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Estimation of Cross-Flow Heat Exchanger Fouling in Phosphoric Acid Concentration Plant using Artificial Neural Networks

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: One of the most frequently encountered problems in industrial heat exchangers is fouling, which degrades the thermal and hydraulic performances of these equipment, leading thus to failure if undetected. And it occurs due to the accumulation of undesired material on the heat transfer surface. So, it is necessary to know about the heat exchanger fouling dynamics to plan mitigation strategies, ensuring a sustainable and safe operation. This paper proposes an Artificial Neural Network (ANN) approach to estimate the fouling resistance in a cross-flow heat exchanger by the collection of the operating data of the phosphoric acid concentration loop. The operating data of 361 was used to validate the proposed model. The ANN attains AARD (Absolute Average Relative Deviation) = 0.048%, MSE (Mean Squared Error) = 1.811×10^{-11}, RMSE (Root Mean Square Error) = 4.256×10^{-6} and r^2 (correlation coefficient) =99.5% of accuracy which confirms that it is credible and valuable approach for industrialists and technologists who are faced with the drawbacks of fouling in heat exchangers.

Keywords: Heat exchanger, estimation, fouling, artificial neural networks, Phosphoric acid concentration loop, fouling resistance.

1. Introduction

Among the serious problems encountered for decades in industry is fouling which reduces the performances of heat exchangers [1]. It is defined as the accumulation of any undesirable deposit on the heat exchanger surfaces [2]. It represents an added thermal resistance which reduces energy performance [3].

Reduction of energy performance represents two significant major problems associated with the fouling occur. The first major problem is the deterioration of the heat transfer equipment performance due to the much lower thermal conductivity of fouling compared to that of pipe materials while the second major problem is that the clogging of tubes which causes a change in the tube diameter substantially increases the pressure drop in the heat exchanger across the fouled fluid side [3].

The fouling in heat exchanger is an influential factor on the proper functioning of the equipment through various ways, including the functioning conditions of the fouled fluid and the heat exchanger, and tubes surface material [4- 5].

A lot of research work has been focused on developing models to predict and identify the behavior of fouling. There are limitations in terms of accuracy by using the classic fouling estimation methods due to the complexity and the non-linearity of the problem [2]. Therefore, industrialists today are oriented toward the use of neural networks due to their ability to solve complex problems. Neural network is recently used as

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

powerful tools for the conception and the control of heat exchangers [6-7] and for the estimation and the prediction [8-9] of the performances of heat exchangers such as fouling resistance [10-11].

Generally, this method is used to explain and predict one or more observable and effectively measured phenomena [12]. It aims to extrapolate new information from hidden information. Among the most learning algorithms used for the training process of ANN is back propagation.

This approach has been applied in various type of heat exchanger in the aim of predicting model of fouling resistance for planning suitable cleaning schedules.

In [10], an efficient model to estimate the fouling resistance in shell and tube heat exchanger using ANN through 295 experimental datasets was developed. The best training algorithms and the optimal numbers of hidden neurons were determined by maximizing certain statistical accuracy indices.

The application of the ANN Multi-Layer Perceptron (MLP) with input structure used to predict the fouling resistance in the shell and tube heat exchanger is comprehensively discussed in [11]. This study applied the Nonlinear Auto-Regressive with eXogenous network. The proposed integrated approach accounts for an alternative to optimize operating conditions and preventive maintenance of shell and tube heat exchanger.

Sundar et al. [13] 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. The authors provide a robust algorithmic framework for fouling prediction that can be generalized and scaled to various types of industrial heat exchangers.

In this study, the dataset used for prediction of fouling resistance in cross-flow heat exchanger was collected from the phosphoric acid concentration unit. The approach used in the present work is the ANNs of the type Multi-Layer Perceptron (MLP).

This paper is organized as follows: the description of the dataset and ANN with its architecture and learning algorithm are introduced in Section II. In Section III, results and discussions are given in order to demonstrate the effectiveness of the proposed technique. Section IV gives the conclusions.

2. Material & methods

Fig. 1.described the experiment which is consists of three phases.

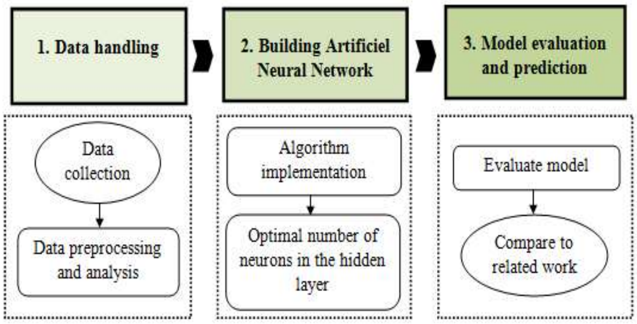

Fig. 1 Process of the project

The first phase is about data collection and preprocessing. The second phase is about building an artificial neural network which includes the choice of learning algorithm and the optimal number of neurons in hidden layer. In this work, the network is trained with back propagation method.

ANN algorithm was considered as fully connected multi-layer perceptrons (MLP). The choice of number of neurons was done using a varied of statistical accuracy indices.

For the best-performing structure of ANN which is determined, a final model is trained and evaluated using the full dataset. And this step represents the third phase.

2.1 Data handling

The operating data used in this study are experimental data collected from the phosphoric acid concentration unit [2]. It was gathered over one year, from April 2010. The dataset was sorted by using statistical analysis method [1].

Dataset selected of seven operating cycles contains a total of 361 observations and six variables.

