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Modelling of fouling in heat exchangers using the Artificial Neural Network Approach

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Abstract— *In this paper, modelling by neural networks was used for obtaining a model for the calculation of fouling factors in heat exchangers. The heat exchangers used in this study are a series of four exchangers where a model was obtained for each exchanger after due estimation of its heat load.*

The basic theme of this paper is the investigation of fouling factors and the determination of relevant indicators followed by combining design and operation factors along with fouling factors in a mathematical model that may be used for the calculation of the fouling factor. The devised model was tested for reliability and its accuracy in predicting new values for the fouling factor was greater than 98% in view of the design of the model

Furthermore, the number of elements related to the design and operation was reduced to four developed formulae (developed factors) to which were added later the four factors selected as indicators of the occurrence of fouling. Both were then used as network input, whereas the output was the value of the fouling factor.

The importance of this modelling lies in the fact that it enables the operator to continually predict the value of the fouling factor in heat exchangers and it assists him in taking appropriate measures to alleviate fouling effects ensuring thereby continuous operation of the unit and prevention of emergency shut downs.

Keywords— ***naphtha hydro rating unit , heat exchanger ,fouling, moduling ,artificial neural network ANNW.***

I. INTRODUCTION

Fouling may be considered as one of the most difficult problems of heat exchangers as it reduces heat exchanger efficiency and increases operating cost. Fouling in general results from the deposition of unwanted materials on heat exchanger surfaces leading to heat exchange temperature drop and pressure difference increase. Control of fouling is often difficult due the complexity of the phenomenon and the multiplicity of the factors concerned. In the present work, the Artificial Neural Network Approach is used in the construction of a model that relates all design and operating variables that affect fouling in order to make possible the prediction of the occurrence of fouling and to enable the operator to take precautionary measures to alleviate the problem and avoid unnecessary shutdowns with resulting loss in production. In this study, actual operating data of a hydrotreating unit at the Homs Oil Refinery in Syria were utilized to refine the model constructed, making this work a pioneering effort in fouling research.

Naphtha hydrotreatment Unit

The Naphtha Hydrotreatment Unit started operation in 1990. In this unit a mixture of light and heavy straight-run and coking naphtha is hydrotreated in order to be used as feed to the isomerisation and reforming units. The Hydrotreatment unit has a capacity of 480×10^3 tonnes/year. The hydrogen gas required for the hydrotreatment reactions is directly supplied from the reforming unit to the amount of 500 m^3/hr.

Light Naphtha (30% wt.) is mixed with straight-run heavy naphtha (70% wt.) in a floating-top tank in which thermal and compositional homogeneity is achieved. The naphtha, pumped at a pressure of 48 bars, is then mixed with hydrogen with a pressure of 46 bars (Fig. 1). The mixture is then heated first in a series of heat exchangers (A, B, C, D) where its temperature increases from 53 to 299°C and then in a furnace where it is vaporized and its temperature raised to the required reaction temperature of 320°C (Table 1). The heated stream is then fed into the catalyst-containing reactor where the hydrogenation reactions take place. The reactor effluent is cooled from which hydrogen is separated and recycled. Further, the light and heavy naphthas are separated with the light naphtha being fed into the isomerisation unit and the heavy naphtha into the reforming unit [1].

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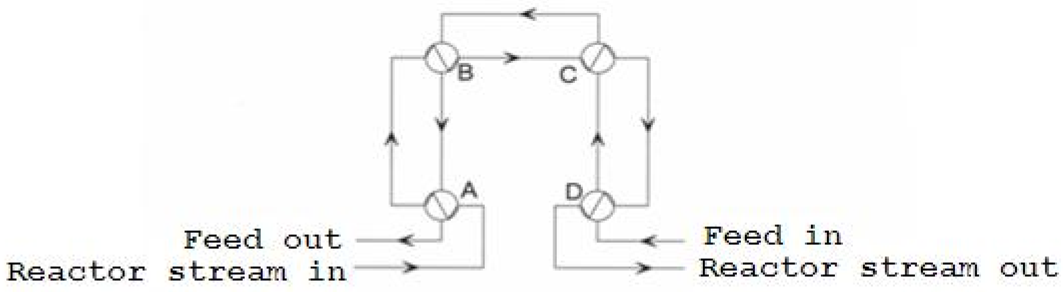

Fig. 1. Schematic drawing of the heat exchanger series

Table.1: design values of the heat exchangers

	Tube-side	Shell-side
Stream (kg/h)	66,116	66,131
Incoming temperature (°C)	250	53
Outgoing temperature (°C)	138	319
Operating pressure (bar)	42	48
Pressure drop (bar)	1	1
Fouling resistance (m^2.h.°C/kJ)	0.00005	0.00007
Allowable corrosion (mm)	3	3
Number of passes	2	1
Heat capacity (kJ/h)	235,72	
Film heat transfer coefficient (kJ/ m^2.h.°C)	1,33	
Tube length (mm)	6,00	
Number of tubes	458	
OD of shell + thickness (mm)	1,012 + 32	
OD of tubes + thickness (mm)	25 + 2.5	

The problem of fouling in the hydrotreatment unit

The problem of fouling in the hydrotreatment unit developed soon after the start of the unit's operation. Fouling affected th e top of the reactor as well as the series of four heat exchangers in the unit. As a consequence the coker naphtha was excluded from treatment because of its high content of impurities and the operating conditions were modified, both of which actions tended to reduce the severity of the fouling problem [2]. The fouling problem, however, re-emerged in the period 1997-2001 and it was more apparent in the heat exchangers' shells and on top of the catalyst in the reactor. This led to a sharp increase in the pressure difference in the reactor (Fig. 2) and a large drop in the temperature of the naphtha from the heat exchangers (Fig. 3). This necessitated periodic shut downs of the unit. The cost of these shut downs amounted in 2000 to $1,265 per annum [3].

On investigating the causes of fouling by analysis of the fouling deposits and the naphtha feed it was found that such deposits were carbon deposits with some carboxylic acids. This indicated air leakage to the naphtha feed due to the fact the feed tank was not tightly closed. As a result, radicals and carboxylic acids were formed which were polymerized at the high temperatures prevailing in the heat exchangers and heaters. These reactions were further reinforced by the solids borne with the feed which were products of corrosion in the distillation units [4].

The fouling problem was then controlled by taking the naphtha feed directly from the distillation units and by increasing the pressure in the storage tanks to prevent air leakage. This was accompanied by reduction of the solids borne with the feed stream. As a result, fouling was reduced and the hydrotreatment unit was successfully operated for two consecutive years (2003-2004) without shutdowns [5].

Selection of the modelling technique

Current research is often directed towards the simulation of phenomena and the derivation of a mathematical model that encompasses all relevant factors. The techniques used for this purpose are many and varied. The artificial neural network approach was deemed the most appropriate for the simulation of fouling in view of the many factors involved, whether physical, chemical or operational and the difficulty and complexity of the calculations, their unreliability in controlling all operational variables, and the non-linearity of the fouling phenomenon in itself. With this approach it would be possible to relate all relevant factors that affect or cause fouling making it possible for the operator to predict the fouling tendency in his heat exchangers and to take appropriate or precautionary measures [3,6].

