CHEMICAL ENGINEERING TRANSACTIONS

VOL. 70, 2018

A publication of AIDIC
The Italian Association of Chemical Engineering
Online at www.aidic.it/cet

Guest Editors: Timothy G. Walmsley, Petar S. Varbanov, Rongxin Su, Jiří J. Klemeš

ISBN 978-88-95608-67-9; **ISSN** 2283-9216

DOI: 10.3303/CET1870060

Diagnosis of the Fouling Effects in a Shell and Tube Heat Exchanger using Artificial Neural Network

Przemyslaw Trzcinski*, Mariusz Markowski

Institute of Mechanical Engineering, Faculty of Civil Engineering, Mechanics and Petrochemistry, Warsaw University of Technology, Lukasiewicza 17, 09-400 Plock, Poland
Przemyslaw.Trzcinski@pw.edu.pl

In this paper, there presents an identification method of the fouling influence on the heat recovery in a heat exchanger. To evaluate the heat losses due to fouling there is proposed the method based on neural network approach. Because the correctness of anticipation of the heat exchanger behaviour depends on measurement data, it is very important to prepare an appropriate data. Unfortunately, the measured data contains errors caused by inaccurate instruments, disturbances in data transmission, transient state of the operated heat exchanger. To overcome this problem the authors proposed a new approach of filtering the row data using objective function based on standard deviation of measured parameters (temperature, flow rate, etc.) in the heat exchanger. Minimising the objective function, it makes it possible to eliminate gross errors and properly select the time intervals of steady state operation of the heat exchanger. The method was validated using measurement data for the heat exchanger belonging to heat exchanger network connected with a crude distillation unit processing 800 t/h of crude oil. Using artificial neural network the time dependencies between heat losses versus time were obtained.

1. Introduction

In process plants deposit building up on heat transfer surfaces of the heat exchanger network lead to economic losses. The effects of these losses are decreased heat recovery and unplanned plant stoppages for cleaning the heat exchanger network.
The detrimental effect of fouling can be reduced by oversizing the heat transfer surface of the exchanger. This method iscommonly used in industry. In the mathematical formulae the thermal resistance of fouling is included into heat transfer surface calculation as follows:

$$A = \int \frac{dQ}{U_f \Delta T} \tag{1}$$

where:

$$\frac{1}{U_f} = \frac{1}{U_c} + R_f \tag{2}$$

The determination of correct values of the fouling resistance R_f is practically impossible because the existing analytical models (Eqs. (1-2)), give poor results. Namely, it is known that the error of estimated heat transfer coefficients can reach 40% (Ullmann's Encyclopedia, 1988). A similar situation takes place with accurate prediction of the fouling resistance of deposits. Here, there are sophisticated models of fouling growth applied. Crittenden et al. (1987) applied a transport-reaction model taking into account reaction and transport of fouling precursor to and from the heated surface. Polley et al. (2002) modified the Ebert and Panchal model as more rigorous than reaction alone models. Ishiyama et al. (2011) described fouling as a combination of deposition and ageing. Pogiatzis et al. (2012) proposed a two-layer model of fouling.
Markowski et al. (2013) elaborated an accurate mathematical model of the heat exchanger under fouling, based on industrial measurements. These measurements are used for upgrading the correlations describing the heat transfer coefficients by adjusting the values of constant, that is, power exponents for Reynolds and Prandtl number, etc. Unfortunately, to obtain correct results, the model require the full set of measurements of process

Please cite this article as: Trzcinski P., Markowski M., 2018, Diagnosis of the fouling effects in a shell and tube heat exchanger using artificial neural network , Chemical Engineering Transactions, 70, 355-360 DOI:10.3303/CET1870060

parameters (flowrate and temperature at the inlet/outlet on tube and shell side of exchanger). Meanwhile in industrial application the measurement devices on process streams are incomplete. Therefore, in that case, the authors propose to give up an estimation of heat transfer coefficients and fouling resistance and instead of it, directly estimate heat recovery losses due to fouling. For this purpose they propose to use an artificial neural network model (ANN) of the heat exchanger. This model is more flexible comparing with analytical one, giving satisfactory results for the case when it is lack of one measurement device (flow rate or temperature).

2. Processing of the measurements

In order to diagnose the influence of fouling resistance on the behavior of heat exchanger, the ANN model requires the following process data, obtained from measurements: inlet and outlet temperature on shell side (T_{si} and T_{so}), inlet and outlet temperature on tube side (T_{ti} and T_{to}), mass flow on tube side (m_{ti}) and shell side (m_{si}) (Figure 1).

