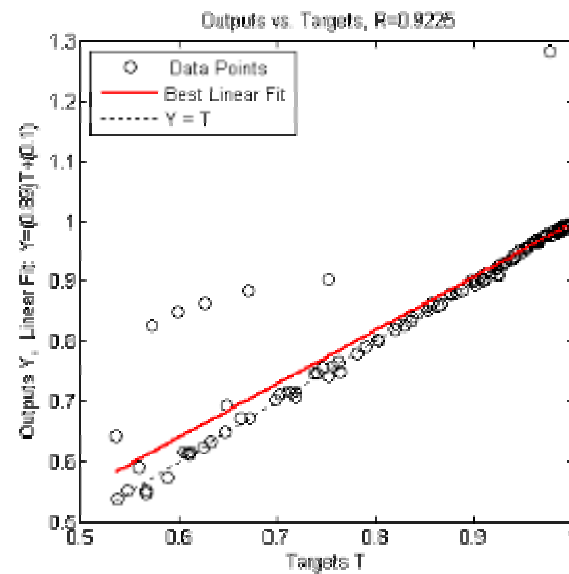
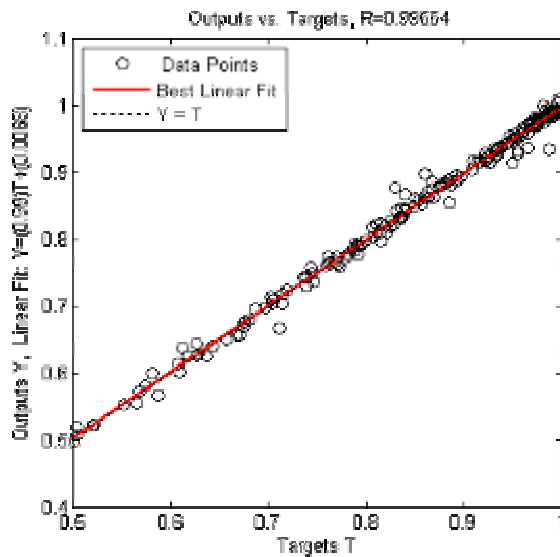
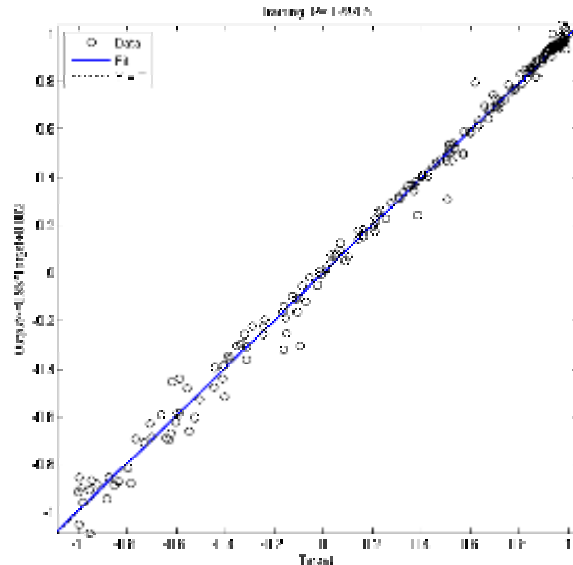
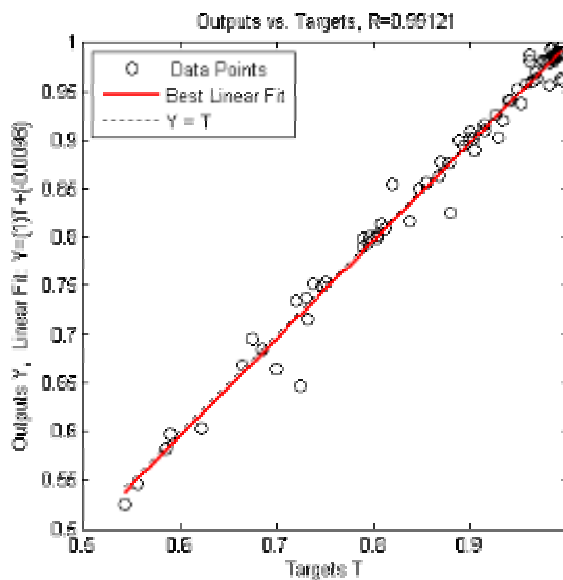
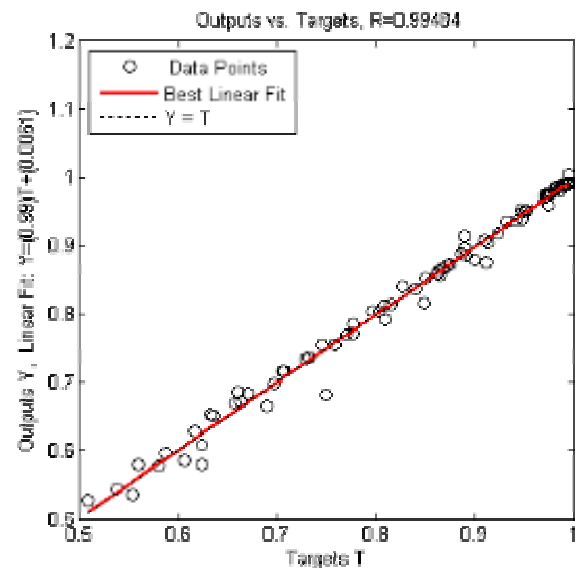


