INTERNATIONAL JOURNAL OF
ENERGY AND ENVIRONMENT

Volume 2, Issue 5, 2011 pp.829-844

Journal homepage: www.IJEE.IEEFoundation.org

Online performance assessment of heat exchanger using artificial neural networks

C. Ahilan[1], S. Kumanan[1], N. Sivakumaran[2]

[1] Department of Production Engineering, National Institute of Technology Tiruchirappalli, India.
[2] Department of Instrumentation and Control Engineering, National Institute of Technology Tiruchirappalli, India.

Abstract
Heat exchanger is a device in which heat is transferred from one medium to another across a solid surface. The performance of heat exchanger deteriorates with time due to fouling on the heat transfer surface. It is necessary to assess periodically the heat exchanger performance, in order to maintain at high efficiency level. Industries follow adopted practices to monitor but it is limited to some degree. Online monitoring has an advantage to understand and improve the heat exchanger performance. In this paper, online performance monitoring system for shell and tube heat exchanger is developed using artificial neural networks (ANNs). Experiments are conducted based on full factorial design of experiments to develop a model using the parameters such as temperatures and flow rates. ANN model for overall heat transfer coefficient of a design/ clean heat exchanger system is developed using a feed forward back propagation neural network and trained. The developed model is validated and tested by comparing the results with the experimental results. This model is used to assess the performance of heat exchanger with the real/fouled system. The performance degradation is expressed using fouling factor (FF), which is derived from the overall heat transfer coefficient of design system and real system. It supports the system to improve the performance by asset utilization, energy efficient and cost reduction interms of production loss.

Keywords: Heat exchanger; Artificial neural networks (ANNs); Modeling; Overall heat transfer coefficient; Fouling factor (FF).

1. Introduction

Heat exchanger process is complex due to its nonlinear dynamics and particularly the variable steady-state gain and time constant with the process fluid [1]. Heat exchangers are used to transfer the heat between two fluids across a solid surface that are at different temperatures. The commonly used shell and tube heat exchangers are used in refrigeration, power generation, heating, air conditioning chemical processes, manufacturing and medical applications [2]. These heat exchangers consist of a bundle of tubes and enclosed within a cylindrical shell. One type of fluid flows through the tube and second type of fluid flows between shell and tubes. The performance of heat exchanger deteriorates with time due to formation of fouling. It is a very complicated phenomenon and can be broadly categorized into particulate, corrosion, biological, crystallization, chemical reaction and freeze. It is exclusively due to single mechanism in many situations. It tends to increase over time, the trajectory being very site specific. Factors that impacts fouling are feed quality, wall temperature, velocity, biological activity and the treatment chemistry.

Performance of heat exchanger is monitored by the following methods: i) Outlet temperature of the hot stream (T_{ho}) profile, ii) Approach temperature (T_{ho} - T_{ci}) profile, iii) Log Mean Temperature Difference (LMTD) with time, iv) Heat load profile, and v) Time series of overall heat transfer coefficient. The first four methods are widely used and are ineffective interms of isolating the net impact of fouling from process upsets. But the overall heat transfer coefficient method requires detailed calculations and knowledge of the geometry of the exchangers [3]. Operators calculate these parameters once or twice in a week based on either instantaneous temperature and flow measurements or daily averaged samples of the measurements. Any deviation from the heat transfer coefficient of design/clean heat exchanger will indicate the occurrence of fouling [4]. Tubular Exchanger Manufacturing Association recommends an allowable fouling factor (FF) or fouling resistance to tolerate some degree of fouling before cleaning must be undertaken. This allowance is given to prevent frequent process interruptions for cleaning of heat exchanger [5]. Hence, monitoring system is needed to assess the performance of heat exchanger. The methodology followed to monitor the system depends mainly on the adopted practice in the plant, application, type of heat exchanger, and experience of the operator. Some of the monitoring approaches are adhoc where as some involve meticulous calculation [3]. To overcome this, heat exchanger performance should be monitored online with intelligent tools and assess the performance periodically. It needs competent predictive model of a system to assess the heat exchanger performance.

Modeling is a representation of physical or chemical process by a set of mathematical relationships that effectively explain the significant process behavior. These models are frequently used for process design, safety system analysis and process control [6]. In experimental studies and engineering applications of thermal science, researchers and engineers are expected to reduce experimental data into one or more simple and compact dimensionless heat transfer correlations [7]. The drawbacks of this method are heat transfer coefficients strongly depend on their definitions and temperature differences, and certainly need iterative method to find correlations when fluid properties are dependent on fluid temperatures [8]. The limitations of correlation methods are addressed by computational intelligent (CI) techniques, such as ANNs and fuzzy logic (FL). ANNs is one of the most powerful computer modeling techniques, based on statistical approach, currently being used in many fields of engineering for modeling complex relationships which are difficult to describe with physical models. It only needs input/output samples for training the network and learn complex nonlinear relationship [9].

In recent years, ANNs have been used in thermal systems for heat transfer analysis, performance prediction and dynamic control [7,9]. Sen and Yang [10] discusses in general the applications of ANN and genetic algorithms in thermal engineering. ANN is applied in heat transfer data analysis [11], evaluating heat transfer coefficients from experimental data [12], identifying and controlling heat exchangers [13], simulation of heat exchanger performance using limited experimental data [14], modeling of heat exchanger dynamic characteristics [15], dynamic modeling and controlling of heat exchangers with GA [16], dynamic prediction and neuro controller design for heat exchangers [17,18], neuro predictive controller design of heat exchangers [19], determining fin-and-tube heat exchangers performance with limited experimental data using soft computing and global regression[20,21], predicting heat transfer rate of a wire-on-tube heat exchanger [22], heat transfer analysis of air flowing in corrugated channels [23] and modeling the thermal performance of compact heat exchanger [24]. From the above mentioned successful applications, ANNs are well suitable for thermal analysis in engineering systems, especially in heat exchangers.

In this paper, an online monitoring system is developed for a shell-and-tube heat exchanger using secondary measurements namely the temperatures and flow rates of the hot and cold fluid (water). Experimental system is developed to investigate the performance of heat exchanger. ANN is applied to model the heat exchanger with experimental data. The input parameters to develop a model for design/clean heat exchanger are inlet temperature and flow rate of shell and tube side fluids and output is overall heat transfer coefficient (U_{Design}). The overall heat transfer coefficient of real/fouled system (U_{Real}) is calculated using online measured values such as inlet temperature, outlet temperature and flow rate of shell and tube side fluids. The heat exchanger performance is assessed by comparing the results of clean/design and fouled/real system. Any deviation from the result of design/clean system indicates that the performance is degraded due to fouling. Its degree is derived from fouling factor (FF) using U_{Design} and U_{Real}.

2. Experimental set-up

The present work is carried out in the process control lab of Instrumentation and Control Engineering department in National Institute of Technology Tiruchirappalli, India.

2.1 Experimental system

Experiments are conducted on a 1-1 shell and tube heat exchanger. Figure 1 shows the schematic diagram of the experimental set up developed in shell and tube heat exchanger and its photographic view is shown in Figure 2. The details of the heat exchanger fabricated are given in the Table 1.