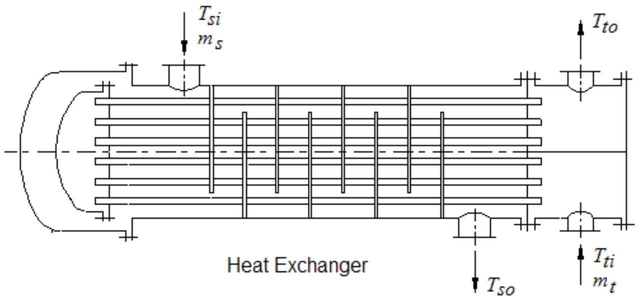

Figure 1: Measured set of process parameters for the heat exchanger

Because the measurements are inaccurate they should be processed to eliminate the gross errors. Assuming that in the steady-state of the heat exchanger operation, the measurements are symmetric about mean value x_m, the gross errors for any set of measurements $\{x_i\}$, can be eliminated using the following criterion:

$$x_i \in (x_m - 3\cdot\sigma,\ x_m + 3\cdot\sigma) \tag{3}$$

where: x_i – i-th measurement, x_m – mean value for the set of measurements, σ – standard deviation.
To select the time span of the steady-state operation of heat exchanger, the authors propose the objective function expressed by the standard deviation σ:

$$OF = \sqrt{\frac{\sum_{i=1}^{N}(x_i - x_m)^2}{N-1}} \tag{4}$$

The minimum of the objective function determines the set of measurements $\{x_i\}$, belonging to the selected time span, for the steady-state operation of heat exchanger.
To verify that the selected measurements $\{x_i\}$, are symmetric about mean value x_m (criterion of steady-state operation of the heat exchanger), the skewness criterion is used:

$$sk = 3\frac{x_m - x_{med}}{\sigma} \tag{5}$$

where: x_{med} – median value for the set of measurements.
It is commonly known that for $sk = 0$ the measurements are symmetric about mean value x_m. The authors assumed that for $-0.1 \le sk \le 0.1$ the measurements are still symmetric because in the industry the ideal symmetry does not exist.

3. Artificial neural network model of the heat exchanger

An artificial neural network is very good approximator for non-linear functions. ANN composed of one hidden layer (Figure 2) makes it possible to approximate arbitrary continuous function (Masters, 1993), while ANN with two hidden layers (or one hidden layer with feedback) makes it possible to approximate functions with a counted number of discontinuities (Hornik et al., 1989).
From the point of view of signals theory, a heat exchanger behaves as a filter, which transforms input signals X and disturbances U into output signals Y. This transformation is non-linear and it can be expressed by the following symbolic relationship:

$$f:(X,U)\to Y \tag{6}$$

This paper presents such non-linear relation between data taken from the industrial heat exchanger.

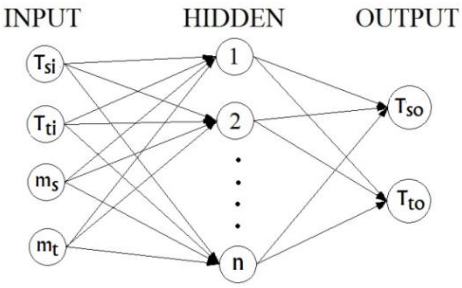

Figure 2: An artificial neural network with one hidden layer; the abbreviations are shown in Figure 1

Because the deposit builds up on the heat transfer surface, the dynamic properties change with time. Therefore in the model, the operating time of the heat exchanger is divided for several continuous periods assuming that for any selected period of time the dynamic properties of object are unchanged. For these assumptions there is adopted a discrete ANN model of the heat exchanger.

For this approach the averaged data (temperature at the inlet/outlet and flowrate on shell and tube side of exchanger) over the selected time span are introduced to ANN. The ANN learning and validation is conducted at the beginning of operating periods (clean heat exchanger). The loss of heating duty due to fouling are determined by comparing duty for the fouled heat exchanger with duty for the clean heat exchanger.

4. Estimation of heat loss due to fouling – the case of heat exchanger for Crude Distillation Unit

The simulation of ANN was carried out on the base of measurements for a selected heat exchanger from Crude Distillation Unit processing 800 t crude oil per hour. The exemplary runs of the raw data are presented in Figures 3 and 4.