Figure-23. A Comparison between ANN and experimental data for testing the network.

**F_T (5-10 Heat exchanger)****Figure-24.** A Comparison between ANN and experimental data for training the network.**F_T (6-12 Heat exchanger)****Figure-26.** A Comparison between ANN and experimental data for training the network.**Figure-25.** A Comparison between ANN and experimental data for testing the network.**Figure-27.** A Comparison between ANN and experimental data for testing the network.

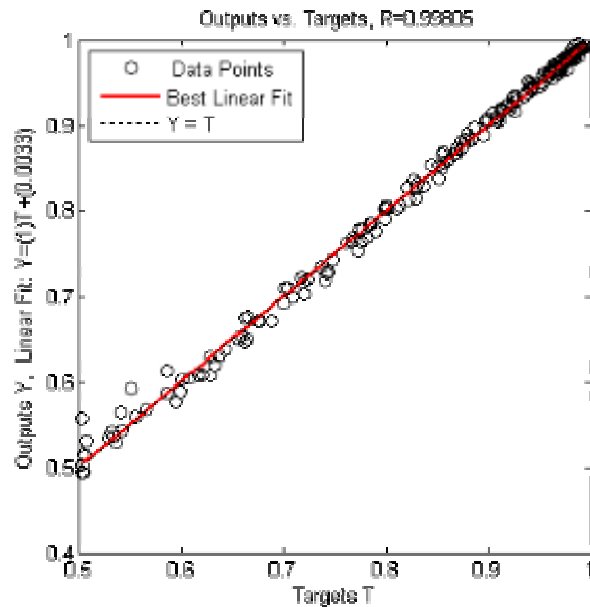
**F_T (1-3 Heat exchanger)**

Figure-28. A Comparison between ANN and experimental data for training the network.

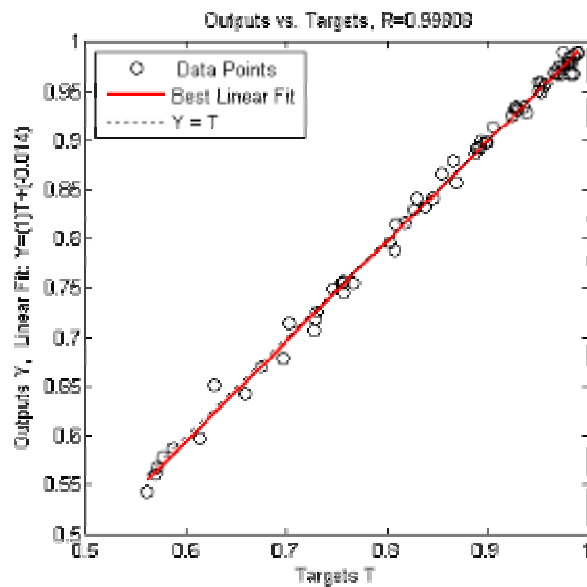


Figure-29. A Comparison between ANN and experimental data for testing the network.

