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Artificial Neural Networks and Response Surface Methodology for Predicting of Cross-Flow Heat Exchanger Fouling in Phosphoric Acid Concentration Plant

Rania Jradi [1, *], Christophe Marvillet [2], Mohamed Razak Jeday [1]

[1]*Research Laboratory " Process, Energy, Environment & Electrical Systems", National School of Engineers of Gabes (ENIG), University of Gabes(UG), Road Omar Ibn-Elkhattab, 6029 Gabes, TUNISIA*

[2] *CMGPCE Laboratory, French Institute of Refrigeration (IFFI), National Conservatory of Arts and Crafts of Paris(CNAM), HeSam University, 292Road Saint-Martin, 75003 Paris, FRANCE*

Abstract: Among the most frequently encountered issues that are occurred in industrial heat exchangers is fouling which results in reducing the performance of heat exchangers while increasing energy losses and damaging the apparatus. This study aims to investigate the comparative suitability of response surface methodology (RSM) and artificial neural networks (ANN) in predicting the thermal resistance of fouling in cross-flow heat exchanger. The employed structure for both techniques is composed by six input variables as time, acid inlet and outlet temperatures, steam temperature, acid density and acid volume flow, and output variable as thermal resistance of fouling. The results show that the model predicted values in both techniques were in close agreement with corresponding experimental values. The results of different accuracy parameters in terms of correlation coefficient, absolute average relative deviation, mean squared error and root mean squared error indicate the functionality of both modeling approaches for fouling resistance prediction. However, RSM model yield better accuracy in simulating the fouling resistance than ANN model.

Keywords: Heat exchanger, artificial neural networks, response surface methodology, fouling resistance, prediction.

1. Introduction

The serious problems frequently encountered in the industry is the fouling of heat exchangers which can be understood as the accumulation of any undesirable deposit or substances on heat exchange surfaces [1- 2]. This deposit formed on one or both sides of the heat exchange surface which has a lower thermal conductivity as compared to the metal constituting the exchange surface generates the considerable increase in overall resistance.

The main result of this phenomenon eventually is the decrease of heat exchanger's performance and also it impacts the cross-section of the fluids, which result in swiftly decreasing the pressure. Crystalline, biological, particulate or product of chemical reaction, on the heat exchanger surface are the different types of fouling [2]. This layer causes additional resistance to heat transfer. Fouling resistance is a numerical indicator for the product of this thermal resistance by the heat exchange surface. This indicator is equal to 0 if the heat exchanger is new and increase progressively over time when the solid materials deposited on the walls of the heat exchanger until this equipment is cleaned [3].

The fouling in heat exchangers poses several problems of their operation and inevitably induces significant additional costs mainly due to the increase

*** Corresponding author :** Rania Jradi
E-mail: raniajradi@yahoo.fr

in energy consumption, production losses, and cleaning and maintenance costs associated with plugging and clogging of pipes [2].

The wide-ranging consequences of fouling demands application of proficient methods to predict and control this issue.

Recently, several works has been conducted on the prediction models of thermal resistance of fouling using artificial neural networks (ANNs). An intelligent model is developed for shell and tube heat exchanger which links fouling resistance to independent operating variables of the system by means of Multilayer Perceptron (MLP) network tool [4]. Sundar et al. [5] developed an accurate and generalized deep neural network framework capable of predicting overall fouling resistance and individual flue-gas side and water-side fouling resistances of a cross-flow heat exchanger used in waste heat recovery. Despite their peculiarities and rarity, new studies on wavelet neural network procedures are presented to determine the degree of fouling [6]. More recently work, Jradi et al [1] used artificial neural networks for both shell and tube and cross-flow heat exchangers to predict the fouling resistance in order to planning suitable cleaning schedules and to control operation of the phosphoric acid concentration plant.

