Development of a Model to predict the efficiency of industrial heat exchanger By Artificial Neural Network (ANN)

Ahmed. S. Nafey [1] , Eldesouki.I. Eid [2] , M.H.M. Hassanean[3] and Talaat. Kaoud [4*]

[1] *Dept. Of mechanical Engineering, Faculty of Engineering, Suez University, Suez, Egypt*

[2] *Dept. Of Engineering mechanical, Faculty of Technology and Education, Suez University, Suez, Egypt*

[3] *Dept. Of petroleum refinery and petrochemical engineering department, Faculty of Petroleum and Mining Engineering, Suez University, Suez, Egypt*

[4*] *General Manager, Nasr Petroleum Company, Suez, Egypt*

Abstract: This paper presents a predict method of industrial heat exchanger efficiency using artificial neural network (ANN). The ANN-developed model can expect the maintenance time prior to reaching the critical time of fouling. In fact, Fouling influence heat exchanger performance and cause sudden mechanical failure. So, must be studied fouling behavior, which is very complicated for heat exchangers because of the difficulty to monitor growth fouling. Three approaches are used for estimating the efficiency and evaluating the performance of the industrial heat exchangers. The first approach, C-factor (experimental method) depends on the pressure drop and volumetric flow rate. The C-factor approach gives results that are relatively accurate but it needs too much reading for a long period. The second approach, thermal analysis (traditional method) is a complicated mathematical model because needs many assumptions and design aspects that give approximated results. The third approach, ANN (modern method) is a very sensitive technic to evaluate the performance of industrial heat exchangers. This work, Uses the Feed-Forward neural network (FFNN) Configuration with the Bayesian regularization (BR) algorithm. Using 285 readings and measurements practical during operating the heat exchanger for training and testing processing to build up model architecture neural network. The maximum deviation between results ANN-based correlation, Thermal analysis, and comparing by experimental results of C-factor is 9.8 % and 33.6 % respectively. Based on ,the good results this assisted model reference strategy of ANN can be used to predict the efficiency of the heat exchangers. The examined network architecture by using 62 readings for another heat exchanger within acceptable certainties. Consequently, the ANN is flexible and capable to update in terms of new sets of weights and biases when the validity range changes in the same network.

Keywords: Artificial neural network (ANN), heat exchanger, efficiency, Fouling, C- Factor, thermal analysis, pressure drop

1. Introduction

Energy-saving and asset safety are the recent challenges in the oil and gas industry, The priority of all petroleum companies are to evaluate the performance of industrial equipment such as refinery towers, pressure vessels, heat exchangers, desalters, heaters, and so on. The shell and tube heat exchanger types are used widely in chemical and petrochemical processes because commonly used for thermal integration between process flows to reduce energy consumption. [1]. Heat exchangers' performance can deteriorate with time, due to the accumulation of unwanted material on the heat transfer surface, which is known as the fouling phenomenon[2]. Since the efficiency of heat exchangers that decreases at 20% when the fouling layer reaches 0.6 mm.

Fouling causes many problems, such as energy losses, which reduce efficiency and increased repair costs [3]. Early prediction of the critical time for fouling is mandatory in the industrial field to establish a schedule for preventive maintenance. So must be study-fouling growth, which increases with time. Evaluation of heat exchanger performance is complex due to its non-linear dynamics so many of approaches study the behavior of fouling growth such as C-factor, thermal analysis and recently artificial neural network.

*Corresponding author

Nomenclature

U_c	*Overall heat transfer coefficient clean [$W/m^{2}\cdot{}^{\circ}C$]*
U_f	*Overall heat transfer coefficient fouling [$W/m^{2}\cdot{}^{\circ}C$]*
R_f	*Thermal resistance [$m^{2}\cdot{}^{\circ}C/W$]*
h_t	*Heat transfer coefficient of fluid (tube side) [$W/m^{2}\cdot{}^{\circ}C$]*
h_s	*Heat transfer coefficient of fluid (shell side) [$W/m^{2}\cdot{}^{\circ}C$]*
k_t	*Thermal conductivity of tube-side fluid [$W/m\cdot{}^{\circ}C$]*
$\dot{m}_t$	*Flow rate in tube [Ton/sec]*
$\dot{m}_s$	*Flow rate in shell [Ton/sec]*
C	*C-factor*
MSE	*Mean square error*
ANN	artificial neural network

Subscripts

t	*Tube*
s	*Shell*
f	*Fouling*
I	*number of neurons*
J	*Number of input*
n	*Net input*
k	*Number of layers*
a	*Scalar output*

Greek symbols

ΔP	*pressure drop [N/m^2]*
ΔT	*temperature different [℃]*
ρ	*Density [Kg/m^3]*
V	*Velocity [m/sec]*
v	*volumetric flow rate [m^3/sec]*
η	*Thermal efficiency [%]*
σ	*stander deviation*
μ	*mean*

In the First approach, C- factor (experimental) method depends on pressure drop and volumetric flow rate shown in the Eq (1)[4].The pressure drop is measured in practice between the inlet pressure and the outlet pressure of the flow through the tube bundle in the heat exchanger. The C-factor approach has several advantages because it is not affected by changes in temperature and fluid properties, avoids any assumptions, and has a limited number of variables. The heat exchanger (HEX) efficiency obtained from the C-factor approach are defined as the ratio of C-factor in the fouling condition to the same under design conditions shown in Eq (2).

The second approach, thermal analysis (traditional) method was based on two methods Kern's and Bell-Delaware to develop the mathematical model based on the design stages for the shell side and the tube side (HEX). The design by using two methods has the same major steps but a difference in shell side design[5]. Indeed the shell side design is more difficult due to the complex geometry of the shell side and has many design aspects such as cross-flow, flow in the baffle and shell area, baffle window flow, tube pattern, leakage currents and baffle spacing[6].