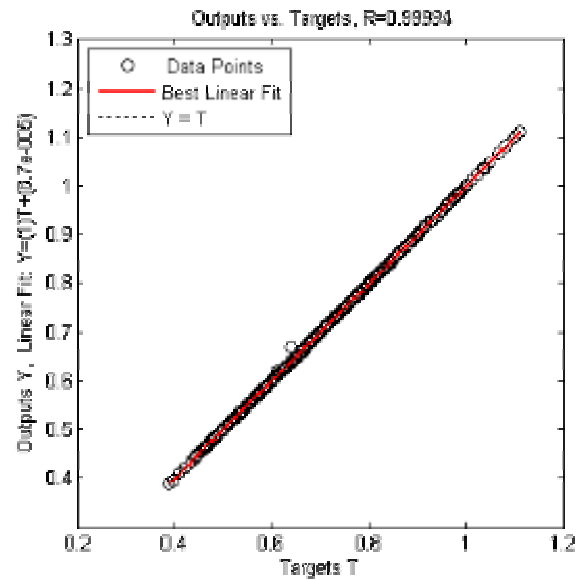
C_p (petroleum)

Figure-30. A Comparison between ANN and experimental data for training the network.

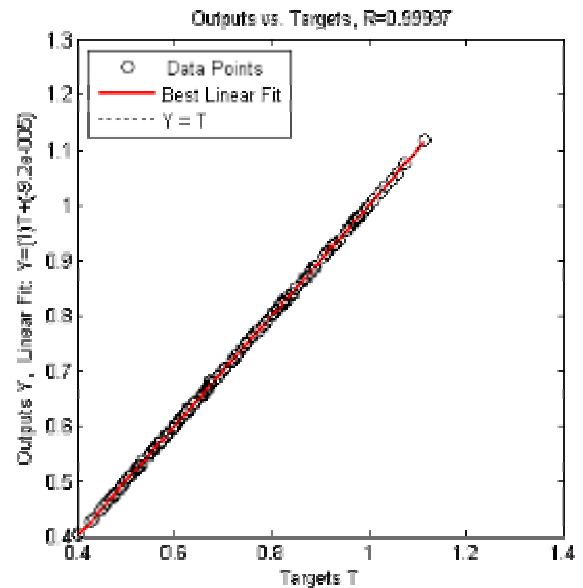


Figure-31. A Comparison between ANN and experimental data for testing the network.

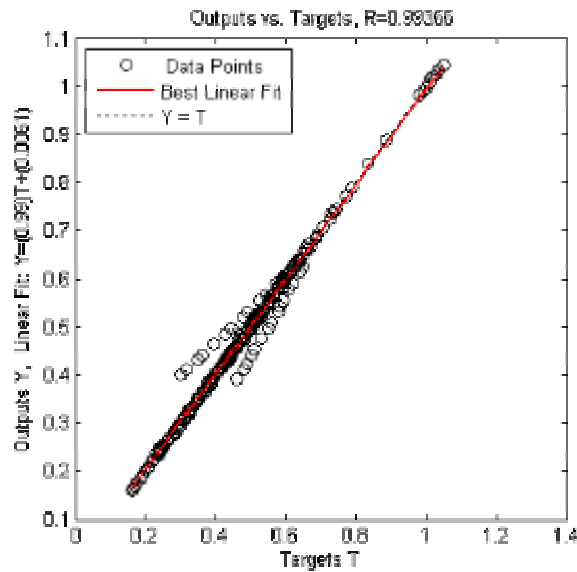
**Cp (non-petroleum)**

Figure-32. A Comparison between ANN and experimental data for training the network.

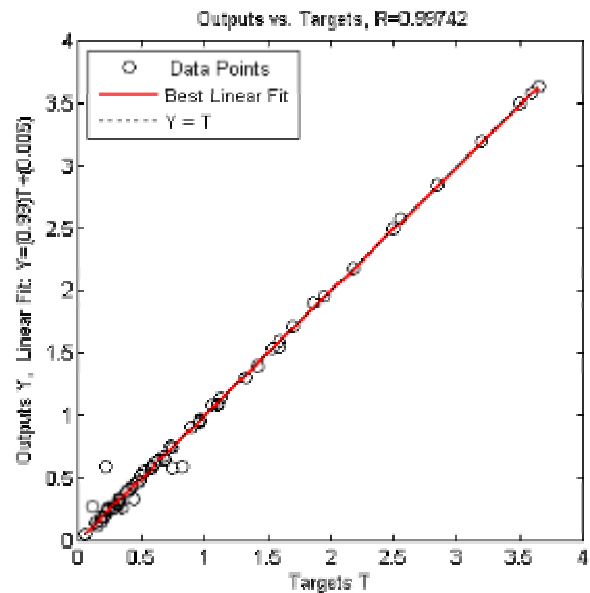
Viscosity (petroleum)

Figure-34. A Comparison between ANN and experimental data for training the network.