Fouling mechanism in heat exchangers and its main causes

It was necessary at first to determine the mechanism and factors of fouling in the heat exchangers series E1. Towards this end, the deposits on the heat exchangers surfaces and the naphtha feed were analysed. The deposits' analysis carried out in accordance with ASTM [7] demonstrated the presence of three fouling mechanisms, namely polymerisation, corrosion and particulate fouling. It further indicated that the nature of deposits had changed during the period 2000-2002 from being organic (polymerization fouling) into inorganic deposits (particulate and corrosion fouling) (Table 2). Polymerisation fouling was, however, the dominant fouling mechanism in all exchangers (Table 3). The analysis of the naphtha feed, on the other hand, pointed clearly to the presence of inorganic deposits on the filters which were for the most parts corrosion products of iron salts and iron sulphides [9].

Periodic analyses were carried out for bromine no., nitrogen, sulphur and solid particles in the feed that may lead to fouling. These indicated the presence of such contaminants that can lead to polymerisation, corrosion and particulate fouling particularly with the presence of such promoting factors as air leakage and high temperature [4].

Calculation of fouling factor

In order to estimate the size of the fouling problem in the heat exchanger series E1, the rate of heat transfer and the fouling factor had to be calculated for each of the heat exchangers. For such calculation measurements of the inlet and outlet temperatures were required. These temperatures, however, were not directly measured and had to be estimated on the basis of the percentage of heat exchange [11].

The variation of heat transfer in the period 2000-2003 is shown in Fig. 4, where it can be seen that the rate of heat transfer dropped to a minimum in 2000 and was then improved in 2001-2002. Comparison of the rate of heat transfer with the design value indicates clearly the effect of fouling on heat transfer, where the rate of heat transfer decreased to about half its design value, which points to considerable loss of the design heat capacity of the exchangers [3].

II. DESIGN STAGES OF THE MATHEMATICAL MODEL

1. Data collection and preparation

The first step in modelling using the neural networks is the collection of operating data in order to obtain an accurate model that approaches the actual conditions with a high prediction efficiency. Towards this end available and reliable daily operation data were collected for three years (2000-2002), about 900 values [3]. The data collected were then examined and filtered and all unreliable or jumbled data were removed using the Excel programme. In Figure 5, the method used for the development of the neural network model based on the back propagation algorithm is shown [11].

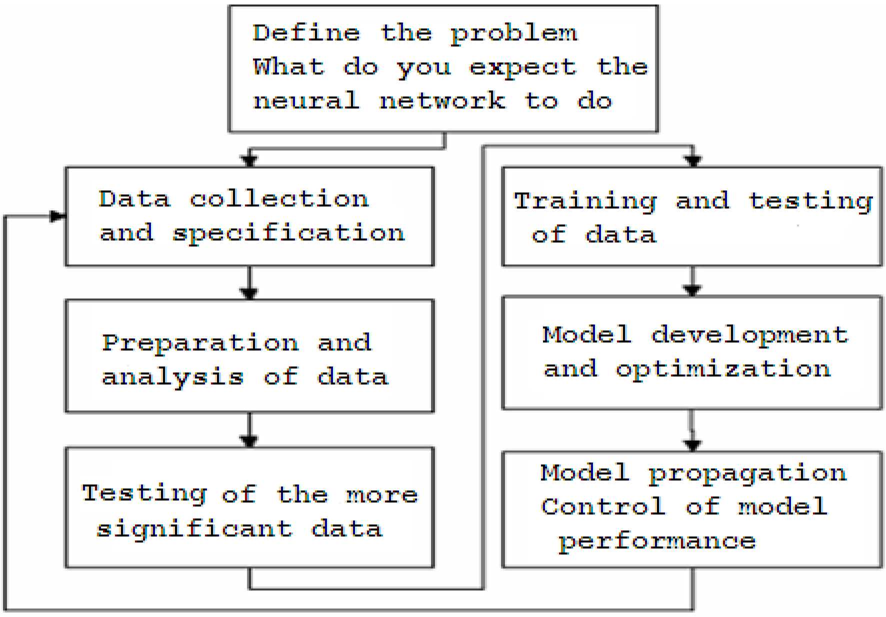

Fig. 5. Development of the neural network

2. Selection of network input data

There are a number of methods for the selection of a greater number of variables to be used as network input data. The selection of such variables will have a great effect on the network result and its prediction capability. There are a great many parameters that may be used in the calculation of the fouling factor, but these can be reduced in general to sixteen factors that represent given design values and measured operating variables [16].

- Measured values

These include special primary operating values such as material capacity and temperatures (to the number of seven). Such values are constantly changing with changing composition and properties of the materials (Naphtha and reaction gas), cold and hot streams temperatures in the heat exchangers, and the heat exchange efficiency (Table 4).

- Calculated values

These include physical properties of the streams such as viscosity, thermal conductivity, heat capacity, gas molecular weight, Prandtl No., Reynolds No. and heat transfer coefficient (eight in all). These values are also dependent on temperatures and quantities and vary with measured values variations. Their values are also different in the four heat exchangers and in the tube and shell sides.

- Constant values

These include the heat exchangers design values such as the area of the heat transfer surface, the shell cross-sectional area, the tube cross sectional area, number of shell passes, length of tubes and the construction material for shell and tubes. These values may be reduced into three coefficients which have constant values for the four heat exchangers.

Table.4: Fouling factor calculation data

Measured values	
Naphtha flow	**m_1 kg/h**
Reaction gas flow	**m_2 kg/h**
Hydrogen in reaction gas	**% wt.**
Input to shell temperature	**t_{1d} °C**
Output temperature of shell	**t_{2a} °C**
Input to tubes temperature	**T_{1a} °C**
Output temperature of tubes	**T_{2d} °C**
Calculated values	

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Viscosity	**μ kg/m.h**
Heat capacity	**C kJ/kg.°C**
Thermal conductivity	**k kj/m.h.°C**
Gas molecular weight	**M kg/mol**
Prandtl No.	**Pr dimensionless**
Reynolds No.	**Re dimensionless**
Heat transfer coefficient	**jH dimensionless**
Constant values	
Shell cross-sectional area	**a_s m^2**
Tube cross-sectional area	**a_t m^2**
Area of exchanger	**A m^2**

3. Developed data

In order to reduce the number of factors used for the calculation of the fouling factor while preserving at the same time its proper representation in the network input without repetition, developed relationships were used instead that combine these properties in four factors which could be calculated for each exchanger using the following known relationships [10]:

- Logarithmic Mean Temperature Difference (LMTD): where the temperatures of the cold and hot streams are involved in its calculation as well as the number of shell passes. LMTD may be calculated for each exchanger using the following equation:

$$\Delta T_{\ln} = LMTD \times \gamma = \frac{(T_1 - t_2) - (T_2 - t_1)}{\ln \dfrac{(T_1 - t_2)}{(T_2 - t_1)}} \times \gamma$$

- Overall flow G_s: This may be calculated in terms of stream flow and the cross-sectional area of the shell using the following equation:

$$G_s = \frac{m^{\cdot}}{a_s} = \frac{m^{\cdot}_1 + m^{\cdot}_2}{a_s} \qquad \text{kg/m}^2\text{hr}$$

Where

$m^{\cdot}_s = (m^{\cdot}_1 + m^{\cdot}_2) =$ shell stream flow

- Prandtl No. which combines the stream physical properties including its viscosity, thermal conductivity and heat capacity; and may be calculated using Eq. 7.21.

$$\Pr_s = \frac{C_s \times \mu_s}{K_s}$$

Where:

C_s = Specific heat kJ/°C.kg

K_s = Thermal conductivity kJ/cm.°C

- Heat transfer coefficient jH: This expresses the dynamic properties of the stream through its relationship with Reynolds No., and may be calculated using the following equation:

$$jH_s = 0.3652 \times \mathrm{Re}^{0.5445}$$

Reynolds No. Re_s may be calculated using the following equation:

$$\mathrm{Re}_s = \frac{G_s \times D_e}{\mu_s} \qquad (7.20)$$

Where:

D_e = Equivalent diameter, m

μ_s = Dynamic viscosity kg/m.h

In this manner all factors that affect the calculation of the fouling factor have been taken into account. The four developed data relative to the shell only have been used as network input (LMTD, G_s, P_r, jH) because of the similarity of the streams in both the tubes and shell sides [3].