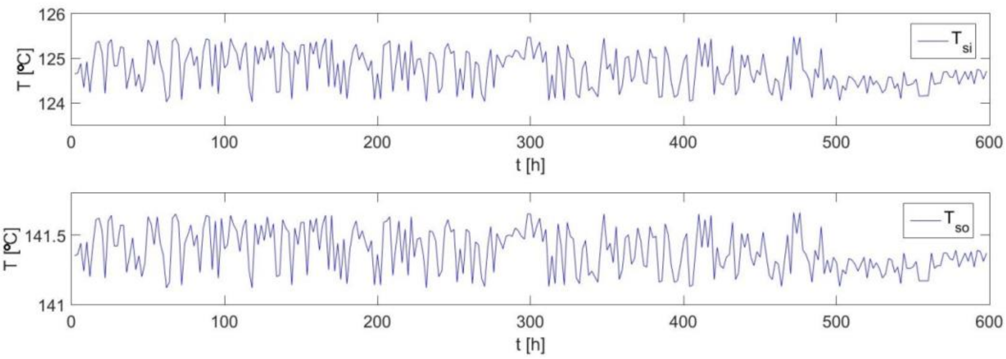

Figure 3: Inlet and outlet temperature vs time graph on shell side

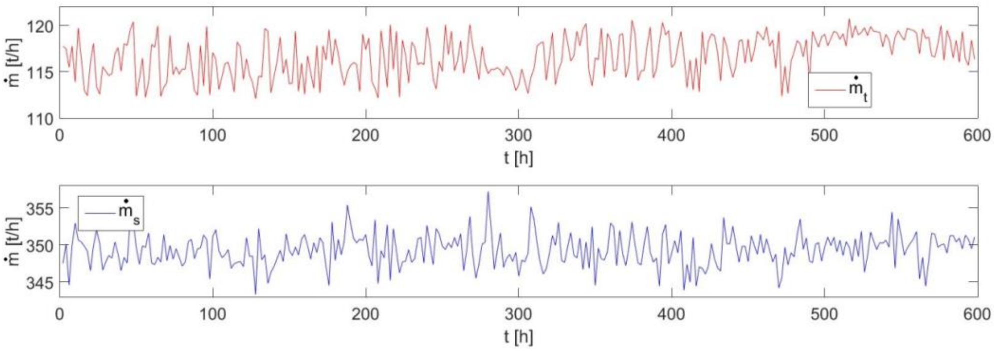

Figure 4: Mass flow vs time graph for tube side and shell side

For the selected time span (2 hours), using Eqs. (3-4), the raw data from Figures 3-4 was pre-processed (elimination of gross errors, data selection with symmetric distribution about mean value).
After that, the coefficient of skewness was calculated and the pre-processed data was filtered for the constraint: $-0.1 < sk < 0.1$, to assure the symmetry of measurements about mean value. Obtained in this way mean values are shown in Figures 5-6. Every point represents mean value of parameters averaged over selected time span for which the heat exchanger is in steady-state.