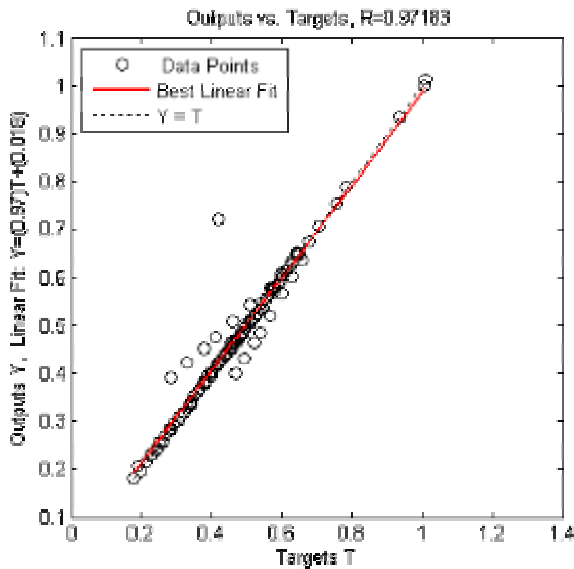


Figure-33. A Comparison between ANN and experimental data for testing the network.

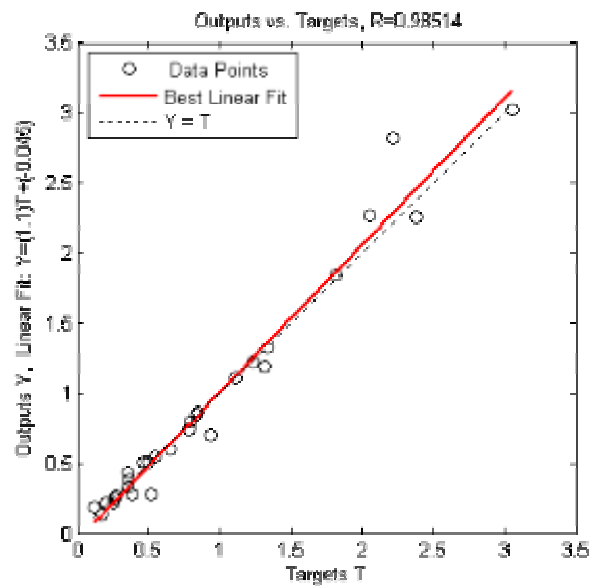


Figure-35. A Comparison between ANN and experimental data for testing the network.



Viscosity (non-petroleum)

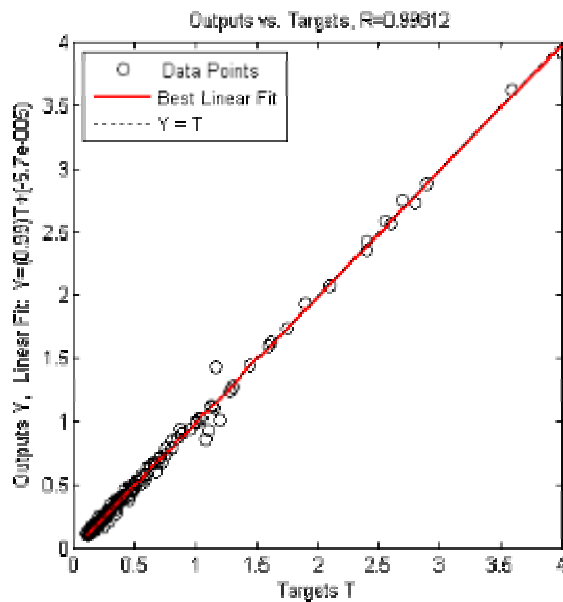
 $V^2/2g$ 

Figure-36. A Comparison between ANN and experimental data for training the network.