Therefore, Bell-Delaware method is more accurate in results than the Kern method. The results obtained from the Bell-Delaware method for two parameters, overall heat transfer coefficients clean and fouling from Eq (3, 4) are very important because evaluate fouling resistance. The fouling resistance R_f is calculated from Eq (5) which gives behaviors the fouling with time and then obtains the Thermal efficiency (η) from Eq (6). Several researchers have used the Bell-Delaware method to modify the design of the shell side to more precisely increase thermal efficiency by improving the correction factor equations which were only available in graphic format and developing the computing program language.

Thus new design reduces pressure drop and the size of the equipment leading a lower cost of fluid pumping energy[7]. Finally, thermal analysis method is very complex due to the multiple design aspects, many complex equations, empirical formulas, and configuration complicated of the heat exchanger. Therefore, the error of the thermal analysis results is reach up to 40%[8].

Recently, Artificial Neural Networks (ANN) has established itself as an analysis tool because it is a simplified mathematical model for solving thermal problems. Artificial Neural Networks (ANN) is a massively parallel computing system consisting of very simple processors with many interfaces[9]. The ANN model attempts to use some organizations to solve problems of interest to computer scientists and engineers. The biggest challenge for neural networks is to find solutions for some application such as pattern classification, function approximation, prediction and optimization, and addressable and controllable content memory.

ANN has been successfully applied in various fields of mathematics, meteorology, economics, psychology, medicine, neuroscience, and many other fields. ANN learns basic rules (such as input-output relationships) from a given set of representative examples. This is one of the main advantages of neural networks over traditional expert systems. Thus, The ANN can be used to predict the efficiency of heat exchangers based on the available experimental database (input and output) by training the ANN to reach the nearest output to the desired target (experimental data output).

$$v = C\sqrt{\Delta p} \quad (1)$$

$$\eta = \frac{(\text{C-factor })fouled}{(\text{C-factor })design}$$
(2)

$$U_c = h_s + h_t + k_t$$
(3)

$$U_f = h_s + h_t + k_t + R_f$$
(4)

$$R_f = \frac{1}{U_f} - \frac{1}{U_c} \quad (5)$$

$$\eta = \frac{u_f}{u_c}$$
(6)

2. Artificial neural networks approach

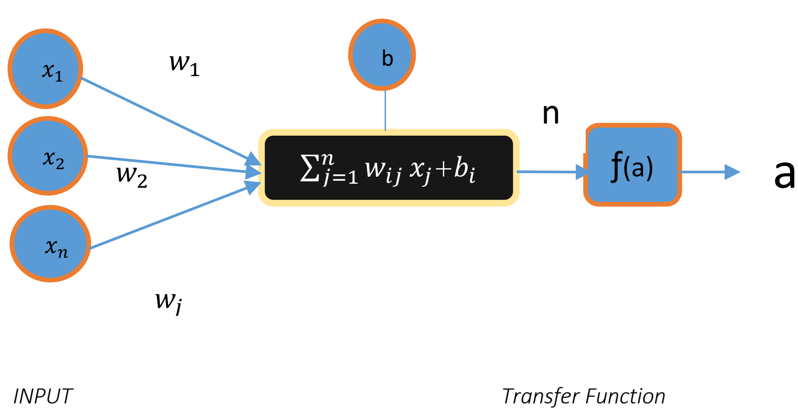
The neural network's approach is the nonlinear parallel structure inspired by the human brain system. ANN consists of several processors called neurons that are analogous to the biological neuron in the brain. Artificial neural network architectures are classified into two categories of supervised and unsupervised networks. In this research, the model is a supervised neural network is training to give desired outputs in response to sample inputs which are very suited to model, control dynamic systems, and predict the efficiency.

Network architectures consist of two groups Feed-forward neural networks (FFNN) and recurrent (or feedback) networks. Feed-forward neural is a family of supervised neural networks and consists of multilayer perceptron (MLP) which are Architecture the model ANN. The main idea is the ability of the ANN to solve new problems using a simplified mathematical model of any physical phenomenon using a set of n samples of patterns.

A process on the sample patterns ANN architectures are illustrated in fig (1) using weight (w_{ij}) and bias (b_i) parameter which net input (n) witch calculated by Eq (7) where the number of neurons (i), number of input (j). Obtain the desired outputs (a) witch calculated by Eq (8) where ***f*** is the transfer function and (k) the number of layer[10]. In fact**,** Artificial intelligence technique operate much as" black-box" which development the models based on process data. SO, The modeling ANN is a popular method for gaining insight into the relationship between the input and the output[11].

$$n = \sum_{j=1}^{n} w_{ij}\, x_j + b_i \quad (7)$$

$$a = f^k\left(\sum_{j=1}^{n} w_{ij}\, x_j + b_i\right)$$
(8)



Summation *OUTPUT*

Figure 1. The simple ANN Architecture

2.1. Multilayer Neural Networks (MLNN) Architecture for ANN

The ANN architecture is used multi-layer feed-forward networks (FFNN) with one or more hidden layers[12]. In fact, an Artificial Neural Network (ANN) is made up of a number of simple processors, called neurons, which are similar to biological neurons in the brain. Neurons are connected by weighted links that pass signals from one neuron to another.

In addition, the network consists of an input layer of source neurons, at least one hidden layer, and an output layer. Input signals propagate in a forward direction from one layer to another. Backpropagation neural networks (BPNN) use a learning algorithm to generate output patterns by training input patterns, calculating the error, and adjusting weights to reduce the error by backpropagation. In this work, the ANN architecture consists of three layers input, output, and one hidden layer. The hidden layer consists of the optimal number of nodes. Moreover, the number of nodes of the input layer is determined by the number of variables entered in the generated model.