Cold and hot water flow into the shell and tubes respectively can be changed using pneumatic control valves. The inlet and outlet temperatures of the shell and tube side fluid were measured using RTDs. Hot water inlet temperature was maintained constant with a ±0.5 °C variation using an inbuilt digital PID controller. Cold water was supplied at the room temperature (27 °C). The inlet flow of the cold water can be varied in the range of 0 - 350 liter per hour (LPH) and that of hot water between 0 and 250 LPH. The flow rate of cold and hot water were measured using flow transmitter. All the sensors and actuators were interfaced with a 16 bit data acquisition system (Advantech ADAM 5000 series hardware). The module consists of eight analog inputs (AI) and four analog outputs (AO) channels. A PC was used to log the data and run the program in MATLAB environment and RS232 cable is used for communication.

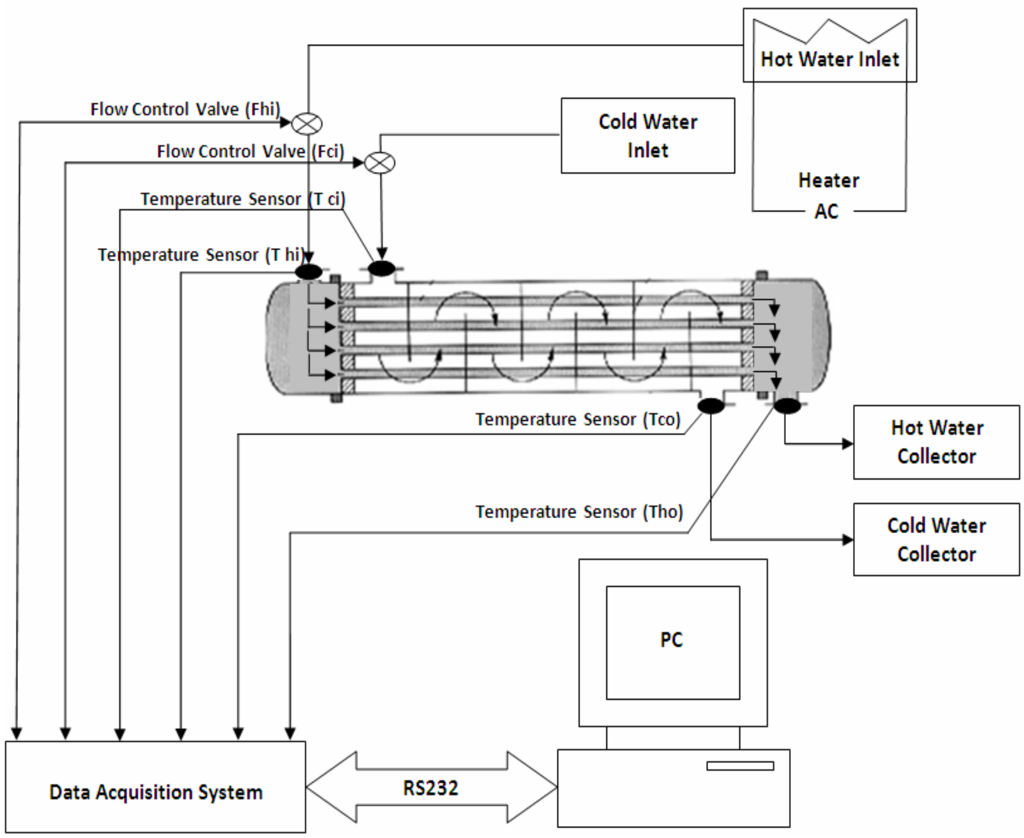

Figure 1. Schematic diagram of experimental set-up in shell and tube heat exchanger

2.2 Data aquisition

In experimental design, three levels of process parameters hot water inlet temperature, cold water flow rate and hot water flow rate were selected and are tabulated in Table 2. In this study, full factorial design of experiments is used and their experimental combinations of process parameters were presented in Table 3. The experiment is carried out in a single phase, both the fluid streams being water and are passed in a co-current fashion. In the overhead tank, water is filled and heated to a particular operating temperature. The hot water then flows from the overhead tank and passes through the tube-side of the heat exchanger. Cold water flows from the reservoir tank into the shell side of the heat exchanger. The overhead tank water temperature is set initially as 40°C, cold water flow rate as 100 LPH and hot water flow rate as 65 LPH. In this set condition, the process was continued until it reaches the steady state. In steady state, the outlet temperatures of cold and hot water are observed. The flow rate of cold water was changed to 200 LPH and 300 LPH and continues the process to reach steady state. Then the outlet temperatures of cold and hot water were observed. The above step can be repeated by changing the hot water flow rate to 75 LPH and 85 LPH and the outlet temperatures were observed. Similarly for the hot water inlet temperature 50°C and 60°C the above procedure was repeated and the readings were observed.

Based on the experimental design combination experiments were conducted for water – hot water system and their results are tabulated in the Table 4. The performance of the heat exchanger is assessed by computing overall heat transfer coefficient. The overall heat transfer coefficient is calculated using log mean temperature difference (LMTD) approach because the inlet temperature, outlet temperature and flow rate of the cold and hot water are known. The overall heat transfer coefficient of shell and tube heat exchanger is calculated by using below equations.

$$Q_h = m_h\, Cp_h\, (T_{hi} - T_{ho}) \quad \text{in kW} \tag{1}$$

(or)

$$Q_c = m_c\, Cp_c\, (T_{co} - T_{ci}) \quad \text{in kW} \tag{2}$$

where

Q_h - heat transfer rate of hot water side
Q_c - heat transfer rate of cold water side
m_h - mass flow rate of hot water in kg/hr
m_c - mass flow rate of cold water in kg/hr
Cp_h – specific heat capacity of hot water in kJ/kgK
Cp_c – specific heat capacity of hot water in kJ/kgK
T_{hi} – hot water inlet temperature in °C
T_{ho} - hot water outlet temperature in °C
T_{co} - cold water inlet temperature in °C
T_{ci} - cold water outlet temperature in °C
A - Heat transfer Area in m^2