Statistical methods may offer an efficient way to predict the input-outputs relationships. Numerous studies explored the use of coupling techniques which combine artificial neural networks and response surface methodology to check their suitability in context of modeling of complex problems in several fields [7].

This study aims to investigate the influences of several parameters of phosphoric acid concentration plant on fouling resistance using RSM and ANN and do a comparative study between the results of two modeling approaches. In this research, ANN and RSM models were constructed using experimental data. Time, acid inlet and outlet temperatures, steam temperature, acid density and acid volume flow rate were considered as input variables and thermal resistance of fouling as output variable. The accuracy of the constructed models was evaluated and compared in terms of statistical parameters, namely correlation coefficient (r^2), mean square error (MSE), root mean square error (RMSE) and absolute average relative deviation (AARD).

2. Material and methods

2.1 Data collection

The experimental data was collected from the phosphoric acid concentration unit [1] over one year, from April 2010. The dataset was sorted by using statistical analysis method [8].

Seven operating cycles contains a total of 361 observations was selected to used in this work containing six variables.

The six variables used are presented in Table 1.

Table 1 Variables used in this work

Variable	Unit	Measurement ranges
Acid inlet temperature	°C	68-78
Acid outlet temperature	°C	77-86.8
Steam temperature	°C	116-125
Acid density	Kg/m^3	1620-1656
Acid volume flow rate	m^3/h	2102-3407
Time	h	0-122

2.2 RSM model

Response surface methodology is a mathematical and statistical techniques used for developing, improving, and optimizing issues where a response variable is influenced by multiple influencing variables. Generally, the central composite design in RSM is a fractional factorial design method used in finding the functional relationship between response variables and independent variables. The quadratic model or second order polynomial which links in this study the response variable (fouling resistance) and the six parameters of the process (time, acid inlet and outlet temperatures, steam temperature, acid density and acid volume flow rate) is given by the following equation: $Y = \beta_0 + \sum_{i=1}^{n} \beta_i X_i + \sum_{i=1}^{n} \beta_{ii} X_i^2 + \sum_{i=1}^{n} \sum_{j=2}^{n} \beta_{ij} X_i X_j ; (i \neq j)$ (1)

Where β_0 is a constant; and β_i, β_{ii}, β_{ij} are the linear coefficient, quadratic coefficient, and interactive coefficient, respectively.

2.3 ANN model

ANN is a data processing system composed by three layers: input layer, one or a few hidden layers, and output layer. Each layer composed by many elementary units called neurons. These units are highly interconnected by links, and a value is assigned to each link called weight, which allows communication between neurons. The many inputs are multiplied by the corresponding weights, summed together, added extra bias and applied to an activation function to form a single output through following equation:

$$z = f\left(\sum_{j=1}^{n} w_j x_j + d \right) \tag{2}$$

Where z is the output from the neuron, x_j is the input value, w_j is the connection weight, d is the bias value, and f is the activation function.

ANN is called Multi-Layer Perceptron (MLP) because of having an input layer, one or more intermediate layers, and an output layer. A feed forward is a part of a MLP that is trained by using the back-propagation (BP) algorithm. BP is a supervised learning technique used for training algorithms that minimize the error by adjusting the weights and the biases. It is most popular and widely used due to its precisely defined, understood learning laws, unique ability to generalize. Various activation functions are commonly used in such networks, such as the hyperbolic tangent, the linear transfer function and the Gaussian functions. In our case we will use tangent sigmoid transfer function as an activation function for the hidden and output layers and we will study the three-layer networks. The tangent sigmoid transfer function is defined by:

$$k = \frac{e^{z} - e^{-z}}{e^{z} + e^{-z}} \tag{3}$$

The input layer is composed of six variables cited previously which are: time, acid inlet and outlet temperatures, steam temperature, acid density and acid volume flow rate. The output layer corresponds to the response which is in our case the fouling resistance.

A single layer in the hidden layer is able to shape any network with acceptable accuracy [2].