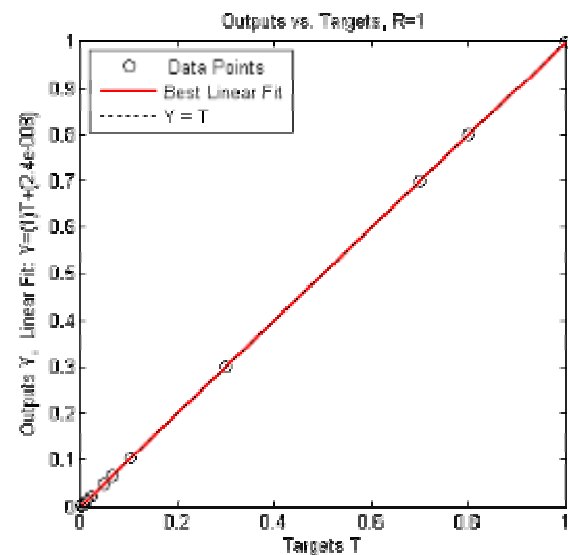


Figure-38. A Comparison between ANN and experimental data for training the network.

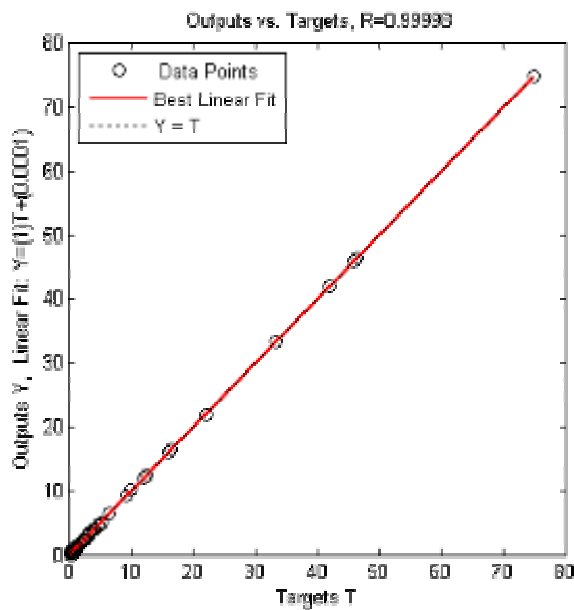


Figure-37. A Comparison between ANN and experimental data for testing the network.

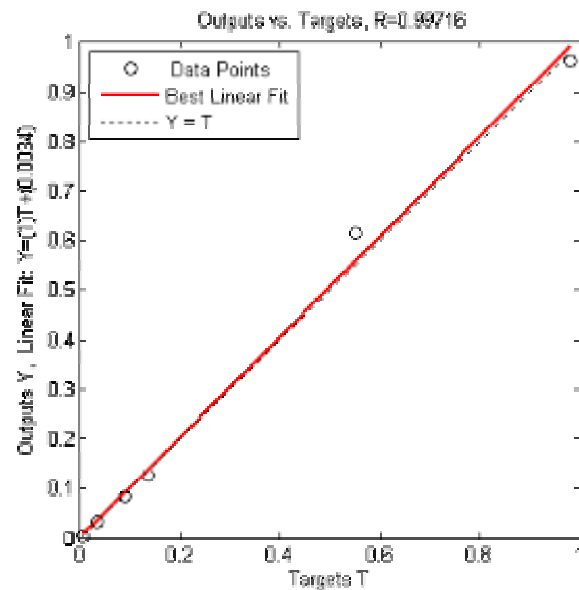


Figure-39. A Comparison between ANN and experimental data for testing the network.