Some variables affect network efficiency and improve performance such as (learning rate, number of iterations, momentum coefficient, and the number of neurons in the hidden layer. Obviously, the momentum coefficient can help the network out of local minima and determined the global minimum by trial and error to speed up the learnings. As well as, an appropriate learning rate is important to performance of the training. The optimum network not only depends on minimum mean square error **MSE** but also the number of neurons in the hidden layer. Mean square error is calculated by using Eq (9) after many of the trials of training the network. Beside, obtain the correlation coefficient (R^2) by using Eq (10) which presents the relationship between the Dj target (experimental),Yj desired output (predictive) and (**n)** is number of patterns hence estimating the efficiency of a network[13].

After many trials optimum network parameters are found; the learning rate is 0.7 and the momentum coefficient is 0.8 and the neuron number at hidden layer is **14**.Therefor, the optimum network configuration [**4-14-1**] shown the effectiveness of the network application.

$$MSE = \frac{1}{n} \sum_{j}^{n}(Dj - Yj)^2 \quad (9)$$

$$R^2 = 1\text{-}\left(\frac{\sum_{j}^{n}(Dj-Yj)^2}{\sum_{j}^{n}(Y_j)}\right) \quad (10)$$

2.2. Training algorithm

Training is the process of determining the optimal weights and bias values after many alterations. There are different learning algorithms. In this research, a more commonly used backpropagation (BP) training algorithm for FFNN. Three types of backpropagation (BP) training algorithms, Lavenberg-Marquardt (LM), Scaled Conjugate Gradient (SCG), and Bayesian Regularization (BR)[14]. The (BP) algorithms used the chain rule several times for the calculation of partial derivatives of the networks to reduce the total error function by updating the weights and bias. In this case, Bayesian Regularization (TRAINBR) is suitable for network architecture as well as good accuracy results. The performance is evaluated based on the mean square error MSE. Hence the modern programming MATLAB 7.0 is chosen as a perfect experiment environment to perform the required computations and visualizations.

2.3. Activation Function

Activation function (f) is an algebraic equation that processes the summation of weighted input ($\boldsymbol{W_{ij}X_j}$) and the bias (b_i). The most common transfer functions are hard-limit, linear, and log-sigmoid. In this research, the hidden layer used the sigmoid transfer function (log-sig) Eq (11) which is commonly used in backpropagation (BP) networks because it was easy differentiable[15]. The output layer used the linear transfer function (Purelin) Eq (12).

$f\ (n) = \frac{1}{1+e^{-n}}$ $0 \le f\ (n) \le 1$ Log-Sigmoid transfer function (11)

$f\ (n) = a$ linear transfer function (Purelin) (12)

Where (n) is the weighted sum and biases of input according to formulation $\sum_{j=1}^{n} w_{ij}\, x_j + b_i$

2.4. Experimental input and output data

In this study, using two heat exchangers from a type (shell and tube) are connected in series, Kerosene API 45.4 in the hot stream and Crude oil API 31.8 cold stream. The physical properties of the two-stream and design parameters for the heat exchanger are shown in tables (1, 2) respectively. The artificial neural networks approach depends on the inputs parameters that have effects on the efficiency such as different temperature ΔT ℃ and flow rate m· ($\frac{ton}{hr}$) for the tube and shell side are shown the values in appendix (A). The neural network approach-based correlation can be updated in terms of new sets of weights and biases using the same architecture (same no.of hidden layers and no.of neurons) dependably on the new plant.

Table 1. Physical properties for streams

Stream	service	Viscosity C.P $at\ T_{IN}/T_{out}$	Total influent (ton/hr)	Specific heat kcal/kg.c	Density (kg/m3)	Thermal conductivities w/m.c	Heat transfer $kcal/hr$
Hot	kerosene	0.35 at 155 ℃ 0.8 at 80 ℃	25	0.575	730	0.132	1.078*106
cold	Crude oil	12 at 25 ℃ 5 at 61 ℃	62.5	0.48	850	0.134	1.078*106

Table 2. Design parameter heat exchanger

No. of tube for one shell	N_T	244
outer diameter tube mm	d_o	25.4
Inner diameter tube mm	d_i	19.86
Length of tube mm	L_t	6000
tube pitch mm	P_t	32
shell inside diameter mm	D_S	686
baffle spacing mm	L_B	150
bundle diameter mm	D_{Otl}	682
Baffle (%)	B_C	20
Thermal conductivities tube of wall (w/m.c)	K_w	55

2.5. ANN training, validation, and testing of model

Important phases of a neural network are the training, validation, and testing steps in order to reach the optimum network. The datasets are divided into three subsets as follows: 70% training set 15% validation set and 15% testing set. The training process continues until the network output matches with the desired output by adjusting the values of weight and biases to reduce the error. Accordingly, the concept of the error is the difference between actual and desired out (experimental data). This error is feedback signal to adjust the values of weight and biases to obtain at least of Mean square error (MSE) is shown fig (2).

The validation process is a very important stage because avoids overfitting the training data. When overfitting occurs, the network loses its ability to find the main relationship between training and testing sets. So the validation data set is used to find the best configuration and training parameters. The test data set is used to evaluate the parameters of the trained neural network. The performance of the network is evaluated using statistical parameters, such as correction coefficient (R^2) and MSE respectively. The regression curve of output efficiency from the training and testing process are shown fig (3) and fig (4).In this case, the values of correction coefficient for training and testing process are 0.998 and 0.997 respectively. The results obtained from this performance are very satisfactory.