2.4 Statistical parameters

The significance of the ANN and RSM models were evaluated with respect to different statistical parameters like the absolute average relative deviation (AARD%), the mean squared error (MSE), the root mean square error (RMSE) and the correlation coefficient (r^2). The representing equations (4)-(7) of these parameters are given below [2]:

$$AARD\% = \frac{100}{N} \sum_{i=1}^{N} \frac{\left| Rf_i - Rf_i^{pred} \right|}{Rf_i} \tag{4}$$

$$MSE = \frac{1}{N} \sum_{i=1}^{N} (Rf_i - Rf_i^{pred})^2 \tag{5}$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N} (Rf_i - Rf_i^{pred})^2}{N}} \tag{6}$$

$$r^2 = \frac{\sum_{i=1}^{N} (Rf_i - \langle Rf \rangle)^2 - \sum_{i=1}^{N} (Rf_i - Rf_i^{pred})^2}{\sum_{i=1}^{N} (Rf_i - \langle Rf \rangle)^2} \tag{7}$$

Where $\langle Rf \rangle$ the average value of the experimental fouling resistance, Rf^{pred} is the predicted value of fouling resistance using ANN and RSM modeling.

3. Results and discussion

3.1 RSM model

Design Expert Software was used to determine the generated mathematical model. The results of the response values obtained by inputting the independent values are the model predicted values shown in Fig.1. The Fig.1 shows the interaction between predicted and actual values. It can be observed from the graph that the points were aligned along straight diagonal indicating high correlation between predicted and actual values. This observation indicates that the CCD is well fitted into the model and hence can be applied to perform the optimization operation of the process. In addition, the statistical parameters values as shown in Table 2 for the RSM were found in agreement with Fig.1. The high (r^2) value (0.9976) near to unity and the very low values of (MSE), (RMSE) and (AARD) indicated satisfactory adjustment of the quadratic model to the actual results.

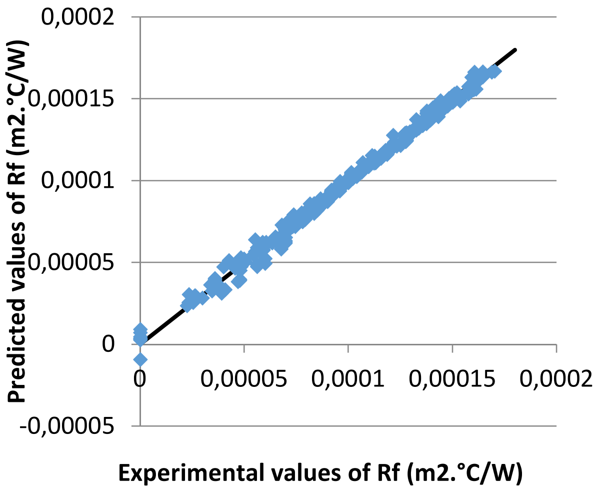

Fig.1. Performance of the RSM model for the prediction of fouling resistance

3.2 ANN model

Generally, it is of great importance to design suitable ANN architecture and algorithm to ensure the accuracy of the predicted values. Following a series of trials, the best results were observed to be obtained by applying six neurons in the hidden layer. The model with 6-6-1 is the structure of fouling resistance.

The actual data were compared to predicted data to check the adequacy of the ANN model, which is depicted in Fig.2. The predicted results were found close to the actual results indicating well-fitted data. The statistical parameters values of the ANN model are displayed in Table 2. It is seen that the values of (r^2) for fouling resistance is 0.9950. In addition, the values of MSE, RMSE and AARD are very low meaning that there is good agreement between the output parameter and their predicted values. Therefore, the prediction of the ANN model is satisfactory.