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4. Network input

The network input include the eight daily measurements data (primary data) (Table 5), seven of which are actual plant measurements whereas the molecular weight of the reaction gas is calculated. From such data the four developed data (LMTD, Gs, Pr. jH) are calculated for each exchanger to which are added the four fouling related factors, namely the Bromine No. br; nitrogen n, an indicator of organic fouling; sulphur s, an indicator of corrosion fouling; and ss, n indicator of particulate fouling. This makes the total number of input data to the neural network: eight, four of which are developed data (LMTD, Gs, Pr. jH) related to the exchanger operation and four related to fouling (br, n, s, ss) [3]. The network output is the fouling factor calculated for each exchanger (Table 6].

Table.5: Measured operation values for the heat exchangers

Measured operation data	Symbol
Naphtha (Tonne/day)	$\dot{m}_1$
Reaction gas (Tonne/day)	$\dot{m}_2$
D-Shell input temperature (°C)	t_{1D}
A-Tubes input temperature (°C)	T_{1A}
D-shell output temperature (°C)	t_{2D}
A-tubes output temperature (°C)	T_{2A}
Purity of hydrogen (wt %)	p_{H2}

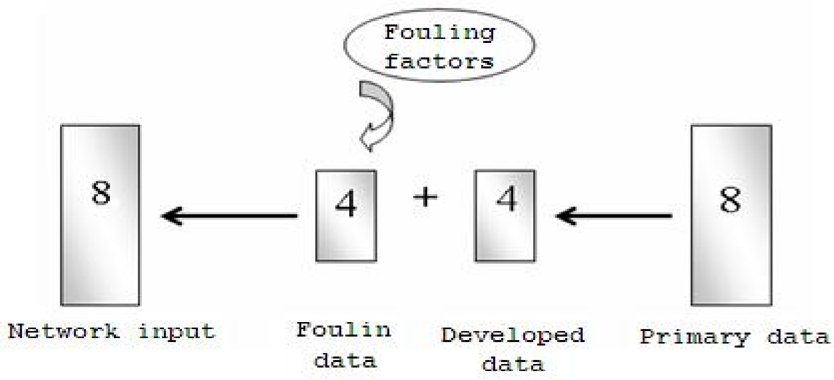

Fig. 6. Preparation stages for network input data

Table.6: Input and output of neural network

Neural network input		
Logarithmic Mean Temp Difference	**LMTD**	°C
Shell-side Total liquid flow	G_s	Kg/m^2 h
Shell side Prandtl No.	**Pr**	Dimensionless
Heat transfer coefficient	jH	Neural network input
Bromine No.	**br**	KOH mg/100g
Nitrogen	**n**	PPM
Sulphur	**s**	PPM
Particulates	**ss**	PPM
Neural network output		
Fouling factor	**F**	M^2 h/kJ

5. Training and testing of data

Two sets of data are used for the training and testing of the network, namely a training set and a testing set. In the training stage, attention is concentrated on arriving at a neural network that is stable, harmonized and able to work efficiently after training completion. In the testing stage, the network is tested by two main tests to ascertain how does the network recall the training data (the preparatory step) and how does it respond to the prediction of new values that had not been part of the training stage (generalization step) [6].

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In order to visually show how the network achieves recall and generalization, a training curve must be found that represents the average error for each recall of training and generalization data and their relationship with the number of training steps. The total number of available eight network input values is 900. This number was divided into two sets: a training set of 600 and a testing set of 300. This means that the training-assigned network input is a matrix [8 600] and the generalization input is [8 300]. The back propagation algorithm will be used in the network training stage as shown in Fig. 7. For a well-trained network, i.e. a network that is able to receive more information, the recall and generalization curves must come close to each other and the average minimum generalization error is 0.1. In general, the error becomes more stable if the number of training steps is increased [11, 12].

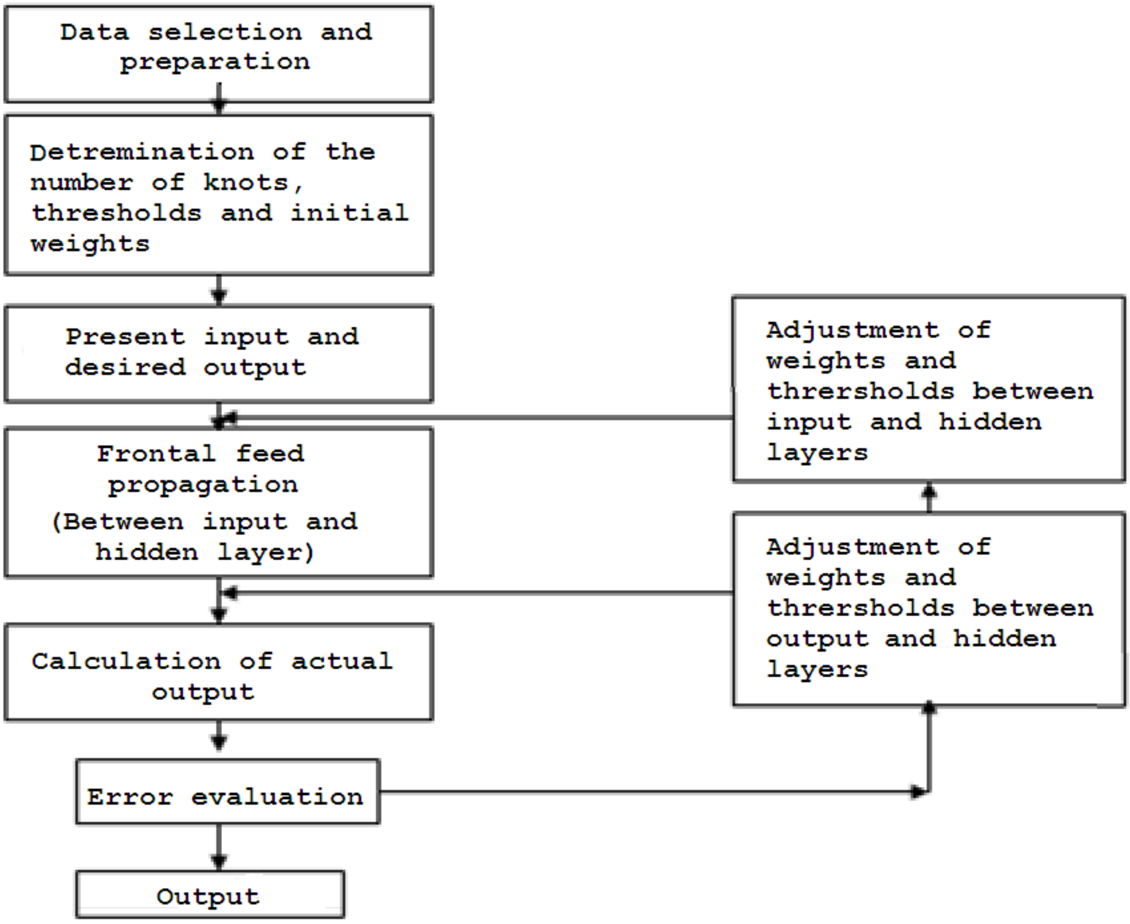

Fig. 7. Learning chart of back propagation algorithm

6. Framework of neural network

After the determination of the input and output of the neural network, the following basic elements for the implementation of the network model were put into place for maximum performance (Equivalence speed and prediction accuracy):

6.1 Equalization of input and output data

The input and output data for each exchanger were equalized and similarly directed, and the greater value was assigned for each factor of the network input and output using the excel programme and the rest of the values divided by it. By this means, all values were controlled within the range 0, +1. In this way, the network may perform its calculations in accordance with the equalized values input. On completion of the calculation, the result will then be reduced into its actual value [3].

