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Detection of fouling in a cross-flow heat exchanger using a neural network based technique

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ABSTRACT

This paper presents a method for the detection of fouling in a cross-flow heat exchanger. A numerical model is used to generate data when the heat exchanger is clean and corresponding data when fouling occurs. In a first step, the model is used to generate a long time series by simulating a clean heat exchanger. This allows the determination of a neural network model of the heat exchanger. Then, hundred sets of data are generated by simulating a fouled heat exchanger and it is checked that the simple Cusum test can be used to detect fouling without any false alarm, whatever the reference time series is.

1. Introduction

The range of industrial fields concerned by fouling is quite broad. It goes from food industry (e.g. [1]), water treatment and use (e.g. [2]), to oil refineries (e.g. [3]) just to name a few. The studies can be divided in three complementary domains: the principles of fouling (chemistry and flow conditions, e.g. [4]), the mitigation of fouling (design phase, water treatment, surface treatment, ..., e.g. [5]), and monitoring fouling (model based techniques, sensors, ..., e.g. [6]). The present study belongs to the model based techniques. As neural networks are now popular in thermal engineering (e.g. [7,8]), they are used here to model a cross-flow heat exchanger. Then a statistical test is used to detect fouling before the sizing fouling factor is reached.

The first part of the paper is dedicated to the description of a mathematical model used to generate data. The model is based on the finite volume method and can accurately simulate transient behaviour in cross-flow heat exchangers, which is important with regard to varying inflow conditions and internal conditions, see [9,10]. By using this model it is possible to compare the outlet temperatures of a clean heat exchanger and a heat exchanger where fouling progressively occurs. The second part of the paper presents the identification process using neural networks. The last section deals with the detection of fouling using a statistical test on estimated values obtained by the neural network.

2. Description of the model used to generate data

The fact that steady state conditions are seldom encountered in practice leads to the use of an accurate dynamic model of a heat exchanger, applicable for general cross-flow conditions. The model is based on a mathematical representation of the flow, where temperature is defined as a position dependent field for both the cold and hot fluid in the exchanger. General conditions in the heat exchanger can therefore be defined as two planar functions, $T_c(x, y)$ for the cold side and $T_h(x, y)$ for the hot side. Fig. 1 shows a graphical layout of the model with the relevant dimensions, in the $x-y$ plane.

In conjunction with Fig. 1, consider a plate heat exchanger with cross-flow along x and y directions. The width of the exchanger in the x direction is W and the height is H. Furthermore, the thickness of the hot and cold passages are d_h and d_c, respectively. It is assumed that the cold stream travels only in the x direction and the hot stream in the y direction, so no internal mixing takes place inside the exchanger. It is also assumed that there is no diffusion (or thermal conduction) along the fluid streams and thus only pure convection is considered.

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Nomenclature

Cus	Cusum (cumulative sum)
c	specific heat
d	water passage thickness
$E[v]$	expectation of variable v
g	coefficient in the cumulative sum test
H	heat exchanger height
h	coefficient in the cumulative sum test
k	sample number
$\dot{m}$	mass flow rate
R_f	fouling factor
T	temperature
t	time
U	overall heat transfer coefficient
W	heat exchanger width
v	dummy variable
x	position in direction of heat exchanger width
y	position in direction of heat exchanger height

Greek symbols

ρ	fluid density
σ	standard deviation

Subscripts

c	cold
clean	when there is no fouling
fouling	when fouling occurs
h	hot
o	at the outlet of the heat exchanger
ref	for the reference time series

The energy balance for this system is described by two coupled partial differential equations (PDE) where the field variables are the temperatures T_c and T_h for the cold and hot side, respectively. The equations are

$$\rho_c c_c d_c \frac{\partial T_c}{\partial t} + \frac{\dot{m}_c c_c}{H} \frac{\partial T_c}{\partial x} = U(T_h - T_c)$$

$$\rho_h c_h d_h \frac{\partial T_h}{\partial t} + \frac{\dot{m}_h c_h}{W} \frac{\partial T_h}{\partial y} = U(T_c - T_h)$$

In this formulation ρ and c could be dependent on the fluid temperature and U can also be dependent on both temperatures of the flow as well as on position in the x–y plane. Also, the cold stream mass flow can depend on y and the hot stream can depend on x, which represents a partially clogged heat exchanger with flow restrictions. It is also assumed that parameters such as heat transfer coefficient U, inflow temperatures and mass flow can be time dependent. Note that the overall heat transfer coefficient incorporates convection on both cold and hot sides, as well as conduction through the walls.

In order to solve the PDEs describing the thermal conditions, a numerical scheme must be used. The chosen scheme is a two dimensional finite volume model with two coupled fields, representing the flow in the cold and hot parts of the exchanger. As mentioned before, it is assumed that no mixing takes place, but at the outlet of both fluids, they are of course mixed and an average temperature is calculated there.