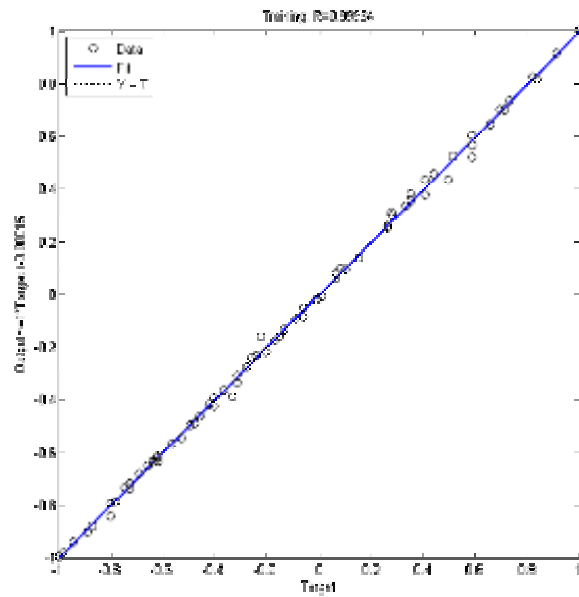
 F_C 

Figure-40. A Comparison between ANN and experimental data for training the network.

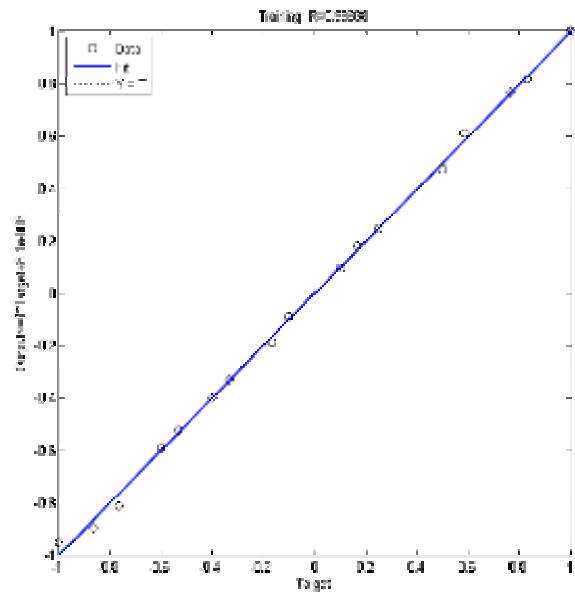
 Φ_t 

Figure-42. A Comparison between ANN and experimental data for training the network.

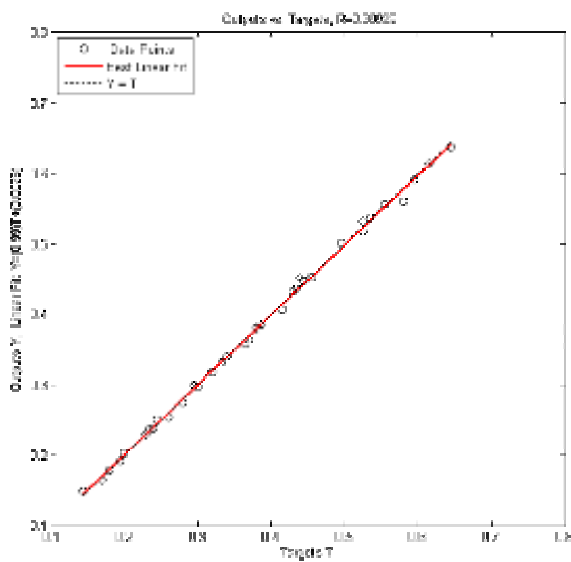


Figure-41. A Comparison between ANN and experimental data for testing the network.

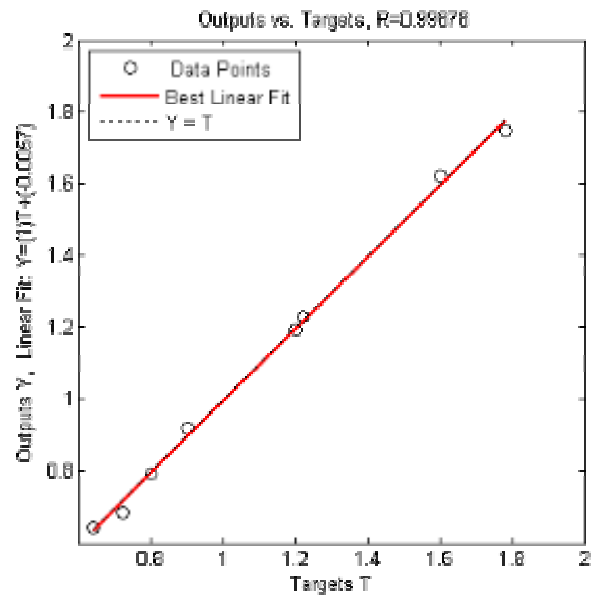


Figure-43. A Comparison between ANN and experimental data for testing the network.