Consideration of the changes of the input and output factors revealed that the changes of the nitrogen factor and the bromine number were less than 1 percent; hence these two values were not equalized. The change range for the other six input factors requires equalization, and was therefore equalized as previously mentioned to bring it within the range 0 to +1. The network output is the fouling factor which is of the order of parts per thousand and was equalized by multiplication by 100. All other data numbering 900 were equalized, i.e. on the training [8, 600] and generalization [8, 300] matrices. The value of the fouling factor given by the network is an equalized value and the result must therefore be divided by 100 in order to obtain the actual fouling factor value. In the network input, the values for the fouling factors (br, n, s, ss) were considered to be similar in all four exchangers because of the difficulty of measuring their changes 2. The change range for the network input for the four exchangers is given in Table 4.

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Table.7: Change range for network input and output for the heat exchangers

	Exchanger A	Exchanger B	Exchanger C	Exchanger D
	Change range of network input			
LMTD	57-99	40-86	46-85	59-98
Pr	4.14-4.65	3.31-3.73	2.72-3.19	2.30-2.72
jH	70-103	85-125	100-143	137-167
G_s	1,112,903-538,306	1,112,903-538,306	1,112,903-538,306	1,112,903-538,306
Br	0.13-0.49	0.13-0.49	0.13-0.49	0.13-0.49
N	0.12-0.95	0.12-0.95	0.12-0.95	0.12-0.95
S	300-460	300-460	300-460	300-460
SS	2-80	2-80	2-80	2-80
	Change range of network output			
F	0.0009-0.0027	0.0002-0.0022	0.0017-0.0039	0.0007-0.0021

6.2. Initial weighting

Before starting the training of the network, weighting factors were placed between the outer layers knots. As there was no previous information on the required system to be modelled, arbitrary factors were used so that they are irregularly distributed within a zero range of figures (i.e. between +0.5 and -0.5). The initial distribution of the weighting factors depends on both the number of input variables and the number of hidden neuron layers [12].

6.3. Structure of neural network

- Training magnitude

The number of training times was selected on the basis of the order of magnitude of the fouling factor (10,000). This number was then increased gradually to 50,000, where the number of training times was related to the change in the number of knots in the hidden layers for better performance, i.e. to the minimum difference between the calculated fouling factor and the factor resulting from the network [13].

- Transfer factor

The other factor controlling the output knot is the transfer factor, as the network gets trained faster when the transfer factor is in a symmetrical network, i.e. in the range between -1 and +1.

The linear function whose range is between -1 and +1 was selected because it agrees with the change in the fouling curve. In polymerization fouling, fouling increases with time since fouling-causing factors are present and the temperature is increasing. Furthermore, the logarithmic factor whose range is between 0 and +1 was selected because it agrees with the change in the fouling factor in particulate fouling, where the accumulation of fouling matter increases to such an extent that fouling becomes constant due to ending of fouling-causing factors [14].

- Number of knots in the hidden layers

The number of knots in the input and output layers is proportional to the number of network input and output values respectively. Two hidden layers were used so that the network may find the required connection. The number of the network input layer knots is eight, four of which are developed relationships calculated according to functions relative to each exchanger and the other four are fouling dependent. The number of output layer knots is one. The network was trained on different numbers of hidden layer knots in each exchanger in order to get a strong network [15].

- Selection of learning rate and kinetic factor

The learning rate and the kinetic factor are significant indicators for the control of the efficiency of algorithmic training. The learning rate regulates the relative direction of weight changes whereas the kinetic factor strengthens the stability of the weighting factors compatibility on training, makes the changes closer and accelerates the approach towards the stable case. It is a constant varying between 0 and +1.

The learning rate and the kinetic factor for back propagation were selected as 0.3 and 0.4 for the first hidden layer and 0.25 and 0.4 for the second layer for a training volume of 10,000 times in accordance with table 8 for learning by back propagation for two different layers [16].

Table.8: Values of learning rate and kinetic factor for the case of learning by back propagation

First hidden layer				
Training cycles	0-10,000	10,000-30,000	30,000-70,000	70,000-150,000
Learning rate	0.3	0.15	0.375	0.234

Kinetic factor	0.4	0.2	0.05	0.00312
Second hidden layer				
Training cycles	0-10,000	10,000-30,000	30,000-70,000	70,000-150,000
Learning rate	0.25	0.125	0.03125	0.0195
Kinetic factor	0.4	0.2	0,05	0.00312

7. Common initial properties for the fouling factor calculation networks in exchangers

The common initial properties for the fouling factor calculation network in the exchangers may be summarized as follows:

- The network is static with regard to the memory as there is no relation between the current and former inputs.
- The network is frontal with regard to the feed.
- Network learning is supervised as the output is already known.
- The connection between the layers is total in order to improve the accuracy of the resulting relationship.
- The network has multiple inputs but a single output.
- The network has three layers, two hidden and one output.
- The learning rates for the first and second layers are 0.3 and 0.25 respectively.
- The dynamic factors for the first and second layers are 0.25 and 0.4 respectively.
- The training rate is 50,000.
- The training is according to the back propagation algorithm.
- The transfer function logsig for the first hidden layer, purelin for the second layer and purelin for the output layer.
- The training function is Trainlm.

Fig. 8 illustrates the general structure for the combined neural network for the four heat exchangers.

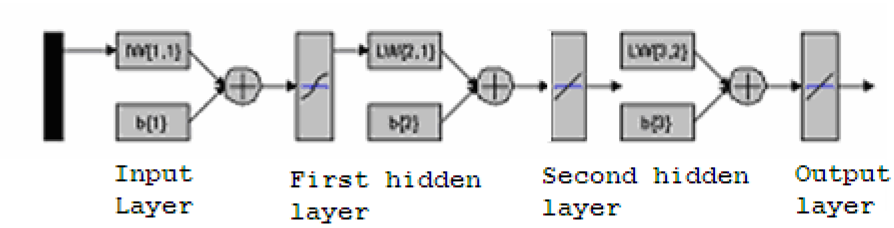

Fig. 8. General structure of the neural network for the four exchangers.

8. The exchanger-specific models and their performance

After specification of the main properties of the neural network for the calculation of the fouling factor, the network was trained for each of the four exchangers in order to complete its properties by determining the number of knots in the hidden layers and showing its performance and efficiency in recovery and generalization [3].

Fouling factor calculation network for Exchanger D

- The measured operating data are input and molecular weight og the reaction gas is added (numbering 8) (Table 9).
- The four developed data are calculated in accordance with the particular function for each exchanger, function.1.
- The input for the neural network includes the input matrix of dimensions [6008], the four fouling factors and the developed four data for 600 readings (Table 10).
- The neural network output is a matrix of dimensions [1600]. It is fouling factor for each exchanger calculated using the equations (Table 11].
- Several models of the neural network were prepared differing in the number of knots in the two hidden layers and the number of training steps. This was carried out in order to study the effect of the number of knots and the number of training steps on the efficiency of the model in order to achieve an optimum model. These models were trained in order to determine their performance and their recall efficiency (Table 12).