The current mathematical problem only includes convection with a source term, but pure convection problems are notorious for their instability in terms of nonphysical overshoots in the solution as well as pure accuracy if low order discretization is used. A well known numerical scheme for convection is the QUICK scheme, see [11], which was used in this case. It is very accurate, but small overshoots can be experienced in solution, especially if the chosen time step is not sufficiently small or if temperature changes are very rapid.

3. Validation of the model

Before using the model to generate transient data, it is necessary to know if steady states are accurately determined. Fig. 2 shows the comparison of the effectiveness obtained by the model and the effectiveness computed using an analytical equation (see e.g. [12]). Here, the model uses 20 finite volume cells in each direction, resulting in a total of 800 cells.

The average relative difference between the two values over the whole dataset is less than 1.1%. So, it can be concluded that steady states are correctly modelled.

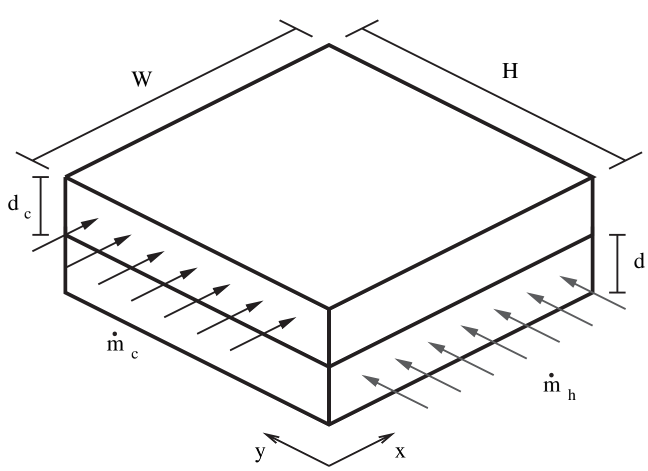

Fig. 1. Graphical representation of the mathematical model describing temperature fields in a cross-flow heat exchanger.

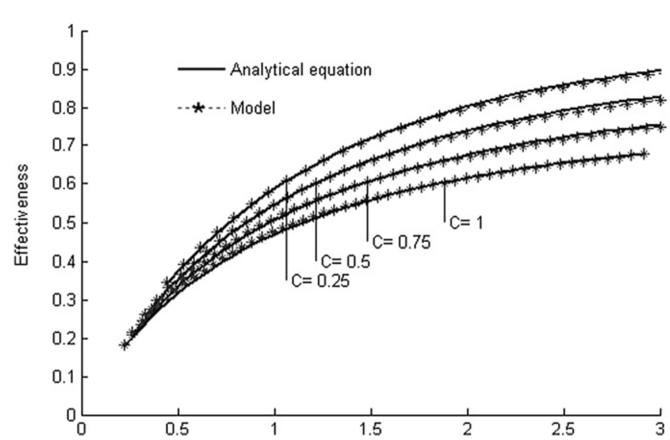

Fig. 2. Comparison of the analytical effectiveness and the effectiveness computed by the model.

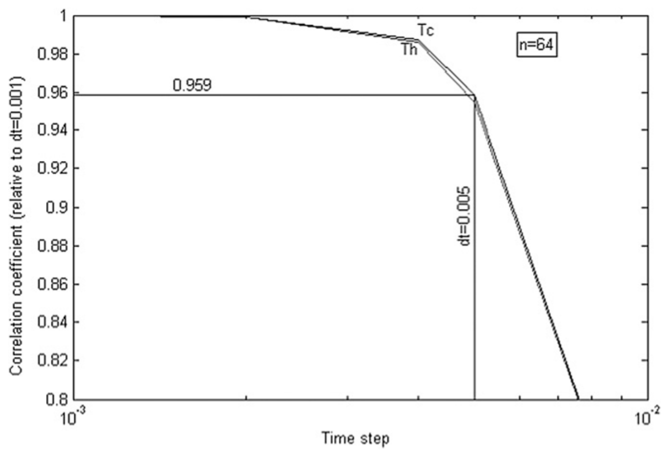

Fig. 3. Determination of the upper value of the time step for the model.

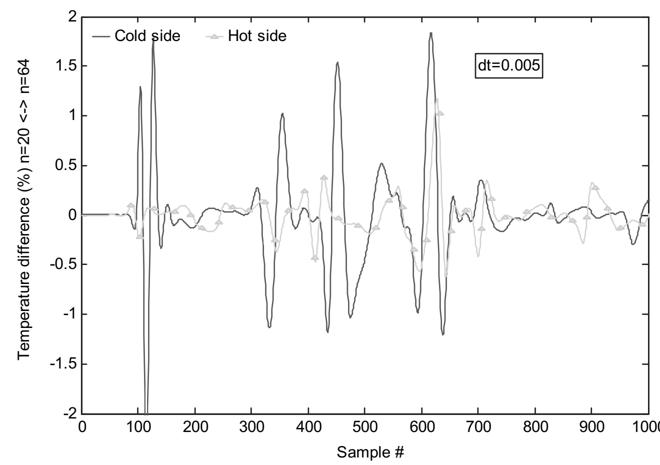

Fig. 5. Temperature difference between the temperatures obtained using the selected number of cells and the temperatures obtained using a reference number of cells.