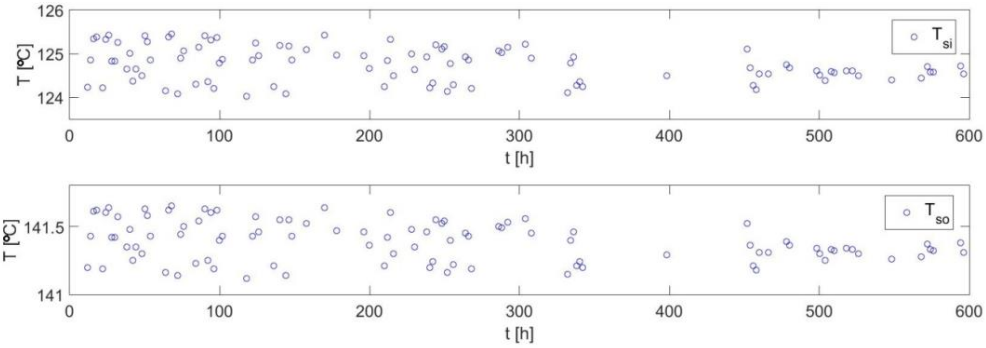

Figure 5: Transformation of the inlet and outlet temperature from Figure 3

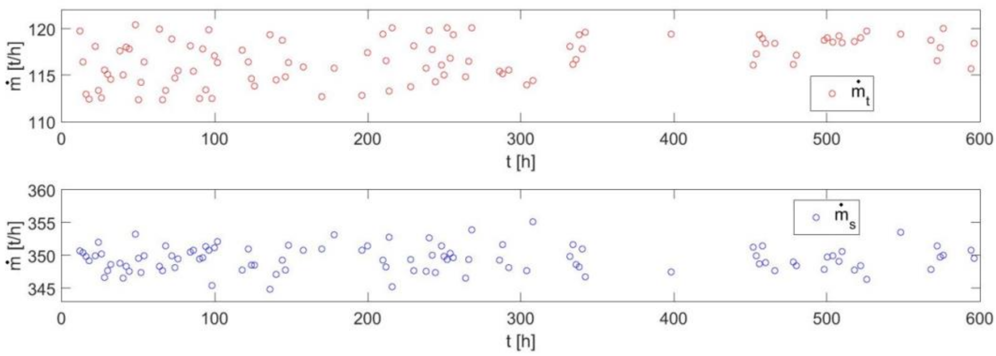

Figure 6: Transformation of mass flow from Figure 4

The model of ANN is shown in Figure 7. The ANN is composed of one hidden layer to approximate continuous function. The number of neurons was selected on the stage of learning and validation of the ANN.

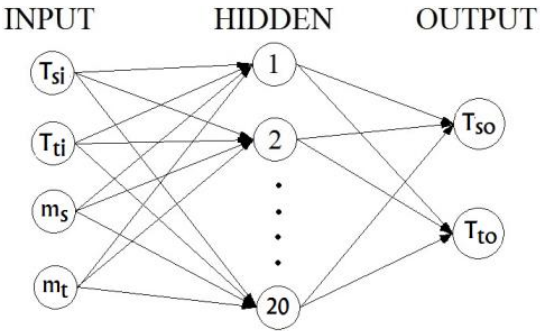

Figure 7: The architecture of ANN

The input signals to ANN, i.e. mean values of process parameters, were selected at the beginning period of 3 months (assuming clean heat exchanger). The selected data was used for learning and validation of ANN. The ANN learning was conducted with the supervisor by comparing the outlet signals from ANN with the outlet signals from the existing heat exchanger.
The trained ANN was used to predict the influence of fouling on heat loss (Figure 8). The input signals to ANN, were selected at the remaining period of 3-22 months. The heat recovery loss was determined by comparing

the temperature difference on outlet from the heat exchanger with outlet from ANN. These temperature differences enabled a determination of the heat recovery loss.
Heat duty in the heat exchanger versus time is presented in Figure 9. Almost linear decrease of heat exchanged versus time is mainly caused by decreasing mass flow of the process streams versus time. For this situation (Figure 9) fouling mechanisms plays less role on the heat decrease.