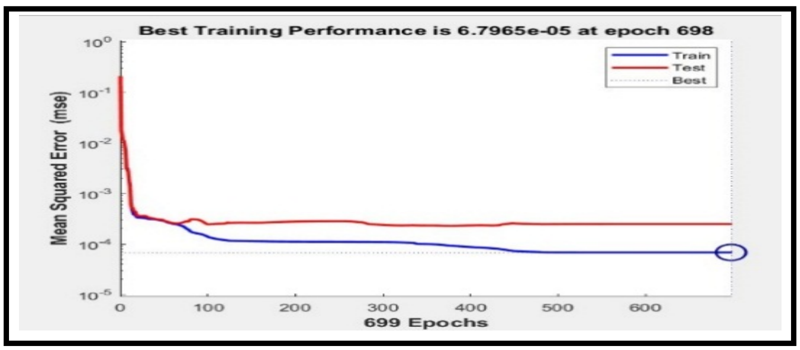


Figure 2. *Train and test performance process*

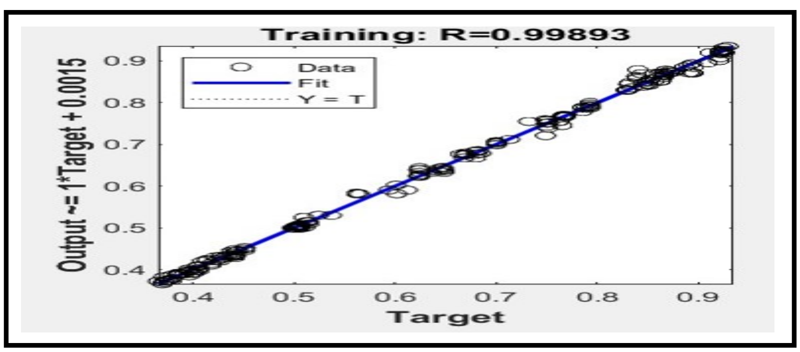


Figure 3. Regression curve of output efficiency from the training process

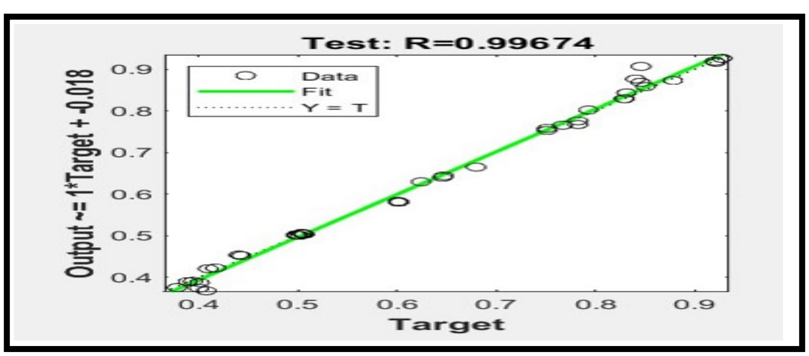


Figure 4. Regression efficiency curve from the testing process

2.6. Verification of the ANN

In fact, verification is a very important stage because it determines the ability of the network to give the prediction of the output closely from experimental data. This stage occurs after the training process, the network was examined with the test data. The results of the regression curve of the output efficiency (η_{ANN}) for the ANN system shown in fig (5) is 0.997 which is very satisfactory. The percentage error for ANN-based correlation and thermal analysis approach reach to 9.8 % and 33.6 % respectively by comparison results of the experimental approach (η_{EXP}) illustrated percentage error curve at shown in fig (6).The percentage error (η_{error}) is defined as Eq. (13)[16].

$$\eta_{error}=\frac{\eta_{ANN}-\eta_{EXP}}{\eta_{EXP}}*100\% \quad (13)$$

According the good results from ANN approach can now derived the mathematical formulation from the values from weights, biases and the activation functions. Obviously, used the ANNs were suitable and accurate for this application.

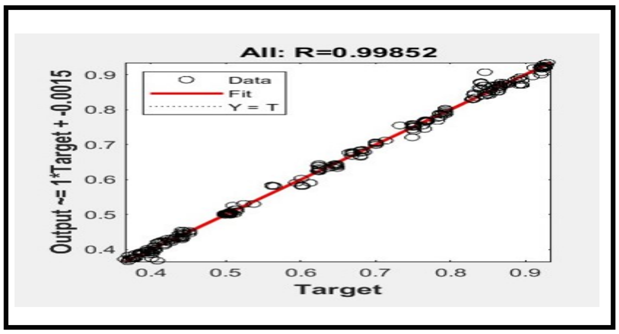


Figure 5. Regression efficiency curve for ANN system

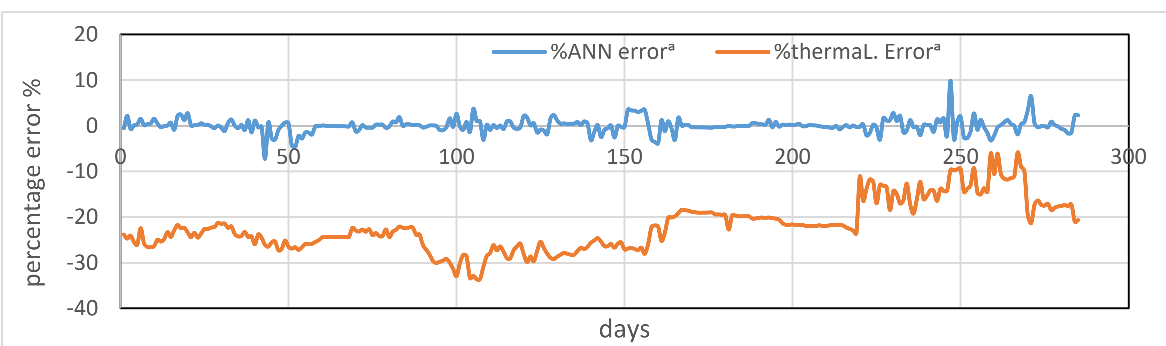


Figure 6. The percentage error curve between ANN efficiency and thermal efficiency