The six variables used in this work 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 Building ANNs

Neural networks [2] have been increasingly used as a useful tool recently to solve non linear and complex problems in various engineering fields due to their designing of robust models. They are also useful for controlling dynamic and aging processes, such as fouling. The use of this new approach started a century ago and it is derived from biological models and is composed of elementary units: neurons. They are simple conventional computing elements, which are highly interconnected constitute the MLP, and they are organized according to architecture.

Generally, the MLP is composed of three layers of neurons totally connected which constitute an extension of the perception model, with one or more hidden layers between the input and the output. Each neuron in a layer is connected to all the neurons of the previous layer and the next layer. 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:

$$B(w) = \frac{e^{w} - e^{-w}}{e^{w} + e^{-w}} \quad (1)$$

The first layer is called the input layer. It 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.

The layer located between the input layer and that of the output is called hidden layer. The MLP may contain one or more hidden layers. Several authors demonstrated that a single layer containing a sufficient number of neurons with logistic sigmoid transfer functions is able to shape any network with acceptable accuracy [2].

The principle of the algorithm is to reduce the error between actual and predicted fouling resistance values. In this study, the network is trained with back propagation method.

The optimal number of neurons in the hidden layer tried to be determined by maximization some statistical accuracy indices which are: the absolute average relative deviation (AARD%), the mean squared error (MSE), the root mean square error (RMSE) and the correlation coefficient (r^2). The mathematical equations of AARD%, MSE, RMSE and r^2 are expressed by the following expressions [2]:

$$AARD\% = \frac{100}{N}\sum_{i=1}^{N}\frac{\left|Rf_i - Rf_i^{pred}\right|}{Rf_i} \quad (2)$$

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(Rf_i - Rf_i^{pred})^2 \quad (3)$$

$$RMSE = \sqrt{\frac{\sum_{i=1}^{N}(Rf_i - Rf_i^{pred})^2}{N}} \quad (4)$$

$$r^2 = \frac{\sum_{i=1}^{N}(Rf_i - \langle Rf \rangle)^2 - \sum_{i=1}^{N}(Rf_i - Rf_i^{pred})^2}{\sum_{i=1}^{N}(Rf_i - \langle Rf \rangle)^2} \qquad (5)$$

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

As shown in Fig. 2, the resulting model consists of one hidden layer with six neurons.

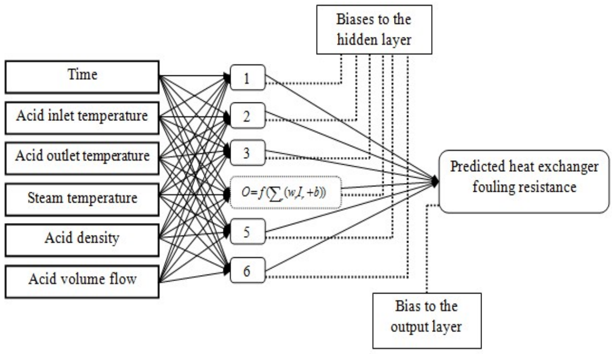

Fig. 2 Structure of the optimal ANN configuration

3. Results and discussion

The contribution of the prediction by ANN approach has been shown in this section. The ANN technology has been used for an industrial problem which is fouling in heat exchanger.

The proposed MLP approach was trained by 70% of the experimental data, called training dataset. The remaining 30% of the experimental data were used to evaluate and validate its performance by the data not seen previously by the model, namely the test and validation dataset.

Fig. 3 shows a comparison between the experimental datasets of the fouling resistance and the corresponding estimated values of the optimal MLP network for the training, the tests, and the validation.

From this figure and Table 2, which present the global AARD%, the MSE, the RMSE and the r^2 of the obtained model, we can conclude that the accuracy rate of ANN method is quite high. So, the proposed technique can provide a high rate than other methods. This method has proven to be effective in prediction the fouling resistance with a high rate of precision.

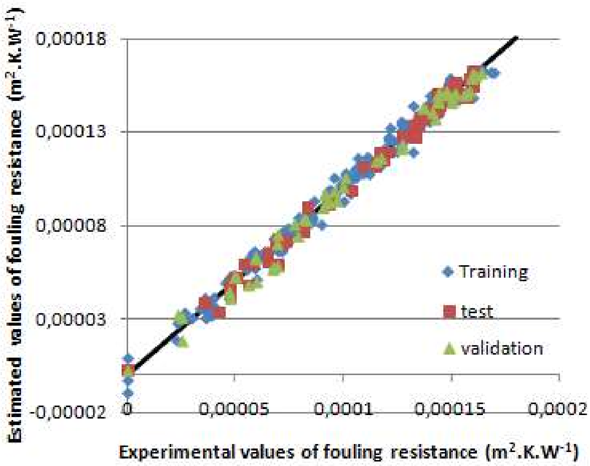

Fig. 3 Performance of the proposed model for the prediction of fouling resistance

Table 2 Accuracy of the obtained model

Symbols	Values
AARD	0.048%
MSE	1.811×10^{-11}
RMSE	4.256×10^{-6}
r^2	0.995

4. Conclusions

In the present study, a non-traditional approach based on the ANN technology has been developed in order to predict the fouling resistance in a cross-flow heat exchanger from the operating data of the phosphoric acid concentration loop. The values of accuracy rate which have been achieved with the proposed method are respectively: AARD = 0.048%, MSE = 1.811×10^{-11}, RMSE = 4.256×10^{-6} and r^2= 99.5%.

The obtained results have shown that the effectiveness of the presented approach is able to predict fouling resistance more accurately than classic fouling estimation methods which have shown limitations in terms of accuracy in front of the complexity and the non linearity of the problem. Experimental results show that the MLP has good predictive effect and high accuracy.

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