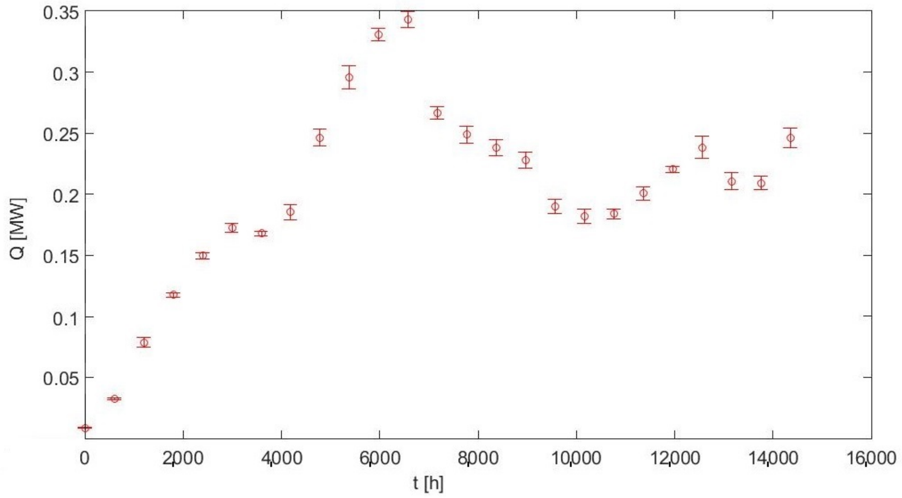

Figure 8: Heat recovery loss vs time graph

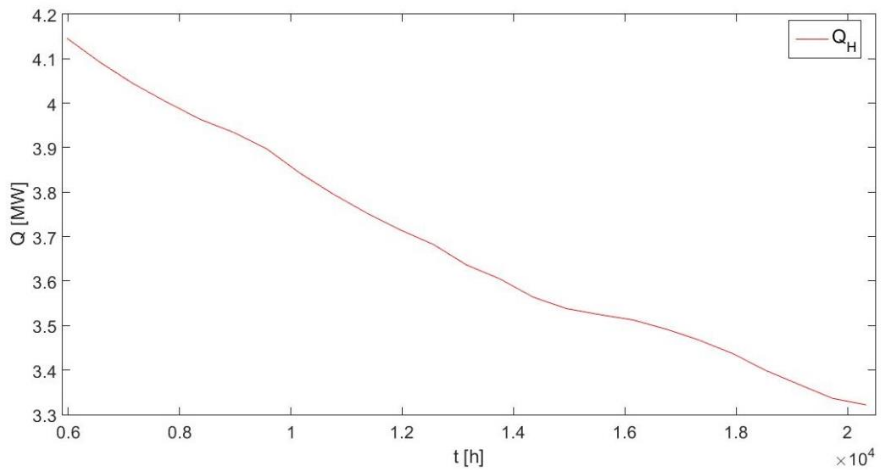

Figure 9: Heat duty vs time graph

The input signal m_s was measured with an error of 10%. Therefore there was carried out sensitivity analysis depending on elimination of signal m_s (Figure10).

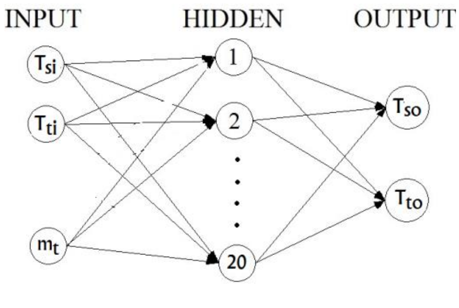

Figure 10: The architecture of ANN after elimination of the signal m_s

For this case the heat recovery loss is presented in Figure 11.

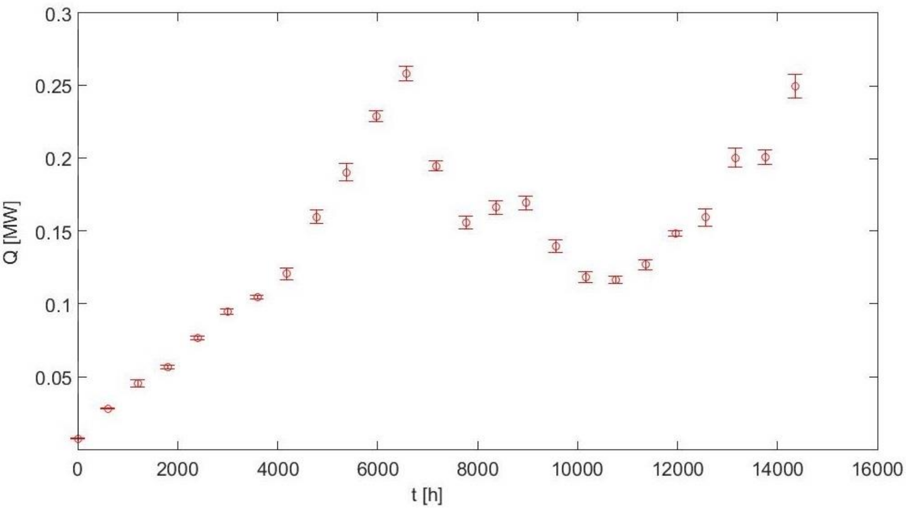

Figure 11: Heat recovery loss vs time graph after elimination of the signal m_s

5. Conclusions

Comparing graph in Figure 8 with the graph in Figure 11, there are acceptable discrepancies between these curves from the point of view industrial applications. It does mean that the ANN model is robust for the case when the set of measurements is incomplete. Meanwhile, the analytical models give correct results after upgrading the correlations describing the heat transfer coefficients by adjusting the values of constant, i.e., power exponents for Reynolds and Prandtl number, etc. But it requires the full set of measurements (Markowski et al., 2013). Therefore, it seems that the ANN model is superior comparing with analytical one for the case when the set of measurements is incomplete.

Symbols

A – area of the heat transfer surface [m^2]
m_t, m_s − mass flow on the tube side and shell side, respectively [kg/s]
Q – heat flow in the heat exchanger [W]
R_f – thermal fouling resistance of deposits [m^2·K/W]
T_{si}, T_{so} - temperature at the inlet and outlet on shell side [°C]
T_{ti}, T_{to} - temperature at the inlet and outlet on tube side [°C]
U_c – overall heat transfer coefficient in the exchanger without fouling [W/(m^2·K)]
U_f – overall heat transfer coefficient in the exchanger with fouling [W/(m^2·K)]
ΔT – temperature difference [K]

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