3. The ANN architecture and based correlation of case study

The optimum architecture of a neural network for a heat exchanger consists of three layers (input, hidden, output) and fourteen neurons in the hidden layer, one neuron in the output layer and four input variables. Besides, using suitable the log-sigmoid transport function in the hidden layer and the linear function in the output layer. SO, the ANN configuration (4-14-1) are given good results to predicted the efficiency is shown in Figure (7).one of the important steps is normalizing the data that improve performance modeling by rescaling the input data and adjusting the weight and bias to obtain the optimal network[8]. Each input variable is scaled up or normalized shown in the Eq. (14) to the range {0:1} after calculating the mean $\boldsymbol{\mu}$ and $\boldsymbol{\sigma}$ stander deviation is shown in table (5) from the experimental data as by Eqs. (15), (16):

$$x^s = \frac{x-\mu}{\sigma} \tag{14}$$

Where:

$$\mu = \frac{\Sigma x}{n} \tag{15}$$

$$\sigma = \frac{\Sigma(x-\mu)^2}{n-1}$$

(16)

Table 5. The mean and stander deviation for input variable

variable (X)	*mean μ*	*σ (stander deviation)*
ΔT_t	*29.09964912*	*13.60362664*
ΔT_s	*76.96392982*	*40.92988591*
m_t	*52.84526316*	*20.95178206*
m_s	*20.89764912*	*5.339906074*

Input layer **hidden layer** **output layer**

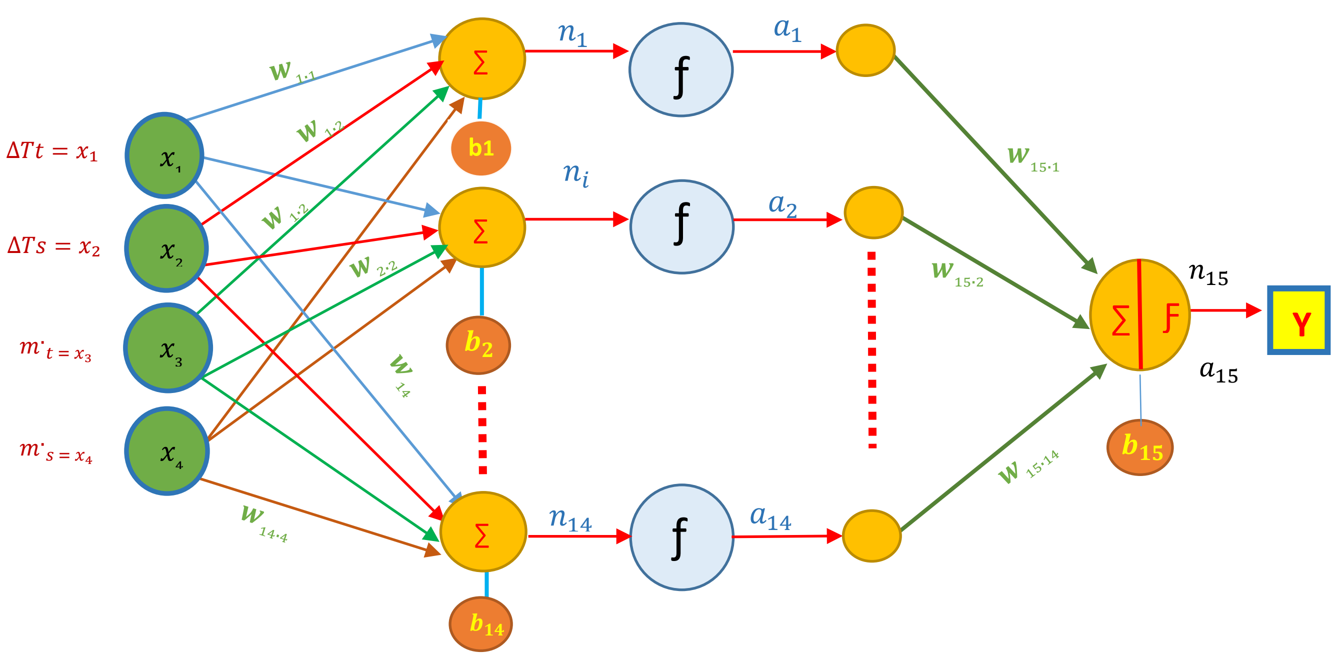


Figure 7. Architecture of the ANN for a case study (4-14-1)

After the establish optimum network is obtained the values of weights and biases for two layers are shown in Tables (6a and 6b) .consequently, the establish ANN-based correlation refers to Eq (7) and (8) to obtained the values of hidden layer outputs ($a_1, a_2 \ldots\ldots a_{14}$) and a_{15} output in output layer.