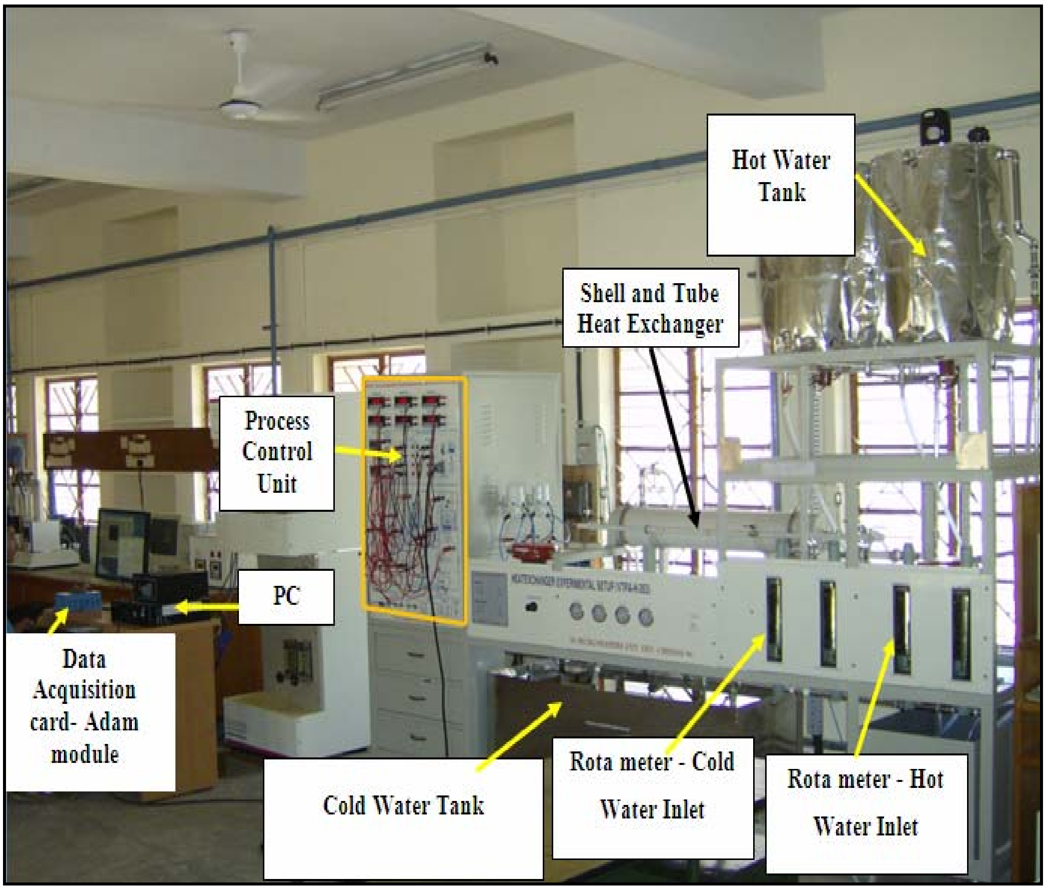

Figure 2. Photographic view of experimental set-up

Table 1. Geometrical parameters and instruments used in heat exchanger

Heat exchanger Type	Shell and Tube in Co-current and Counter current mode
Shell material	SS 316
Tube material	Copper
Shell Length	900 mm
Shell diameter	150mm
Tube length	750mm
Number of Tubes	37
Tube Outer Diameter (OD)	6 mm
Tube Inner Diameter (ID)	4.6 mm
Pitch	Triangular 15 mm
Passes	Single
Fluid (Cold and Hot)	Water
RTD Transmitter	Type: PT-100(3 wire), Range: 0-100oC, Output: 4-20 mA.
Flow Transmitter	Type: Differential Pressure Transmitter, Output 4 - 20mA
Pump	Discharge: 800 L/hr
Rota meter	Ranges: (0-150) LPH/ (41-410) LPH
Control Valve	Type: Air to close (Cold fluid)/ air to open (Hot fluid), Characteristics : Equal percentage, Input : 3-15 PSI, Flow rate: 1000/500L/hr (max)
Data Acquisition System	Interface converter: Adam 5000 Input module: Adam 5017 (8 Channel AI) Output module: Adam 5024 (4 Channel AO)
Communication Cable	RS232 serial Interface
Power Supply Unit	Input: 230 V,50 HZ AC Output: 24 V, 500 mA DC
Process Tank with Heater	Capacity: 75 L, Power: 1.5 kW*3 with thyristor power driver
Disturbance Tank with Heater	Capacity: 75 L, Power: 1.5 kW*2 with thyristor power driver
Reservoir Tank	Capacity : 250 L

Table 2. Selected parameters and their levels

Parameter	Unit	Level 1	Level 2	Level 3
Cold water Flow rate	LPH	100	200	300
Hot water Flow rate	LPH	65	75	85
Hot water inlet temperature	°C	40	50	60

Capacity ratio $R = (T_{hi}-T_{ho}) / (T_{co}-T_{ci})$ (3)

Effectiveness $S = (T_{co}-T_{ci}) / (T_{hi}-T_{ci})$ (4)

F - Correction factor for LMTD to account cross flow

$F = [(R+1)^{1/2} \times \ln((1-SR)/(1-S))]/(1-R) \times \ln\{[2-S(R+1-(R-1)^{1/2}]/[2-S(R+1+(R+1)^{1/2}]\}$ (5)

LMTD for Counter current flow $= ((T_{hi}-T_{co})-(T_{ho}-T_{ci})) / \ln((T_{hi}-T_{co}) / (T_{ho}-T_{ci}))$ in °C (6)

LMTD for Co current flow $= ((T_{hi}-T_{ci})-(T_{ho}-T_{co})) / \ln((T_{hi}-T_{ci}) / (T_{ho}-T_{co}))$ in °C (7)

$U = [Q_h \text{ or } Q_c] / [A*F*LMTD]$ in $kW/m^2.°C$ (8)

Initially the heat transfer rate (Q) of the hot or cold water was calculated based on secondary measurements such as temperatures and flow rates using equation (1) or (2). Then the heat transfer area of the heat exchanger (A) was calculated based on the geometrical parameters. Next the capacity ratio R and effectiveness S were calculated with inlet and outlet temperatures of cold and hot water by using equation (3) and (4) respectively. The correction factor (F) for LMTD to account cross flow was computed using equation (5). LMTD for co current flow of cold and hot water was computed with inlet and outlet temperatures of cold and hot water using equation (7). Based on the calculated values of Q, A, F and LMTD the overall heat transfer coefficient was calculated using equation 8. The overall heat transfer coefficient of design/clean heat exchanger is computed and are presented in Table 4.

Table 3. Experimental design using full factorial design of experiments and their outputs

Ex. No.	T_{hi} (°C)	F_{hi} (LPH)	F_{ci} (LPH)	Experimental observation	
				T_{co} (°C)	T_{ho} (°C)
1	40	65	100	32.5	34
2	40	65	200	32	33.5
3	40	65	300	31.5	33
4	40	75	100	33.25	35
5	40	75	200	33	34.5
6	40	75	300	32.5	34
7	40	85	100	33.5	36
8	40	85	200	33.25	35.25
9	40	85	300	32.75	34.75
10	50	65	100	34	36
11	50	65	200	33.5	35.5
12	50	65	300	32.5	34.5
13	50	75	100	34.5	37
14	50	75	200	34	36
15	50	75	300	33	35
16	50	85	100	35	38
17	50	85	200	34.25	37
18	50	85	300	33.5	35.5
19	60	65	100	36	40.5
20	60	65	200	35.5	38.5
21	60	65	300	34.5	37
22	60	75	100	38	42.5
23	60	75	200	37	41
24	60	75	300	36.5	39.5
25	60	85	100	40	44
26	60	85	200	39	42.5
27	60	85	300	37.5	41

3. Design and development of performance assessment system for heat exchanger

3.1 Design of performance assessment system

An online monitoring system for shell and tube heat exchanger was designed based on the current need to evaluate the performance. In this an ANN is used to develop the model for predicting the overall heat transfer coefficient (U_{Design}) of the design system using secondary measurements temperature and flow rates. Inputs of the developed network were T_{hi}, flow rate of cold water F_{ci} and flow rate of hot water F_{hi} and output was U_{Design}. Data acquired from the design of experiments were used for training, validation and testing the ANN model. Heat transfer coefficient of real system (U_{Real}) is derived using secondary measurements such as T_{ci}, T_{hi}, T_{co}, $T_{ho,}$ F_{ci} and F_{hi}.

This system imitate the real time system and used for performance assessment (fouling) of the system. Online measured values of T_{ci}, T_{hi}, T_{co}, $T_{ho,}$ F_{ci} and F_{hi} are used to predict the value of U_{Design} and compute the value of U_{Real}.

FF value is computed with the predicted value of U_{Design} and the computed value of U_{Real}. It is used to identify the performance degradation or degree of fouling of the heat exchanger. If the FF value is greater than or equal to the set value (allowable) of design heat exchanger, warning message will be given for cleaning or maintenance of heat exchanger and the heat exchanger continue to work and monitor the system. Otherwise no warning message will be given and the heat exchanger continues to work and monitor the system. The proposed scheme and flow chart of the online performance monitoring system is shown in Figures 3 and 4.