Table 12. The efficiency of exchanger D network models

Network model	Performance		Recall efficiency	Generalization efficiency

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1	2.860E-05		0.98%	0.89%
2	7.575-E05		0.97%	0.92%
3	2.690E-05		0.99%	0.89%
4	2.82E-05		0.98%	0.98%
5	9.985E-06		0.99%	0.77%
6	1.568E-05		0.99%	0.87%

After due consideration of the differences between the former models, the fourth model was selected for the calculation of the fouling factor in exchanger D where its recall of trained values efficiency is o.977, its efficiency for the generalization values 0.984, its performance 2.82×10^{-5} and its weighting factors as given in Appendix 1.

- Performance

Figure 9 shows the model training curve according to the function (2).

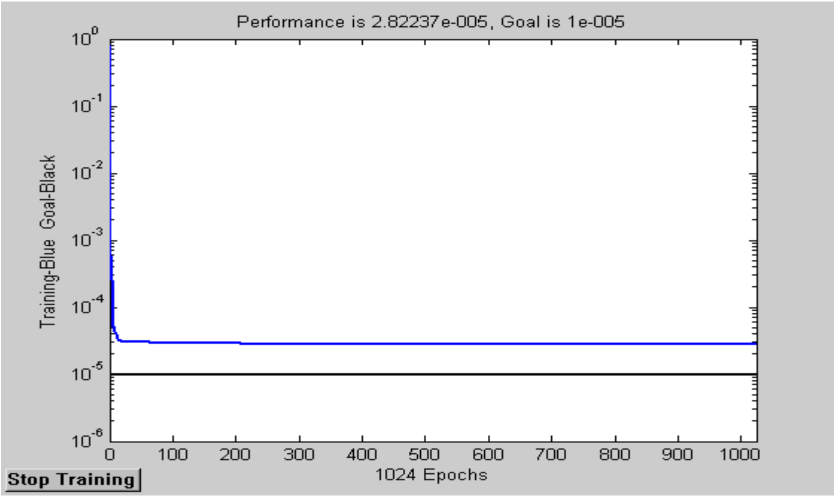

Fig. 9. Model training curve for exchanger D.

- Recall efficiency

On carrying out simulation for the model with the values on which it has been trained, input matrix [600 8] according to the function (3), the agreement ratio was 97.7% and the slope of the function 0.955 (Fig. 10).

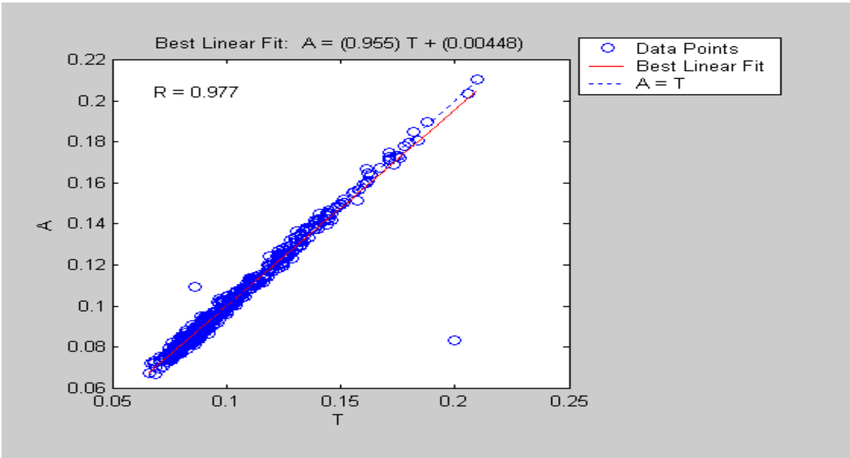

Fig. 10. Model recall efficiency for exchanger D.

- Generalization efficiency

For the model evaluation, a simulation was carried out on a new input matrix with dimensions [8300] according to the function (4). The agreement ratio was 0.984 and the function slope 0.987 (Figure 11).

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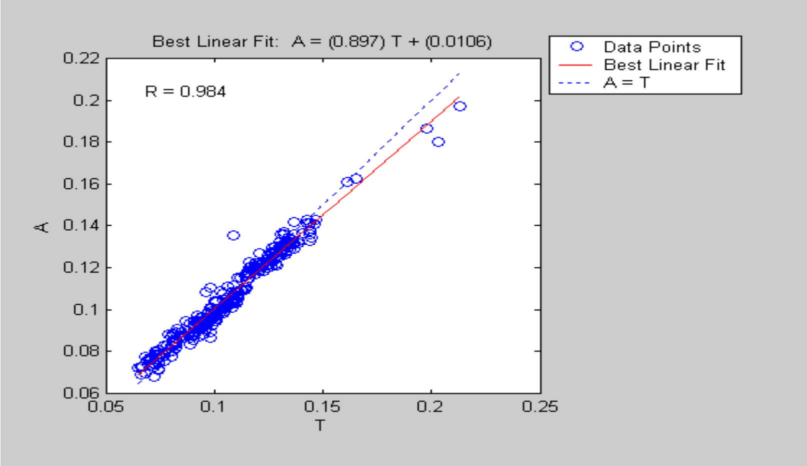

Fig. 11. Model generalization efficiency for exchanger D.

Comparing the value of the fouling factor as calculated by the relevant equations and its value resulting from the model of exchanger D in training and generalization, we find that they are closely similar and within the model efficiency in the two steps (Table 13).

Table 13. Comparison between the values of the fouling factor for exchanger D as calculated by the equations and according to the model

Calculated value of the fouling factor for exchanger D								
Training feed	0.086	0.086	0.082	0.081	0.075	0.075	0.086	0.086
Generalization feed	0.094	0.093	0.092	0.094	0.093	0.090	0.096	0.094
Value of the fouling factor according to the network model net_d								
Training feed	0.084	0.085	0.086	0.084	0.082	0.076	0.080	0.084
Generalization feed	0.091	0.090	0.090	0.091	0.091	0.089	0.094	0.092

In this manner, the optimum neural network for the calculation of the fouling factor in exchanger D was obtained. This procedure was repeated for the other three exchangers, where there were for each exchanger a function for the calculation of the developed data and input and output matrices. Several models were prepared for each exchanger that differ in the number of knots in the two hidden layers and in the number of training steps. An optimum model for each exchanger was obtained. Table 14 shows a comparison between the calculated fouling factors according to the proposed model and the mathematically-calculated values.