Where:-

1- Weight matrix [w_{ij} where neuron (i) with hidden layer

$$w^2 = \begin{bmatrix} w_{1,1} & w_{1,2} & w_{1,3} & w_{1,4} \\ w_{2,1} & w_{2,2} & w_{2,3} & w_{2,4} \\ \vdots & \vdots & \vdots & \vdots \\ w_{14,1} & w_{14,2} & w_{14,3} & w_{14,4} \end{bmatrix}$$

2- Weight matrix [w_{ij} where neuron (i) with output layer

$$w^3 = \begin{bmatrix} w_{15,1} & w_{15,2} \ldots\ldots w_{15,14} \end{bmatrix}$$

3- Summation the neurons in hidden layer using liner equation matrix

$$\begin{bmatrix} n_1 \\ n_2 \\ \vdots \\ n_{14} \end{bmatrix} = \begin{bmatrix} \text{Weight matrix for} \\ \text{hidden layer} \end{bmatrix} * \begin{bmatrix} x_1 \\ x_2 \\ x_3 \\ x_4 \end{bmatrix} + \begin{bmatrix} b_1 \\ b_2 \\ b_3 \\ \boldsymbol{b}_{14} \end{bmatrix} \tag{17}$$

Substitute the previous values into the equation Eq (11).The results obtained from this equation present the outputs values in hidden layer (a_n) and meanwhile, present the input in the outputs layer.

4- Summation the neurons in output layer using liner equation matrix

$$\begin{bmatrix} n_{15} \end{bmatrix} = \begin{bmatrix} \text{Weight matrix for} \\ \text{output layer} \end{bmatrix} * \begin{bmatrix} a_1 \\ a_2 \\ \vdots \\ a_{14} \end{bmatrix} + \begin{bmatrix} b_{15} \end{bmatrix} \tag{18}$$

Likewise, Substitute the previous values n_{15} into the equation Eq (12). The result obtained from this equation present the output value in this network ($\mathbf{a_{15}} = Y$).

From above cascade, correlation obtained the required output network (η) after converting the each input variable to scaled up or normalized at Eq (14). Create a perceptron Network (nnstart) from MATLAB are illustration in Fig (8)

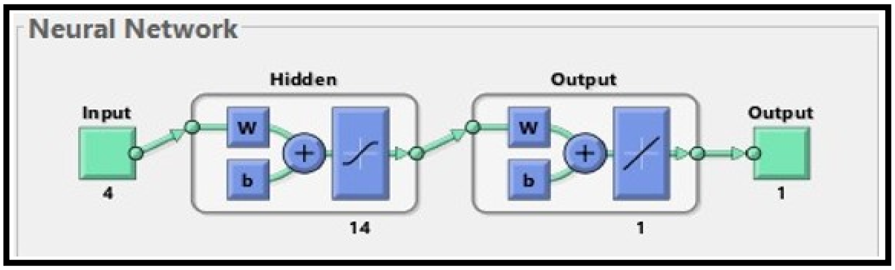


Figure 8. The theoretical model developed with Artificial Neural Network

Confirm the ability of the architecture neural network by using new sample data of 62 measurements from the same field. The neural network gives good relation between target and ANN predicted for efficiency (outputs). Clearly, by correction coefficient R^2 =0.99, as shown in Fig (9).

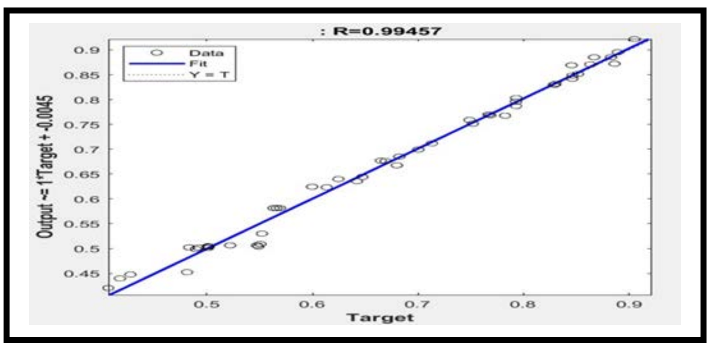


Figure 9. Comparison of target and ANN predicted for efficiency

Table 6a. The w_{ij}^2 and b_i^2 Second layer (hidden layer)

no-neuron	w^2				b^2
1	-0.314	3.35	1.2789	-0.05268	-0.974
2	-1.8435	2.715008	-1.67086	2.6514	-2.004
3	0.66163	-0.92674	1.047079	-2.5776	1.0085
4	-1.7687	-101738	-0.3588	0.50352	0.0624
5	3.537	-0.12238	-1.891	1.40706	-0.9763
6	-2.028	-0.5699	0.2709	-1.44843	1.1293
7	0.11411	0.10004	-3.21514	2.9659	-0.61072
8	1.888	-4.682	0.1459	-0.72949	2.7135
9	-1.808	2.1359	-0.95025	1.2124	-0.0587
10	-0.749	4.3189	0.4486	-0.2147	-2.83038
11	-0.634	2.81068	1.6375	-0.7985	-1.329

12	1.12514	-1.0203	-0.78598	0.91684	0.5688
13	-1.81317	3.80325	-2.12665	-1.62708	1.7074
14	2.7265	-2.1465	0.17883	-0.66351	0.3795

Table 6b. The w_{ij}^3 and b_i^3 third layer (output layer)

no-neuron	w^3														b^3
1	2.321	2.002	1.903	1.314	-1.518	-1.764	-1.411	1.318	2.742	2.018	2.45	2.084	-8468	1.507	-0.95578

7. Conclusion

The priority of all petroleum companies is to evaluate the performance of industrial heat exchangers. Because commonly used for thermal integration between process flows to reduce energy consumption. By the time, the performance of heat exchangers deteriorates due to the fouling phenomenon. Not knowing the critical time of fouling caused reduced efficiency and sudden mechanical failure. Therefore, researchers from all over the world have different points of view to solving this problem. Therefore, much popular research makes investigations related to thermal analysis of heat exchangers and modification shell side design.