Table 4. Heat transfer rate (Qh) and overall heat transfer coefficient (U) of experimental data

Ex. No.	Q_h (kW)	A*F*LMTD (m^2.°C)	U_{Design} (kW/m^2.°C)
1	0.4514	2.4791	0.1821
2	0.4891	2.5176	0.1943
3	0.5267	2.5640	0.2054
4	0.4341	2.5901	0.1676
5	0.4775	2.4480	0.1951
6	0.5209	2.4791	0.2101
7	0.3936	3.0124	0.1306
8	0.4674	2.7380	0.1707
9	0.5166	2.7600	0.1872
10	1.0442	4.2305	0.2468
11	1.0814	4.2973	0.2517
12	1.1560	4.4517	0.2597
13	1.1187	4.4919	0.2491
14	1.2048	4.2305	0.2848
15	1.2909	4.3708	0.2953
16	1.1704	4.7367	0.2471
17	1.2679	4.6708	0.2715
18	1.4142	4.2973	0.3291
19	1.4480	7.1912	0.2014
20	1.5965	6.3741	0.2505
21	1.7079	6.2025	0.2754
22	1.4994	6.9553	0.2156
23	1.6279	6.7811	0.2401
24	1.7565	6.2284	0.282
25	1.5537	6.4825	0.2397
26	1.6994	6.2622	0.2714
27	1.8450	6.4210	0.2873

3.2 NN model development

Feed forward back propagation (FFBP) NNs model is the best general purpose model and probably the best at generalization. In this study, FFBPNN is selected to model the heat exchanger performance. NNs model development has the following stages: data collection, pre processing of data, network design and training, validation and testing the performance of the network.

The input data T_{hi}, F_{ci} and F_{hi} are tabulated in Table 3 and their corresponding overall heat transfer coefficient (U_{Design}) of the heat exchanger (output data) is presented in Table 4.

Before training the network, the input/output datasets were normalized within the range of -1 to 1, using the Matlab function. The normalized value for each raw input/output dataset is calculated by using a formula

$$pn = 2 \text{ X } (p\text{-}minp) / (maxp\text{-}minp) - 1 \quad (9)$$

where, p is input/output data, pn is normalized value of p, minp is minimum value of p and maxp is maximum value of p.

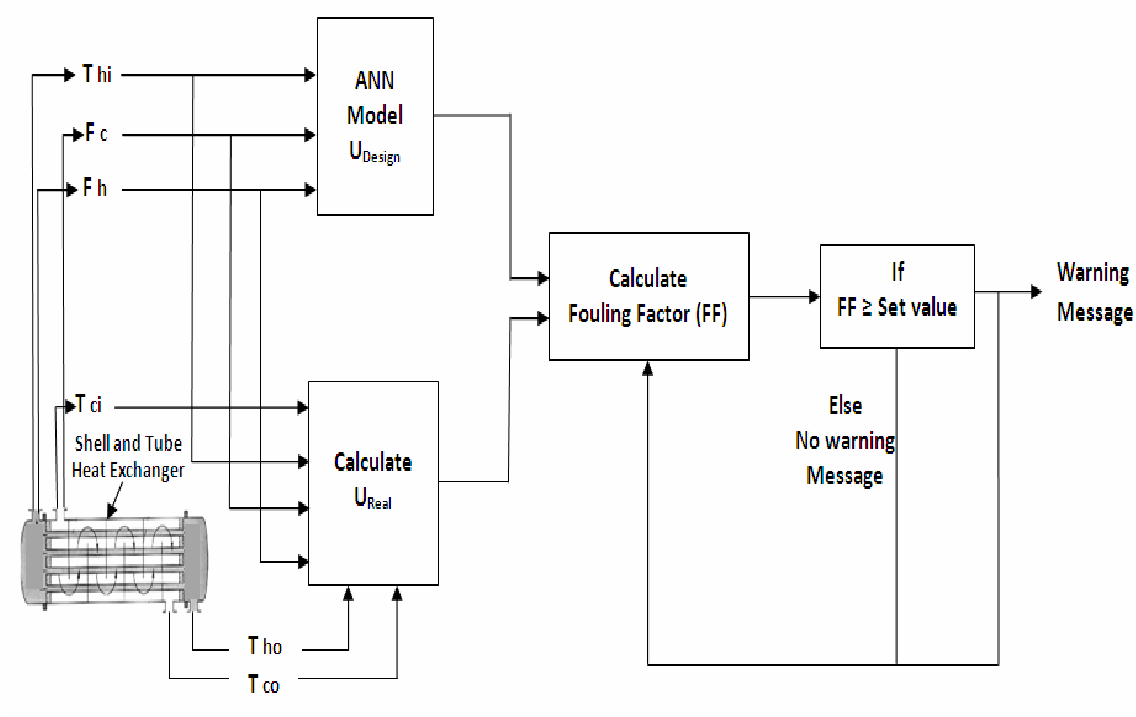

Figure 3. Schematic diagram of proposed online performance monitoring system

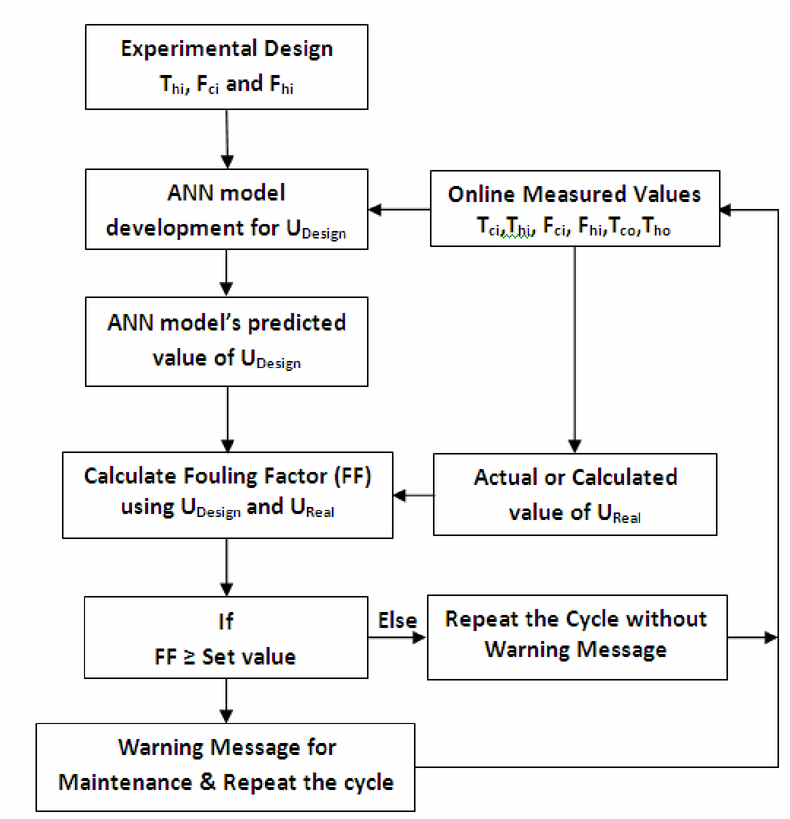

Figure 4. Flow chart of the proposed online fouling monitoring system

The network architecture or features such as number of neurons and layers are very important factors that determine the functionality and generalization capability of the network. For the model, a standard multilayer feed forward back propagation hierarchical neural network is designed with MATLAB NN Toolbox [25]. The networks consist of three layers: the input layer, hidden layer, and output layer. In order to determine the number of hidden layers and neurons are by trial and error method. The neural networks for U_{Design} has three neurons in the input, corresponding to each of the three process input parameters T_{hi}, F_{ci} and F_{hi} and one neuron in the output layer, corresponding to the process response U_{Design}. The topography of the ANN model (3-8-1) for U_{Design} is shown in Figure 5 and the developed model in MATLAB environment is shown in Figure 6. In this one hidden layer with eight neurons is found to be most suitable for model development by trial and error method. For networks, linear transfer function 'purelin' and tan sigmoid transfer function 'tansig' is used in the output and hidden layer respectively. Experimental data set are used to train, validate and test the U_{Design} network. In this, twenty one data set are used for training, three data set are used for validation and remaining three data set are used for testing the network. The training of ANN for 21 input-output patterns has been carried using 'trainlm' algorithm. The learning factors are set as goal of 10^{-10} and epochs of 1000. The variation of MSE during the training is shown in Figure 7. In the present study, the desired MSE is achieved after 6 epochs.