Table 14. Comparison between the values of the fouling factor as calculated by the equations and according to the model

Calculated value of the fouling factor for exchanger C								
Training feed	0.024	0.026	0.074	0.041	0.026	0.042	0.042	0.024
Generalization feed	0.094	0.093	0.092	0.094	0.093	0.090	0.096	0.094
Value of the fouling factor according to the network model net_d								
Training feed	0.036	0.042	0.038	0.041	0.029	0.043	0.041	0.036
Generalization feed	0.087	0.087	0.087	0.086	0.087	0.083	0.091	0.088

Calculated value of the fouling factor for exchanger B								
Training feed	0.145	0.132	0.240	0.161	0.134	0.163	0.165	0.145
Generalization feed	0.342	0.343	0.340	0.361	0.342	0.332	0.351	0.341
Value of the fouling factor according to the network model net_d								
Training feed	0.151	0.131	0.234	0.152	0.135	0.145	0.161	0.151
Generalization feed	0.335	0.342	0.332	0.350	0.338	0.330	0.342	0.335

Calculated value of the fouling factor for exchanger A								
Training feed	0.099	0.086	0.086	0.082	0.081	0.075	0.075	0.099
Generalization feed	0.093	0.093	0.091	0.093	0.093	0.089	0.095	0.093

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Value of the fouling factor according to the network model net_d								
Training feed	0.098	0.088	0.086	0.081	0.081	0.078	0.071	0.098
Generalization feed	0.089	0.089	0.088	0.089	0.089	0.086	0.092	0.089

Thus it was possible by using the neural networks to find the four models that relate the operation factors of the heat exchangers to the fouling agents with an efficiency of the order of e^{-5} (1-4), an average recall efficiency in the range 0.993-0.997 and a generalization efficiency in the range 0.94-0986 (Table 15).

Table 15. Properties of the fouling factor calculation models in the four heat exchangers

Models	No. of knots network	Performance	Recall	Generalization
Exchanger D	2-6	2.824E-5	0.977	0.984
Exchanger C	4-2	4.38E-5	0.985	0.94
Exchanger B	4-2	1.3E-4	0.977	0.979
Exchanger A	20-12	1E-5	0.993	0.966

Thus it becomes possible for the operator to predict the value of the fouling factor and its different effects in different exchangers. All he has to do then is take the appropriate measures to alleviate the severity of fouling in order to avoid emergency shut downs. Such measures include for example blending a low-bromine-number crude with the crude with a high bromine number. If the nitrogen content is high, its source must then be sought whether it is from additives and also th e type of additives. It may then be necessary to reduce the amounts of additives or change their type. If there are large amounts of particulates, a filtering system must be used; but for a high sulphur content, different measures may be used such as avoidance of humidity with the naphtha stream or improving the naphtha stabilization process in the distillation unit. These are some of the examples that may be resorted to by the operator in order to alleviate the fouling problem and extend the proper working with a higher efficiency and for longer periods of time.

III. CONCLUSION

The fouling in heat exchanger is considered the most important factor in reducing heat exchange efficiency and increasing operating cost. In this study, the quality of the waste was determined in a series of four heat exchangers in the naphtha hydrogenation unit. The foulinf factor was calculated in each of them for three years.The most important factors causing the pollution were determined: solide suspended, Chlorine , sulpher and bromine no. The method of the inductive networks was used to find four mathematical models to calculate the factor facture in each exchanger that linked the factors of operation and design to the factors causing the fouling , and then these modules were tested in the reliability statement. Its accuracy in devising new values for the agent was greater than 98%, this is due to the size of the initial data that has been used to design the model. The importance of this modeling is that it enables the operator to continuously predict the value of the heat agent in the heat exchangers, and help him to take appropriate measures to mitigate it as much as possible, so as to continue the work of the unit and prevent the emergency stop.

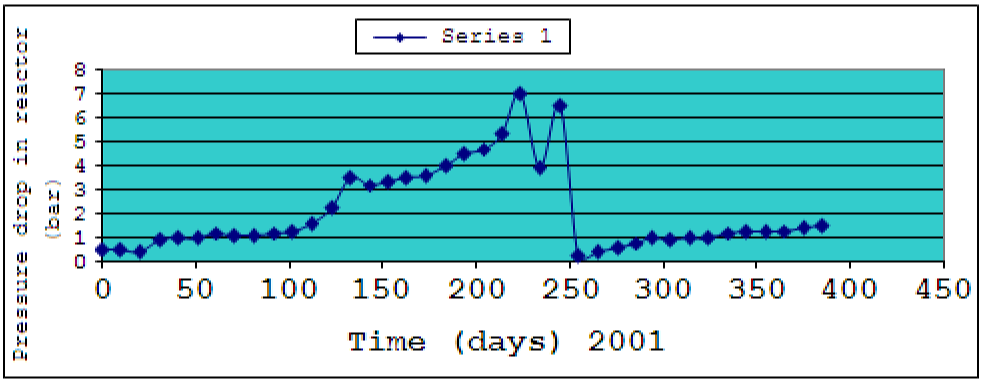

Fig.2. Reactor pressure drop vs time in naphtha hydrotreater.

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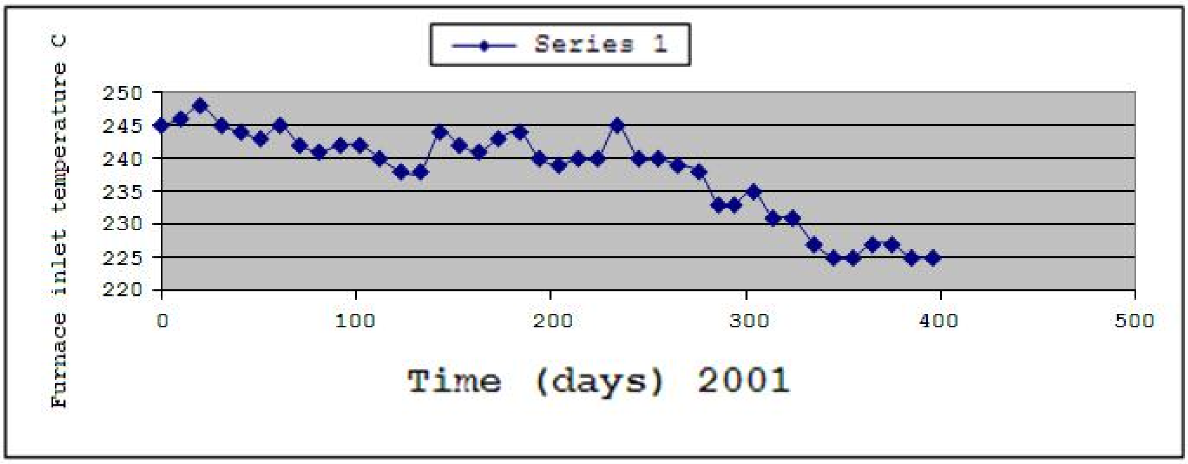

Fig. 3. The degradation of inlet furnace temperature vs time ***in*** *heat exchanger A*

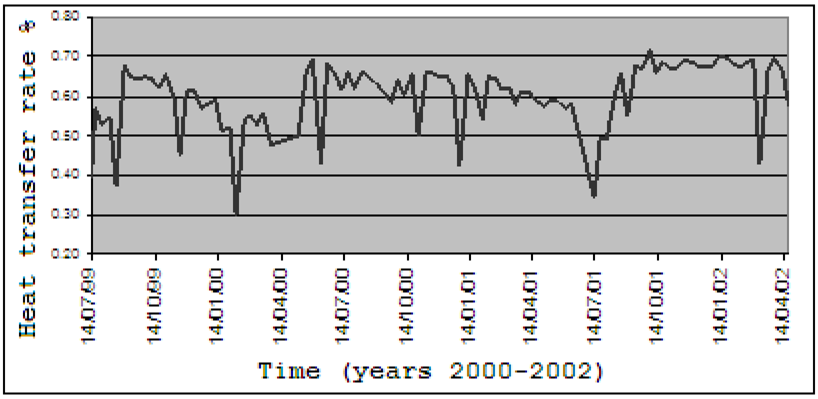

Fig. 4. Heat transfer rate in exchangers during 2000-2002

Table 2. Summary of deposit analyses between 1999 and 2002.