This work confirmed that ANN modeling are successful to predict efficiency and giving accurate results comparing of efficiency obtain by thermal analysis method. ANN techniques are an accepted way to tackle complex and ill-defined problems. Hence, ANN modeling predict the efficiency based on the available database and it develops correlation for estimating the efficiency. The ANN architecture are multi-layer feed-forward networks (FFNN) using the back propagation (BP) technique. The architecture consists of three layers with Bayesian regularization (BR) algorithms. The good architecture has been selected after the training and testing process.

Consequently Some statistical methods, such as the mean square error (MSE) and correlation coefficient (R^2) are applied to network performance evaluation. Moreover, some important parameters such as learning rate is 0.7 and momentum coefficient is 0.8. ANN model architecture with (fourteen neurons in the hidden layer) and sigmoid, linear transfer function is capable of prediction the target η_{ANN}. The maximum deviation between results ANN-based correlation and Thermal analysis (traditional techniques) by comparing experimental results based on correlation the C-factor method are 9.8 % and 33.6 % respectively. Therefore, the configuration [4-14-1] is the optimal architecture for this problem.

Also The examined network architecture by using 62 readings for another heat exchanger within acceptable certainties. The neural network give satisfactory correction coefficient equal R^2 =0.99.The results show that the predicted the efficiency by ANN technique are much closer to experimental results, indicating that ANN technique is more suitable in the prediction efficiency than traditional techniques. The developed formula can be employed with any spreadsheet program or programming language for predicting the efficiency. In the future work, ANN can be modification when more experimental data to using in training process in order to increase prediction accuracy.

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Appendix (A)

Input variables data

Day	temperature different ΔT_t (°c)	temperature different ΔT_s (°c)	Flow rate $\dot{m}_t$(ton/hr)	Flow rate $\dot{m}_s$(ton/hr)	Day	temperature different ΔT_t (°c)	temperature different ΔT_s (°c)	Flow rate $\dot{m}_t$(ton/hr)	Flow rate $\dot{m}_s$(ton/hr)
1	35	83	60	25	48	33.7	80	59	23.5
2	34	84	59.5	24	49	34	81	59	23.5
3	34.5	83.5	59.8	24	50	33.8	80	60	23.5
4	34.2	83	60	24	51	33.9	83	59	23
5	33.9	83	60	24	52	34	83	59	23
6	35	83	59	24	53	33.3	83	59	23.5
7	34	83	60	24	54	33.5	83	59	23.5
8	33.7	82.7	60	23.5	55	34	82	58.5	23.5
9	33.8	82.3	60	23.5	56	34	82	58.5	23.5
10	34	82	60	23.5	57	34	82	58.6	23.5
11	33.6	83	60	24	58	34	81	58.5	24
12	33.3	83	60	23	59	34	80	58.8	24
13	33.5	83	60	23	60	34	80	58.5	23
14	34	83	60	23	61	34	80	58.5	23
15	33.8	83	60	23	62	34	80	58.5	23
16	33.9	83	60	23	63	34	80	58.5	23
17	34	83	58.7	23	64	34	80	58.5	23
18	33.8	83	58.9	23	65	34	80	58.5	23
19	34	83	59	24	66	34	80	58.5	23
20	33.5	83	59	23	67	34	80	58.5	23
21	34	85.7	58.9	24	68	34	80	58.5	23

22	34	84.6	58.7	24	69	34	80	56	22
23	34	85.3	59	24	70	34	81	56	22
24	34	84	58.4	24	71	34	81	56	22.5
25	34	84	58.7	23	72	34	80	56	22.8
26	34	84	58.8	23	73	34	81	56	22.6
27	34	84	58.8	23	74	34	80	56	22.7
28	34	83	58.8	24	75	33.4	81	56	24
29	34	83.5	58.7	23.5	76	33.4	83	56	24
30	34	83	58.8	23.5	77	33.4	82	56	24
31	34	83	59	23.5	78	33.4	82	56	24
32	34	82	58.9	23.5	79	33.4	82.8	56	24
33	34	82	58.8	23	80	33	81	56	24
34	33.7	84	59	22	81	33	80.2	56	23
35	33.5	84	59	22	82	33	80.3	56	23
36	33.7	84	59	23	83	33	81	56	23
37	33.9	84	59	23	84	33	81.7	55	23
38	33.4	84.3	59	23	85	33	80	55	23
Day	**temperature different ΔT_t (°c)**	**temperature different ΔT_s (°c)**	**Flow rate m_t(ton/hr)**	**Flow rate m_s(ton/hr)**	**Day**	**temperature different ΔT_t (°c)**	**temperature different ΔT_s (°c)**	**Flow rate m_t(ton/hr)**	**Flow rate m_s(ton/hr)**
39	33.6	84	58.8	24	86	33	80.2	55	23
40	33.6	82	58.5	24	87	33	80	55	23
41	34	85	60	23.5	88	33	80	55	23
42	34	85	60	23	89	33	80	55	23
43	34	82	60	23.5	90	32	79	55	23
44	34	80	60	23.5	91	32	77.8	55	23
45	34	81	60	23.5	92	31	79	54	23
46	34	81	60	23.5	93	31	79	54	23
47	33.9	82	59	23	94	31	78.5	54	23
95	31	78.3	54	22	142	29	81	53	22
96	31	78.6	54	22	143	29	82.5	53	22
97	31	79	54	22	144	29	81.8	53	22
98	31	79.6	54	22	145	29	80.5	53	22
99	31	80.2	55	22	146	29	81	53	22
100	30	82	55	23	147	29	80	53	22
101	31	84	54	22	148	29	81	53	22
102	32	83	54	22	149	29	81.3	53	22
103	31.8	83.2	54	22	150	28	80.7	51	20
104	30	83.22	54	22	151	28	79.6	51	20
105	30	82.3	54	22	152	28	79.6	51	20
106	30	82	55	22	153	28	79.3	51	20
107	30	82	55	22	154	28	79	51	20
108	30	82	55	22	155	28	79.6	51	20
109	30	81	55	22	156	28	78	51	20
110	30.2	82	54	22	157	28	77.8	51	20
111	30.8	82	54	22	158	28	79.3	51	20
112	30.4	82	54	22	159	28	79.3	51	20