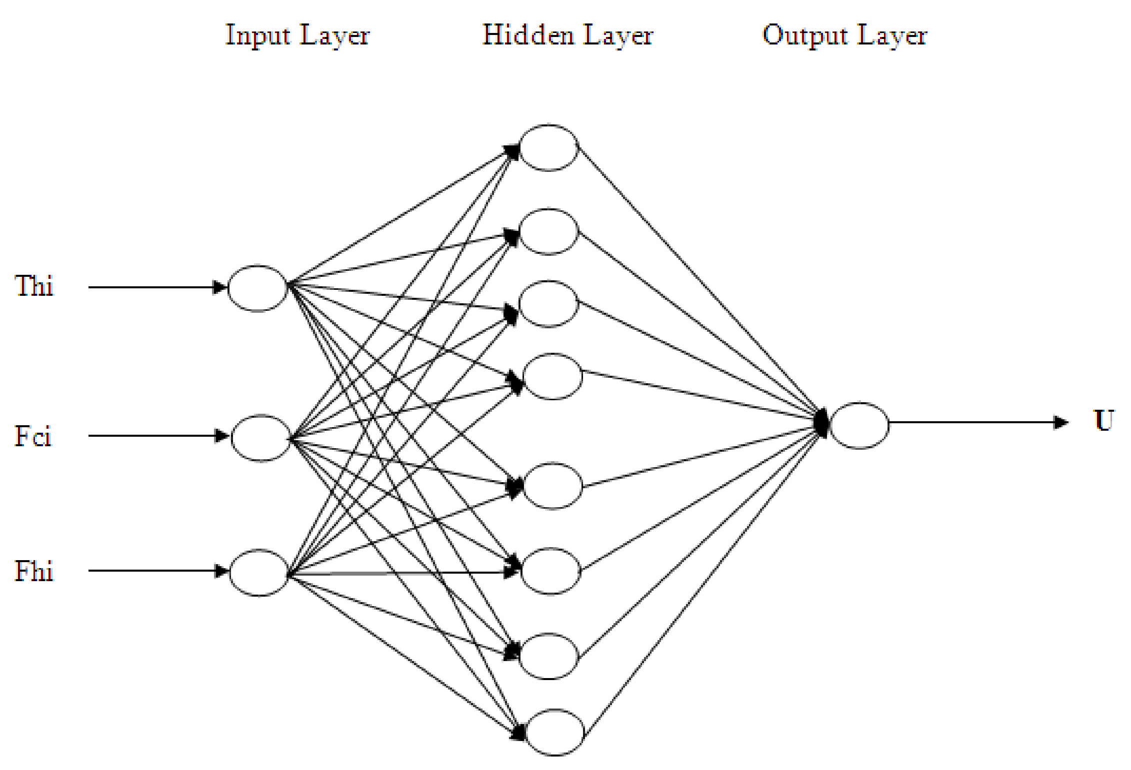

Figure 5. Topography of developed ANN Model (3-8-1) for U_{Design}

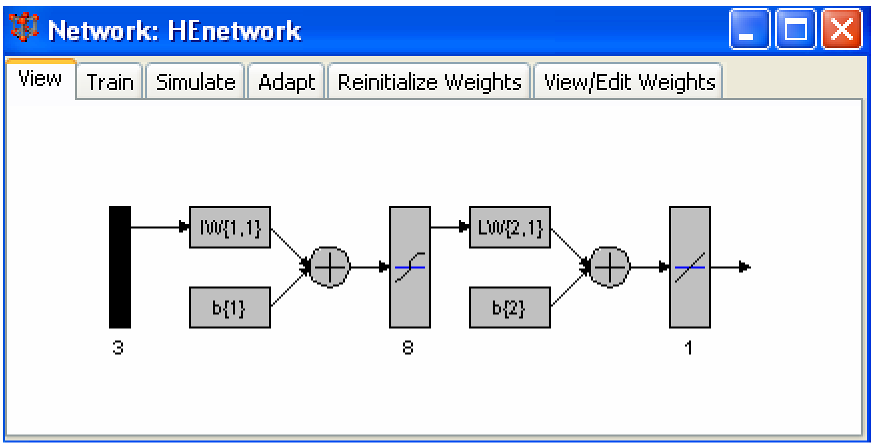

Figure 6. Developed ANN Model (3-8-1) for U_{Design}

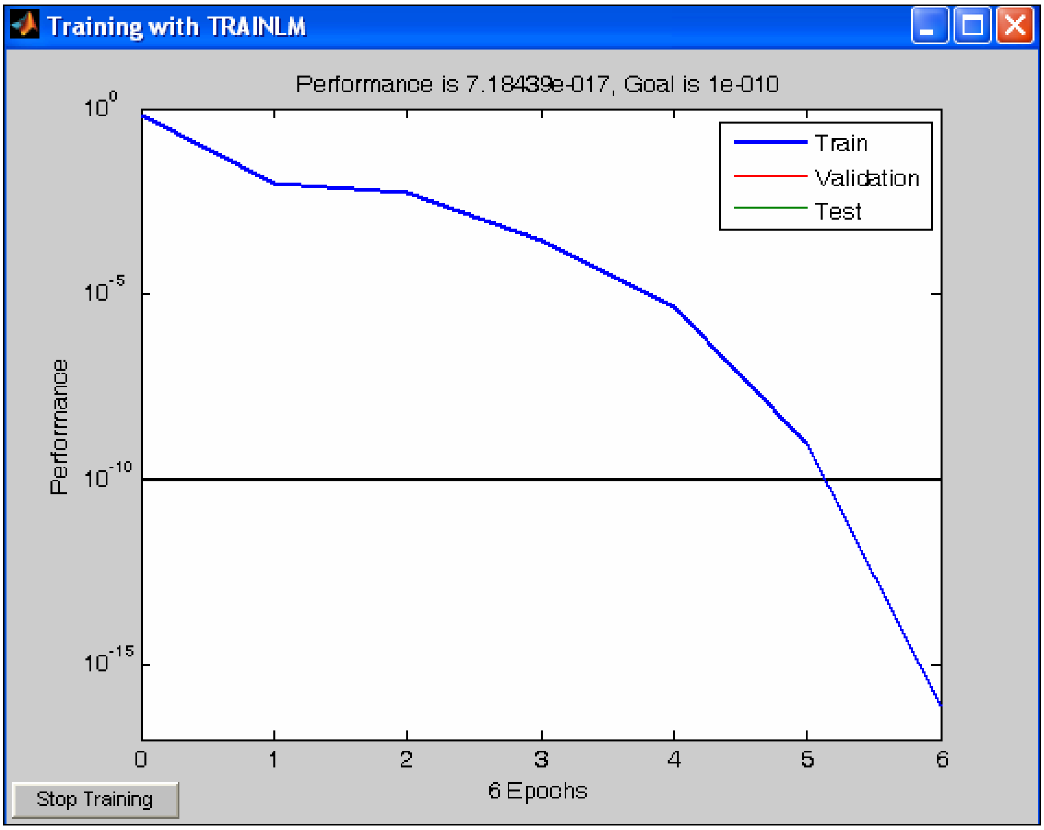

Figure 7. Training graph of developed ANN model for U_{Design}

The trained ANN is initially tested by presenting 21 input patterns, which are employed for the training purpose. For each input pattern, the predicted value of overall heat transfer coefficient is compared with respective output data and absolute percentage error is compared, which is given as

$$\% \text{ Absolute error} = \left| (Y_{i,exp} - Y_{i,pred})/(Y_{i,exp}) \right| X100 \quad (10)$$

where, $Y_{i,\,exp}$ is the measured value and $Y_{i,\,pred}$ is the ANN predicted value of the response for i^{th} trial.