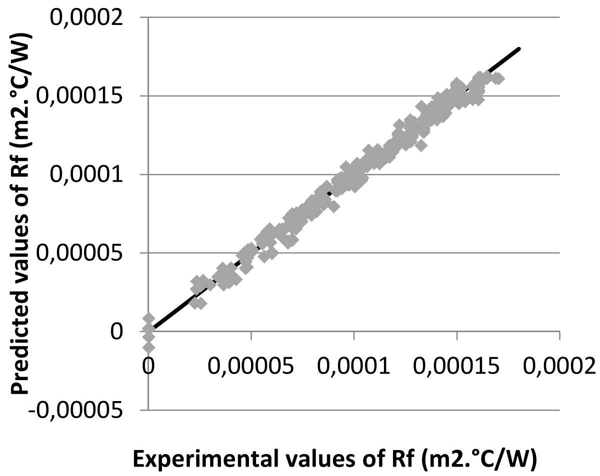

Fig. 2 Performance of the ANN model for the prediction of fouling resistance

3.3 Validation and comparison of ANN and RSM models

In this research, ANN and RSM methods were implemented for predicting the fouling resistance. To measure the accuracy of the developed ANN and RSM models, the predicted data were compared with the mean actual data, which are displayed in Fig.3. The finding shows that the model predicted values in both techniques for fouling resistance were in close agreement with corresponding experimental values.

However, RSM model is found slightly flawless in predicting the response than ANN. The performance of the developed RSM and ANN models was estimated by statistical parameters mentioned previously and depicted in Table 2. The correlation coefficient of fouling resistance in ANN and RSM has a value of 0.9950 and 0.9976, respectively. The (r^2) estimated by RSM showed more accuracy, and the values was comparatively closer to 1 than ANN approach. This implies that the model developed by RSM was more effective and better and predicted the response more precisely. The RSM yet shows clear perfection comparing to ANN since RMSE, MSE and AARD take lower values for RSM than those of ANN. These also refer that RSM model has less deviation in prediction which can be visualized in Fig.3, indicating better-fitted data with more accuracy than ANN.

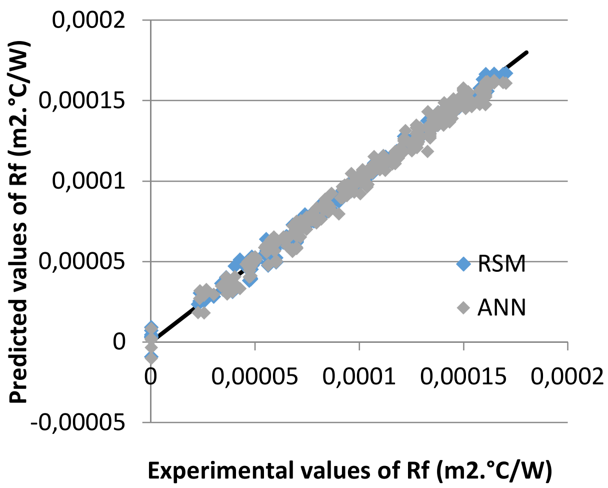

Fig. 3 Plot of predicted versus Actual

Table 2 Summary of statistical parameters values for RSM and ANN models

Parameter	RSM	ANN
AARD	0,0397	0,0480
MSE	$8{,}2525\text{x}10^{-12}$	$1{,}8114\text{x}10^{-11}$
RMSE	$2{,}8727\text{x}10^{-6}$	$4{,}2561\text{x}10^{-6}$
r^2	0,9976	0,9950

4. Conclusions

In the present study, the prediction of the fouling resistance in a cross-flow heat exchanger from the operating data of the phosphoric acid concentration loop was determined using RSM and ANN. According to the above discussion of outcomes, the following main important conclusions are listed:

- The results of ANN and RSM models, which constructed by actual data, proved that these models are potential and useful for accurate simulation of fouling resistance.
- The finding from the comparison results between both approaches showed that RSM model is better in prediction than ANN with a good and higher correlation coefficient (r^2) close to 1. This was also verified by RMSE, MSE and AARD since these parameters have lower values in RSM than those of ANN.

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