	1999	2000	2001	2002
Organic (wt %)	99.2	94.9	84.5	47.2
Non Organic (wt %)	0.1	5.1	16.3	53.5
Carbon (wt %)	36.6	-	61.2	10.4
Chloride (wt %)	57.5	Trace	5.3	2.2
Sulphur (wt %)	3.6	18.6	14.4	26.5
Iron (wt % of ash)	0.1	4.4	9.3	34.6

Table 3. Changing nature of fouling during 2000-2002

	1999	2000	2001	2002
Exchanger D		Polymerization	Particulate Polymerization	Particulate Polymerization
Exchanger C			Polymerization	Particulate Polymerization
Exchanger B	Polymerization		Polymerization	Particulate Polymerization
Exchanger A			Corrosion Polymerization	Corrosion Polymerization
Reactor		Polymerization		Particulate

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				Polymerization

Table 9. calculated operation data for the heat exchangers.

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M_1	M_2	T_{1a}	T_{2d}	t_{1d}	t_{2d}	H%	M_{H2}	data
Kg/hr	Kg/hr	C	C	C	C	نقاوة	Kg mol	
848	48	255	114	30	319	88.1	6.0	14/07/1999
1300	54	252	117	37	319	85.3	7.0	20/07/1999
1233	53	245	114	53	319	82.2	7.9	30/07/1999
1250	53	244	114	65	319	89.7	6.2	10/08/1999
761	55	258	120	69	319	81.6	7.9	20/08/1999
1542	54	248	116	80	319	82.2	7.9	30/08/1999
1502	56	242	116	85	319	89.7	6.2	10/09/1999
1458	52	240	112	90	319	90.2	5.1	20/09/1999
1460	52	242	113	91	319	88.9	5.7	30/09/1999
1501	52	235	111	94	319	88.9	5.6	10/10/1999
1507	55	231	111	88	319	89.9	5.3	20/10/1999
1512	50	236	110	85	319	89.5	5.2	30/10/1999
1410	53	232	110	90	319	87.9	6.0	10/11/1999
1042	52	231	109	83	319	89.6	5.4	20/11/1999
1465	49	230	107	86	319	88	6.2	30/11/1999
1510	50	228	107	79	319	88.6	6.5	10/12/1999
1465	56	225	110	78	319	87	5.9	20/12/1999
1454	56	224	110	86	319	90.9	4.9	30/12/1999
1466	53	225	108	86	319	88.6	5.3	10/01/2000
1346	53	218	106	86	319	85.7	6.5	20/01/2000
1298	49	220	104	86	319	88.1	5.8	30/01/2000
694	52	220	106	88	319	86	6.5	10/02/2000
1356	49	222	104	82	319	87	5.9	20/02/2000
1409	49	220	104	82	319	86.5	6.2	29/02/2000
1358	46	218	101	80	319	84.4	7.1	10/03/2000
1393	45	220	101	82	319	85.9	6.3	20/03/2000
1166	47	222	103	85	319	84.7	6.7	30/03/2000
1173	50	245	112	37	319	85.3	7.0	10/05/2000
1529	48	246	111	53	319	82.2	7.9	20/05/2000
1548	49	248	113	65	319	89.7	6.2	30/05/2000
945	50	245	112	69	319	81.6	7.9	10/06/2000
1564	49	244	111	80	319	82.2	7.9	20/06/2000
1512	53	243	114	85	319	89.7	6.2	30/06/2000
1380	55	245	116	75	319	90.2	5.1	10/07/2000
1491	53	242	113	91	319	88.9	5.7	20/07/2000
1409	56	241	115	94	319	88.9	5.6	30/07/2000
1507	54	242	114	88	319	89.9	5.3	10/08/2000
1450	51	242	112	85	319	89.5	5.2	20/08/2000
1449	54	240	114	90	319	87.9	6.0	30/08/2000
1435	56	238	114	83	319	89.6	5.4	10/09/2000

Table 10. Neural network input and output for exchanger D (Training and recall values) (Matrix 1600)

Output	Network input							
F	SS	S	N	Br no	jh	pr	gs	LMTD
0.123	0.57	0.76	0.35	0.39	0.699	0.915	0.53	0.59

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0.099	0.64	0.78	0.38	0.35	0.703	0.921	0.68	0.59
0.095	0.60	0.82	0.25	0.32	0.815	0.909	0.72	0.60
0.091	0.61	0.78	0.28	0.28	0.841	0.925	0.78	0.64
0.078	0.69	0.73	0.59	0.35	0.866	0.905	0.81	0.58
0.078	0.93	0.89	0.25	0.38	0.906	0.911	0.87	0.61
0.072	0.79	1.01	0.28	0.39	0.932	0.902	0.87	0.58
0.078	1.00	1.00	0.28	0.36	0.941	0.929	0.92	0.65
0.078	0.93	0.67	0.13	0.26	0.946	0.927	0.93	0.65
0.082	0.71	0.78	0.12	0.21	0.956	0.924	0.94	0.67
0.076	0.36	0.77	0.28	0.24	0.957	0.913	0.95	0.64
0.073	0.46	0.76	0.45	0.26	0.969	0.904	0.95	0.62
0.071	0.47	0.82	0.46	0.21	0.983	0.897	0.95	0.60
0.075	0.43	0.89	0.56	0.23	0.985	0.925	0.96	0.64
0.076	0.57	0.91	0.43	0.29	0.976	0.937	0.96	0.66
0.073	0.36	0.96	0.33	0.31	0.971	0.932	0.95	0.64
0.079	0.14	0.98	0.33	0.34	0.971	0.949	0.95	0.69
0.084	0.50	1.00	0.45	0.37	0.955	0.954	0.95	0.70
0.076	0.57	0.89	0.62	0.33	0.946	0.951	0.95	0.68
0.076	0.61	0.87	0.52	0.38	0.955	0.949	0.95	0.67
0.077	0.67	0.84	0.24	0.35	0.959	0.938	0.93	0.66
0.084	0.73	0.89	0.44	0.38	0.959	0.943	0.92	0.68
0.085	0.43	0.87	0.15	0.28	0.948	0.939	0.93	0.68
0.085	0.79	0.84	0.33	0.22	0.954	0.945	0.93	0.68
0.085	0.47	0.80	0.22	0.13	0.954	0.944	0.91	0.69
0.087	0.43	0.78	0.18	0.26	0.941	0.944	0.91	0.70
0.085	0.41	0.82	0.13	0.33	0.937	0.930	0.91	0.67
0.070	0.36	0.76	0.23	0.44	0.947	0.896	0.93	0.59
0.072	0.86	0.80	0.15	0.39	0.987	0.904	0.93	0.61
0.084	0.50	0.82	0.95	0.37	0.981	0.931	0.94	0.68
0.083	0.60	0.93	0.46	0.33	0.962	0.945	0.94	0.69
0.074	0.43	0.84	0.38	0.26	0.955	0.925	0.94	0.64
0.082	0.29	0.78	0.35	0.33	0.976	0.956	0.94	0.70
0.083	0.43	0.89	0.36	0.34	0.952	0.942	0.94	0.67
0.085	0.14	0.91	0.25	0.28	0.959	0.941	0.95	0.69
0.085	0.03	0.93	0.85	0.37	0.961	0.946	0.95	0.70
0.084	0.07	0.87	0.34	0.32	0.961	0.940	0.93	0.68
0.080	0.11	0.78	0.43	0.33	0.958	0.929	0.92	0.66
0.081	0.14	0.71	0.35	0.28	0.963	0.927	0.93	0.65
0.078	0.50	0.67	0.74	0.24	0.967	0.912	0.93	0.63
0.080	0.64	0.71	0.56	0.35	0.978	0.918	0.92	0.64
0.085	0.69	0.69	0.16	0.29	0.966	0.945	0.92	0.68
0.089	0.66	0.72	0.24	0.38	0.951	0.926	0.90	0.68
0.100	0.60	0.73	0.39	0.33	0.960	0.934	0.86	0.71
0.093	0.04	0.71	0.28	0.22	0.934	0.918	0.94	0.71
0.101	0.14	0.78	0.22	0.39	0.978	0.925	0.94	0.75
0.101	0.10	0.80	0.27	0.43	0.969	0.924	0.95	0.75
0.103	0.29	0.82	0.17	0.45	0.971	0.933	0.95	0.77