The performance capability of network is examined based on the absolute error percentage between the network predictions and the experimental values. It is found that the predicted and experimental values are very fairly close to each other. The error of overall heat transfer coefficient for 21 input trials of training patterns are zero. Another way of measuring the performance of a trained network is by performing a regression analysis between the network response and the corresponding targets. This is carried out by using 'postreg' function in MATLAB. The graphical output of 'postreg' is shown in Figure 8 for U_{Design}. The correlation coefficient (R) between the outputs and targets is a measure of how well the variation in the output is explained by the targets. If R value is 1 then it indicates perfect correlation between the target (T) and predicted outputs (A). In this case, the R value of the output overall heat transfer coefficient is 1, it indicates that the model had very good correlation.

In validation, three new data set are used which do not belong to the training data set. For this validation data set, the overall heat transfer coefficient is predicted using the ANN model and then compared with the actual (real) values. It is observed that predicted values of U_{Design} are very closer to the actual values that are shown in Figure 9. It is also found that maximum absolute error of U_{Design} is 3.47 % is tabulated in Table 5. This indicates that the model accuracy for predicting the process responses is well adequate.

For testing, other three new data set are used which do not belong to the training and validation data set. For this testing data set, the overall heat transfer coefficient is predicted using the ANN model and then compared with the actual values. It is observed that predicted values of U_{Design} are very closer to the actual values that are shown in Figure 10. It is also found that maximum absolute error of U_{Design} is 2.53 % is presented in Table 6. This indicates that the model for predicting the process responses is well adequate for generalization. NN model for U_{Design} is developed to study the performance degradation by estimating the fouling of the shell and tube heat exchanger.

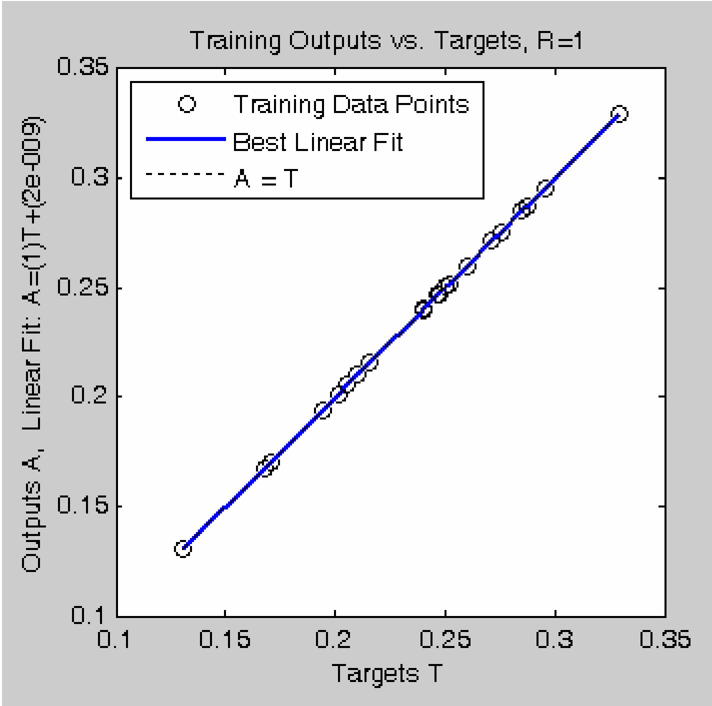

Figure 8. Training Output value graph of developed ANN model for U_{Design}

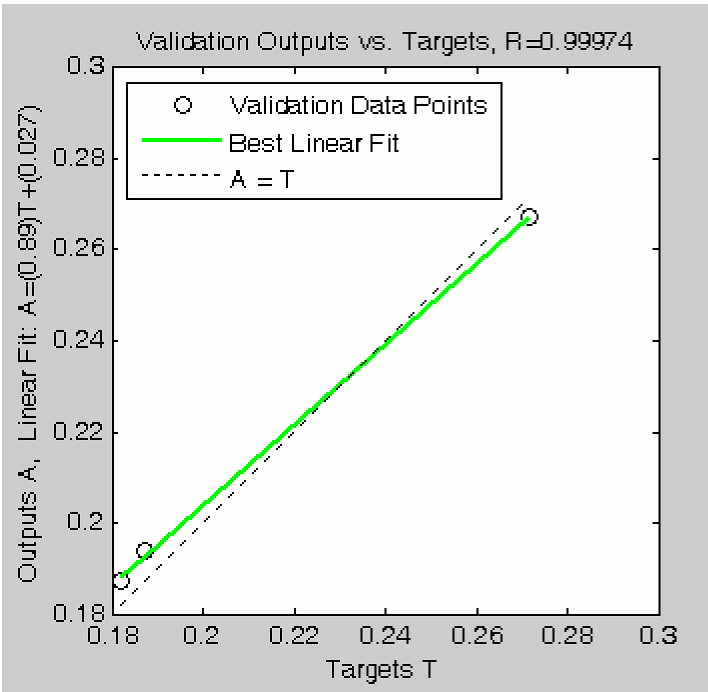

Figure 9. Validation Output value graph of developed ANN model for U_{Design}

Table 5. Experimental results vs ANN prediction results for validation

T_{hi} °C	F_{hi} Lph	F_{ci} Lph	T_{co} °C	T_{ho} °C	U_{Design} (kW/m^2.°C) Actual value	ANN	% Error
40	65	100	32.5	34	0.1821	0.1872	2.80
40	85	300	32.75	34.75	0.1872	0.1937	3.47
50	85	200	34.25	37	0.2715	0.2673	1.55