113	30.7	82	54	22	160	28	79	51	20
114	30.3	82	54	22	161	27	76	50	20
115	29	79	53	22	162	27	76	50	20
116	29	79	53	22	163	27.5	75.5	50	19
117	29.5	79	53	22	164	27	75.5	50	19
118	29.7	79	53	22	165	27	77	50	19
119	29.9	79	53	22	166	27	77	51	19
120	29.6	81	53	23	167	27	75.2	51	19
121	29	81	53	23	168	27	76.7	51	19
122	29	81	53	23	169	27	75	51	19
123	29	82	54	23	170	27	76.2	51	19
124	29.5	81.6	54	23	171	27	76.1	51	19
125	29.9	82.5	54	23	172	27	76	51	19
126	29.7	81.6	54	23	173	27	76	51	19
127	29	82	54	23	174	27	76	51	19
128	29	82.3	53	22	175	27	76	51	19
129	29	82	53	22	176	27	76	51	19
130	29	82.5	53	22	177	27	75.5	51	19
Day	**temperature different** ΔT_t (°c)	**temperature different** ΔT_s (°c)	**Flow rate** m_t**(ton/hr)**	**Flow rate** m_s**(ton/hr)**	**Day**	**temperature different** ΔT_t (°c)	**temperature different** ΔT_s (°c)	**Flow rate** m_t**(ton/hr)**	**Flow rate** m_s**(ton/hr)**
131	29	83	53	22	178	27	75.5	51	19
132	29	83.5	53	22	179	27	75.4	51	19
133	29	83.2	53	22	180	27	75.3	51	19
134	29	83	53	22	181	25	77	52	21
135	29	83	53	22	182	27	75.2	51	19
136	29	83.8	53	22	183	27	75.2	51	19
137	29	82.8	53	22	184	27	75	51	19
138	29	82.2	53	22	185	27	75	51	19
139	29	82	53	22	186	27	75	51	19
140	29	83	53	22	187	27	75	51	19
141	29	82	53	22	188	27	75	51	19
189	27	75	51	19	236	25	76	47	19
190	27	75	51	19	237	25	78	46	18
191	27	75	51	19	238	25	67	45	16.8
192	26.7	76.2	51	19	239	24.8	69	46	19
193	26.5	77	51	19	240	25	68	46	19
194	26.5	72	51	19	241	25.1	69	46	18
195	26.5	76.7	51	19	242	25	67.5	46	19
196	26.4	72	51	19	243	25	75	47	18
197	26.5	75.6	51	19	244	25	77	46	18
198	26.7	76	51	19	245	24.8	68	46	18.5
199	26.5	75	51	19	246	25	67	46	19.5
200	26.5	75	51	19	247	24	62.2	45	16
201	26.2	76	51	19	248	24.5	68	45	15.9
202	26	72	51	19	249	24.2	66	45	16.33
203	26.4	75	51	19	250	24	70	45	16
204	26.2	75.5	51	19	251	25	68	46	19

205	26	76.3	51	19	252	25	66.3	46	19
206	26	76.2	51	19	253	24.6	67	46	18
207	26	76.2	51	19	254	24	65	45	16.4
208	26	76.2	51	19	255	25	73	46	18
209	26	76	51	19	256	24.8	64	46	19
210	26	76	51	19	257	24.8	64	46	19
211	26	76	51	19	258	25	71	46	18
212	26	76	51	19	259	24	65	45	16
213	26.5	77	51	19	260	24.2	65	46	18
214	26	75.8	51	19	261	23.5	59	45	15.7
215	26	74	51	19	262	23.6	64	46	17
216	26	77	51	19	263	24	65	46	18.2
217	26	75	51	19	264	24	65	46	18.5
218	26	75	51	19	265	24	65	46	19
219	26	78	51	19	266	24	65	46	19
220	25.5	62	45	16	267	24	72	45	16
221	26	68	46	19	268	23.9	62	46	17
Day	**temperature different** ΔT_t (°c)	**temperature different** ΔT_s (°c)	**Flow rate** m_t**(ton/hr)**	**Flow rate** m_s**(ton/hr)**	**Day**	**temperature different** ΔT_t (°c)	**temperature different** ΔT_s (°c)	**Flow rate** m_t**(ton/hr)**	**Flow rate** m_s**(ton/hr)**
222	25	69	46	17	269	23.5	67	46	18.7
223	25.4	66	45	16	270	23.3	68	50	20
224	25.2	69.6	45	16	271	23	67	50	20
225	25.7	68	46	18	272	24	67	50	20
226	25.4	68	45	16	273	24	67.5	50	20
227	25	69.5	45	16	274	24	66	50	20
228	25	69.2	45	16	275	24	65.6	50	20
229	25	70	46	19	276	24	66	50	20
230	25	65	45	16	277	24	64	50	20
231	25	68	45	16.5	278	24	63.5	50	20
232	25.2	68.2	46	18	279	24	63.6	50	20
233	25.4	67.2	46	18	280	24	63	50	20
234	25	67.8	45	16.7	281	24	63	50	20
235	25.4	67	46	19.5	282	24	62.4	50	20
					283	24	62.7	50	20
					284	24	62.3	50	20
					285	24	62.5	50	20