Table 11. Neural network input and output for exchanger D (generalization values) (Matrix 1300)

Output	Network input							
F	SS	S	N	Br no	jh	pr	gs	LMTD
0.100	0.41	0.89	0.27	0.48	0.963	0.916	0.93	0.71
0.097	0.71	0.87	0.15	0.39	0.966	0.897	0.93	0.68
0.098	0.40	0.84	0.27	0.32	0.972	0.902	0.93	0.69
0.103	0.56	0.93	0.66	0.49	0.967	0.906	0.92	0.70
0.115	0.11	0.87	0.48	0.45	0.960	0.913	0.85	0.73
0.117	0.14	0.89	0.49	0.37	0.919	0.904	0.84	0.71
0.120	0.39	0.82	0.39	0.43	0.917	0.909	0.81	0.71
0.108	0.67	0.84	0.24	0.35	0.901	0.897	0.85	0.68
0.106	0.73	0.89	0.44	0.38	0.931	0.893	0.87	0.67
0.115	0.43	0.87	0.15	0.28	0.945	0.902	0.84	0.70
0.122	0.71	0.78	0.12	0.21	0.924	0.916	0.83	0.73
0.114	0.36	0.80	0.28	0.24	0.909	0.918	0.87	0.72
0.123	0.46	0.76	0.45	0.26	0.934	0.919	0.81	0.72
0.121	0.47	0.82	0.46	0.21	0.903	0.922	0.82	0.72
0.090	0.43	0.89	0.56	0.23	0.908	0.919	0.81	0.60
0.094	0.57	0.91	0.43	0.29	0.902	0.925	0.82	0.62
0.086	0.36	0.96	0.33	0.31	0.905	0.926	0.93	0.65
0.091	0.14	0.98	0.33	0.34	0.955	0.926	0.93	0.67
0.087	0.50	1.00	0.45	0.37	0.954	0.914	0.92	0.63
0.086	0.57	0.89	0.62	0.33	0.961	0.938	0.94	0.65
0.087	0.61	0.87	0.52	0.38	0.959	0.939	0.92	0.65
0.093	0.67	0.84	0.24	0.35	0.954	0.932	0.93	0.68
0.085	0.73	0.89	0.44	0.38	0.955	0.916	0.93	0.63
0.086	0.43	0.87	0.15	0.28	0.969	0.914	0.93	0.63
0.088	0.79	0.84	0.33	0.22	0.966	0.860	0.98	0.63
0.103	0.47	0.80	0.22	0.13	0.996	0.917	0.82	0.64
0.103	0.43	0.78	0.18	0.26	0.908	0.917	0.82	0.64
0.121	0.41	0.82	0.13	0.33	0.908	0.911	0.74	0.65
0.099	0.36	0.76	0.23	0.44	0.849	0.915	0.87	0.65
0.092	0.86	0.80	0.15	0.39	0.932	0.913	0.94	0.65
0.089	0.50	0.82	0.95	0.37	0.973	0.901	0.95	0.64

Functions of Exchanger d
Function (1) Function of developed values for exchanger D

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```
function [f_d]=get_fdparam(v)
m1=v(1);   m2=v(2);   t1d=v(3);   t2a=v(4);   n=v(5);   mh=v(6);   T2=v(7);
T1a=v(8);
h = t2a - t1d;
t2d = t1d + (h * 0.32);
m1 = (m1 * 1000) / 24;
m2 = (m2 * 1000) / 24;
x = (t2d + t1d) / 2;
cpn = 0.0045 * x + 2.0669;
dt = (t2d - t1d)  ;
wh = n * 2.016 / (mh * 100)     ;
hh = 4.19 * (6.8 + 0.0006 * x);
cph = (hh / 2.016) * wh;
whg = 1 - wh;
cpg = (0.00428 * x + 1.5606) * whg;
cptotal = cph + cpg       ;
T1 = T2 + (T1a - T2) * 0.24;
h = (T1 - t2d);
c = (T2 - t1d);
lmtd = (h - c) / log((h / c));
lmtd = lmtd * 0.94;
m = m1 + m2;
mg = m2 / (m);
umix = 1.5484 * exp(-0.0064 * x) * (1 - mg) + 0.0327 *exp(0.0016 * x)
* mg;
gs = m / 0.062;
re = (gs * 0.025) / umix;
jh = 0.3652 * power(re, 0.5445);
c = mg * cptotal + (1 - mg) * cpn;
k = (-0.0003 * x + 0.5675) * (1 - mg) + 0.245 * mg;
z = c * umix / k;
pr = power(z, 0.333);
```

التابع 2 تابع تدريب الشبكة العصبونية في المبادل D

Appendix 1. weighting factors for the network model of exchanger D

w1 = 1.0e+003 *

```
Function out_d=train_d(input,f)
net_d=newff(minmax(input),[6,2,1],{'logsig','pureli
n','purelin'},'trainlm');
net_d.trainParam.show = 5;
net_d.trainParam.epochs = 5000;
net_d.trainParam.goal = 1e-5;
[net_d,tr]=train(net_d,input,f);
```

Columns 1 through 6

1.0014	-0.2151	2.1518	-0.7096	-0.1884	-0.0818
-0.0181	-0.0246	0.0436	0.0378	0.0038	0.0008
-0.0038	0.0090	-0.0046	-0.0049	-0.0009	-0.0003
-0.4237	0.8263	-0.2406	-0.0972	0.1333	0.1299
-0.0065	-0.0148	0.0666	-0.0028	0.0042	0.0035
0.0185	-0.0021	-0.0184	-0.0057	-0.0012	-0.0006

Weighting factors for input layer

Columns 7 through 8

0.4699	0.0954
0.0023	0.0012

Hidden area weighting factors 1

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-0.0008	-0.0004
0.3997	0.0501
0.0040	0.0025
-0.0008	-0.0007

w2 = Hidden area weighting factors 2

0.2935	-0.1036	-1.3388	-0.3438	-0.2406	0.8049
-0.4125	0.5061	-0.3847	0.5295	0.7779	0.2279

w3 = 0.0812 0.0433

b1 = **1.0e+003 *** First hidden layer deviation factor

-2.5961
-0.0401
0.0083
-0.6656
-0.0458
0.0101

b2 = Second hidden layer deviation factor

-0.3010
0.6923

b3 = 0.1696 Output layer deviation factor

Function (3) Network training simulation function for exchanger D
recall =sim (net_d, input)
[m,b,r]=postreg (recall,f)

Function (4) Network generalization simulation function for exchanger D
generate =sim (net_d, newdata)
[m,b,r]=postreg (generate, newf)

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