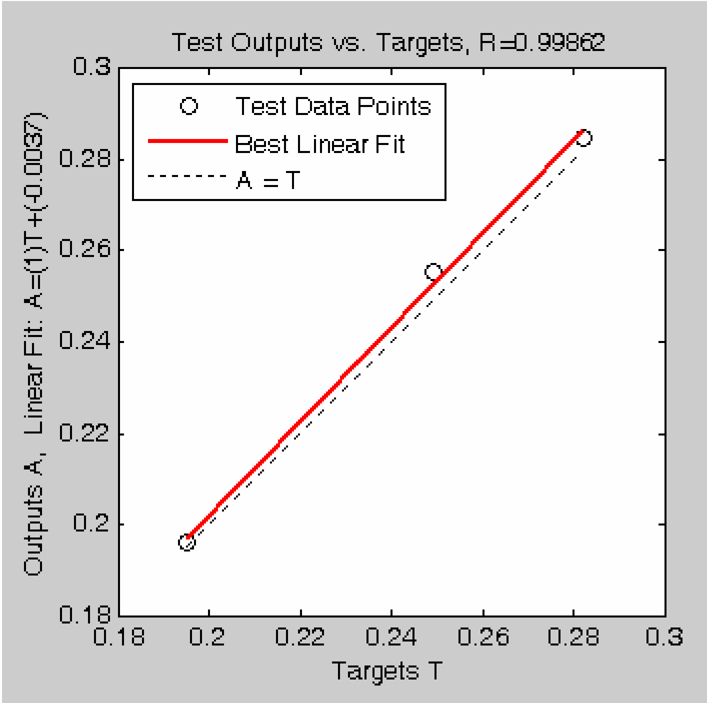

Figure 10. Testing Output value graph of developed ANN model for U_{Design}

Table 6. Experimental results vs ANN prediction results for testing data

T_{hi} °C	F_{hi} Lph	F_{ci} Lph	T_{co} °C	T_{ho} °C	U_{Design} (kW/m^2.°C)		% Error
					Actual value	ANN	
40	75	200	33	34.5	0.1951	0.1961	0.51
50	75	100	34.5	37	0.2491	0.2554	2.53
60	75	300	36.5	39.5	0.2820	0.2848	0.99

3.3 Performance assessment

Heat exchanger's performance will degrade with the time from design to real conditions. The rate at which this will occur is dependent on the application of heat exchangers. Fouling detection is able to present the degradation of heat exchanger performance, which is responsive for changes in the FF across the heat transfer surface. Effective and majorly applied method for fouling detection is to compare the U_{Design} and U_{Real}. It cannot be measured directly and it uses the secondary measurements such as flow rates and temperatures as inputs from the experimental data to estimate it.

From the online measured values such as T_{ci}, T_{hi}, T_{co}, $T_{ho,}$ F_{ci} and F_{hi} the performance of the heat exchanger is assessed. T_{hi}, F_{ci} and F_{hi} were used to predict the value of U_{Design} using developed ANN model. U_{Real} value is computed using LMTD approach with T_{ci}, T_{hi}, T_{co}, $T_{ho,}$ F_{ci} and F_{hi}. The performance of heat exchanger is assessed by comparing the U_{Real} value with U_{Design} value. The decrease in U_{Real} value indicates the degradation of performance by formation of fouling.

In this, performance degradation or fouling is estimated using FF approach and this will indicate the degree of fouling. The degradation in performance is expressed by the FF, as calculated by the equation:

$$FF= [(1/U_{Real})-(1/U_{Design})] \quad (11)$$

The FF value of heat exchanger is calculated using the equation (11). In design stage, the allowable fouling resistance i.e. FF is specified for all the heat exchangers by manufacturer's to avoid frequent cleaning or maintenance. The tolerance value of FF is obtained from the specification or from the data book. If the estimated FF value is greater than or equal to set value of FF, it gives warning message for cleaning or maintenance and continues the operation. Otherwise, no warning message is given and the operation continues. This system is useful for the industries to get online response of performance assessment/fouling effect with simple and effective experimentation.

4. Results and discussion

The proposed online performance monitoring scheme is implemented in the developed experimental set-up located in the process lab. The online data of heat exchanger such as T_{ci}, T_{co}, T_{hi}, T_{ho}, F_{ci} and F_{hi} are captured by running the MATLAB program in PC, which is connected to the data acquisition system. The system initially predicts the U_{Design} value with ANN model and computes the U_{Real} value through the online observed values. Then the system computed the FF value using U_{Real} and U_{Design} values.

Based on the FF value the system gives the information to the operator. The results of the system for typical condition are shown in Figure 11. From the results it is identified that the heat exchanger performance is with in the tolerance value (set by field engineer/maintenance engineer) of FF. It shows no warning message to field engineers. Another typical condition results are shown in Figure 12. This inferred that the performance of the heat exchanger is above the tolerance value of FF. It needs immediate maintenance or corrective action to recover the heat transfer efficiency. This gives intimation to the operator for planning maintenance well ahead to minimize operational disturbance due to unplanned shutdowns.

The advantage of this system is that it could be easily implemented in the industries to get online response of performance assessment/fouling effect with simple and effective experimentation. This gives comprehensive information to field engineers for improving the performance of heat exchanger by asset utilization, energy efficient and cost reduction interms of production loss and maintenance.

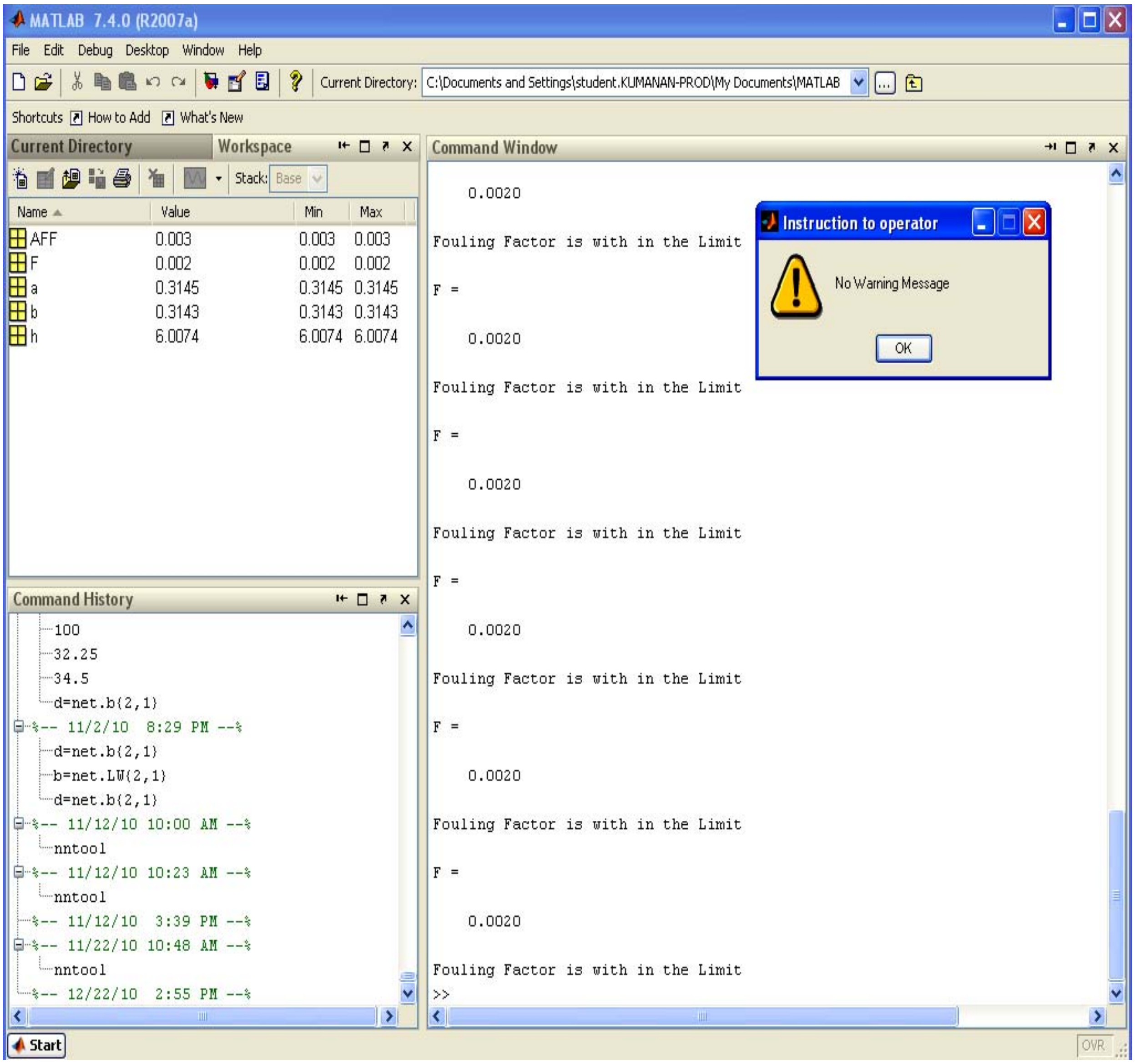

Figure 11. Screen shot of developed system for acceptable system with no warning message