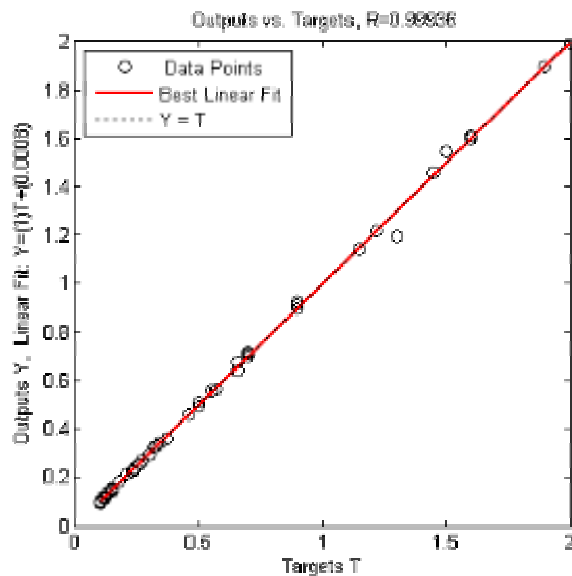
K_C

Figure-44. A Comparison between ANN and experimental data for training the network.

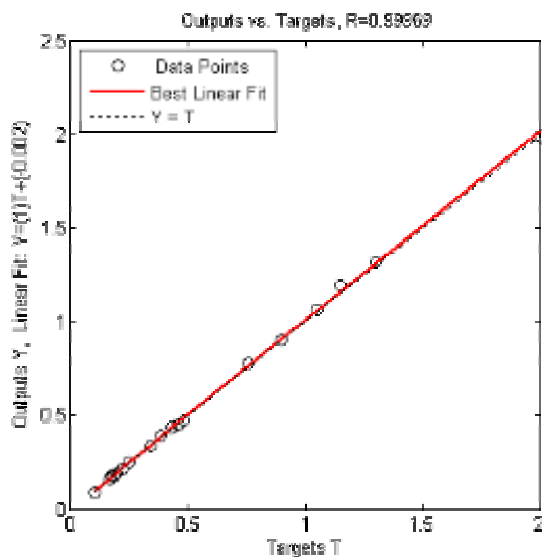


Figure-45. A Comparison between ANN and experimental data for testing the network.

7. CONCLUSIONS

This work investigated the ability of ANN in modeling and analysis the Shell and Tube Heat Exchangers. The MLP neural network architectures were used for the purpose. Results showed good agreement with experimental data. An important feature of the model is that it requires no theoretical knowledge or human experiences during the training process. The model was trained based on the experimental data. All unknown relationships were represented approximately using neural networks instead of traditional relationships.

REFERENCES

- [1] Sadik Kakaç and Hongtan Liu. 2002. Heat Exchangers: Selection, Rating and Thermal Design (2nd Edition ed.). CRC Press. ISBN 0849309026.
- [2] R.H Perry. 1984. Perry's Chemical Engineers' Handbook (6th Edition ed.). McGraw-Hill. ISBN 0-07-049479-7.
- [3] Donald Q.Kern. 1965. Process Heat transfer (23rd printing 1986). McGraw-Hill companies. ISBN 0-07-Y85353-3.
- [4] M.T. Hagan, H.B. Demuth, M. Beal. 1996. Neural Network Design. PWS Publishing Company, Boston.
- [5] A. R. Moghadassi, F. Parvizian, Sayed Mohsen Hosseini1 and Amir Sharifi 2008. Prediction of PVT properties of Ammonia by using Artificial Neural Network and equations of state. ARPN Journal of Engineering and Applied Sciences. 3(6): 18-27.
- [6] A. R. Moghadassi, F. Parvizian, S. M. Hosseini and A. R. Fazlali. 2009. A New Approach for Estimation of PVT Properties of Pure Gases Based on Artificial Neural Network Model. Brazilian Journal of Chemical Engineering. 26(01): 199-206, January - March.
- [7] Richard C. Byrne Secretary. 1968. Tubular Exchanger Manufacturers Association, INC. (8th Edition ed). 25 North Broadway Tarrytown, New York 10591.