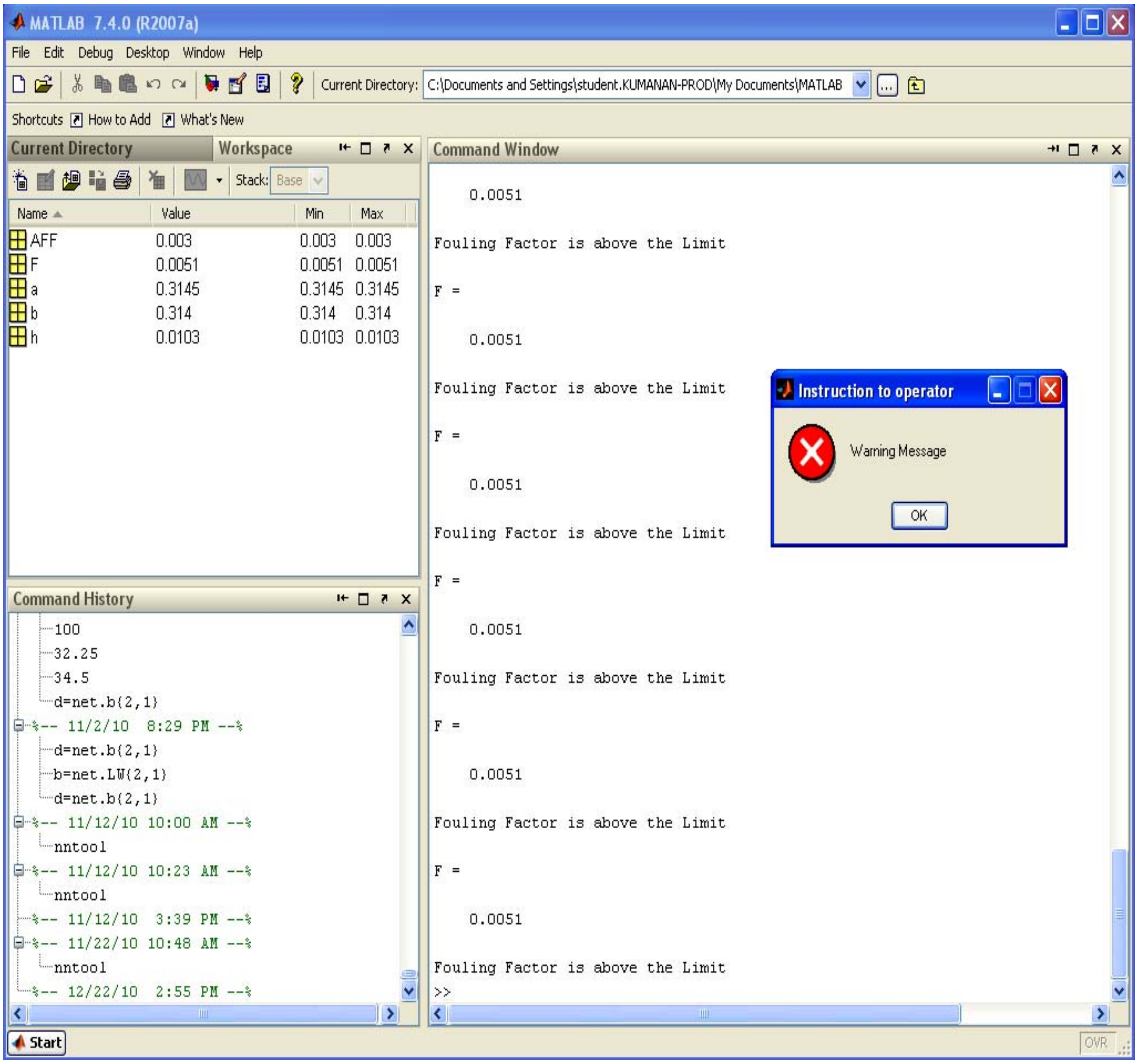

Figure 12. Screen shot of developed system for unacceptable system with warning message

5. Conclusion

Experiments were conducted on a 1-1 shell and tube heat exchanger with different cold water flow rates, hot water flow rate, and hot water inlet temperature to assess the performance of the system. The experimental observations were incorporated into the ANN model development. A feed forward neural networks model was developed to predict overall heat transfer coefficient U_{Design} of the design heat exchanger system and the model was trained, validated and tested for generalization. Good agreement was identified between the predictive model results and the experimental results. It was found that the maximum error of validation and testing data set for overall heat transfer coefficient U_{Design} of the design system were 3.47 % and 2.53 % respectively. NN model was used to predict the value U_{Design} and U_{Real} was derived from measured values. FF is found from the predicted U_{Design} and U_{Real} value. From the estimated FF value, the performance degradation/fouling effect was with in the tolerance limit (margin) or not is identified. Based on the results, degree of fouling and precaution information like warning or maintenance was given. Further, it needs intelligent approach to do fouling analysis and maintenance decision.

Acknowledgment

The authors express their sincere thanks to Ministry of Human Resource and Development (MHRD), India and National Institute of Technology Tiruchirappalli (NITT), India for giving the sponsorship under its research and development scheme.

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C. Ahilan is a research scholar in Production Engineering at the National Institute of Technology Tiruchirappalli, India. He received his BE in mechanical engineering from the PSG College of Technology, India in 1997 and MTech in manufacturing technology from the National Institute of Technology Tiruchirappalli in 2007. He has worked as a Research Assistant in the Department of Production Engineering, National Institute of Technology Tiruchirappalli. He has published 5 papers in international conferences, and 4 international journals. His research area includes intelligent industrial energy management systems.
E-mail address: ahilan_c@yahoo.co.in

S. Kumanan is a Professor in the department of Production Engineering, National Institute of Technology Tiruchirappalli, India. He received his BE, ME in production engineering from National Institute of Technology Tiruchirappalli and obtained his Doctorate degree from Indian Institute of Technology Madras, India. He has published more than 80 papers in national/international conferences, 52 international journals and 26 national journals. His research interests are in the areas of intelligent manufacturing systems, product and process optimization, intelligent maintenance systems, and intelligent industrial energy management systems.
E-mail address: kumanan@nitt.edu

N. Sivakumaran is an Assistant Professor in the Department of Instrumentation and Controls Engineering, National Institute of Technology Tiruchirappalli, India. He received his BE in electronics and instrumentation from Bharathidhasan University, India, ME in process control and instrumentation engineering from Annamalai University, India and Ph.D. in the area of process control and instrumentation from National Institute of Technology Tiruchirappalli. He has published more than 22 papers in national/international conferences, 13 international journals and 3 national journals. His teaching and research interests are in the areas of Process control and Control systems.
E-mail address: nsk@nitt.edu