Concerning transient states, the two main parameters having an influence on the accuracy are the number of cells and the time step. Plotting the outlet temperatures for various values of the time step does not lead to a clear view. So, it has been decided to plot (Fig. 3) the evolution of correlation coefficient between outlet temperatures obtained for one particular time step and the outlet values obtained for the smallest time step taken into account (0.001 s), and for the maximum number of cells taken into account (64 in each direction for each fluid, 8192 in total).

From these results, it has been decided to take a time step of 0.005 s for the rest of the study. The influence of the number of cells is presented in a similar way. Fig. 4 shows the correlation coefficients for the selected time step.

From these results it has been decided to use 20 cells in each direction for the rest of the study. Fig. 5 shows the temperature difference between outlet temperatures obtained using 20 cells and 64 cells for the selected time step.

4. The neural network model of the heat exchanger

The identification process applied to thermal problems using neural networks has been described in previous papers (see e.g. [13–15]) and will not be detailed here (see e.g. [16–18] for general information on neural networks for identification and modelling). It could have been possible to model both sides of the heat exchanger, as done in [8], but it has been decided to try to detect fouling using just one side (the cold side). Hence, only one time series will be studied. Although the time step for the generation of the data is 0.005 s, it has been chosen to take one sample out of ten for the identification. So, the whole database is composed of a long clean period (10 000 samples). Learning is carried out during the first 8000 samples. After the usual procedure, the final architecture is obtained and is as follows:

- the hidden layer is composed of 5 neurons; 4 are nonlinear; 1 is linear
- the output layer is composed of a linear neuron.

In comparison, the corresponding numbers for a simple tube-in-tube heat exchanger are 2 nonlinear and 1 linear hidden neurons, the output neuron being linear, see [8].

The inputs are:

- 4 past values of the estimated outlet temperature of the cold fluid
- 4 past values of the inlet temperature of the cold fluid
- 4 past values of the inlet temperature of the hot fluid
- 4 past values of the mass flow rate of the cold fluid
- 4 past values of the mass flow rate of the hot fluid.

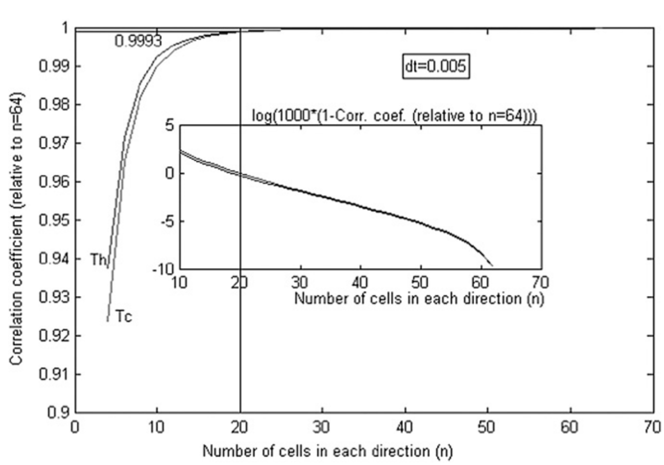

Fig. 4. Influence of the number of cells in each direction on the accuracy of the model.

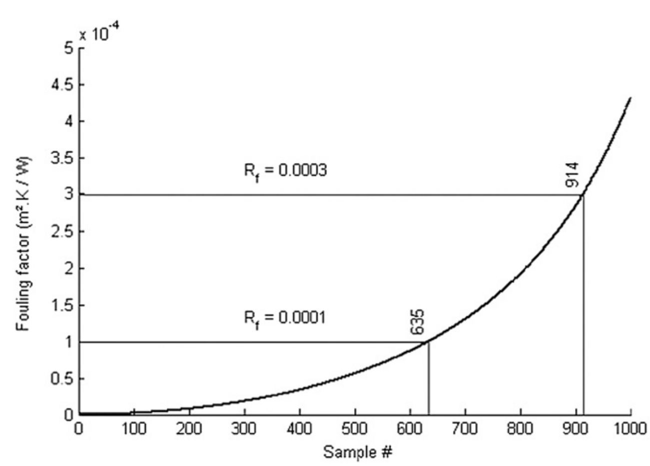

Fig. 6. Evolution of the fouling factor versus the sample number.

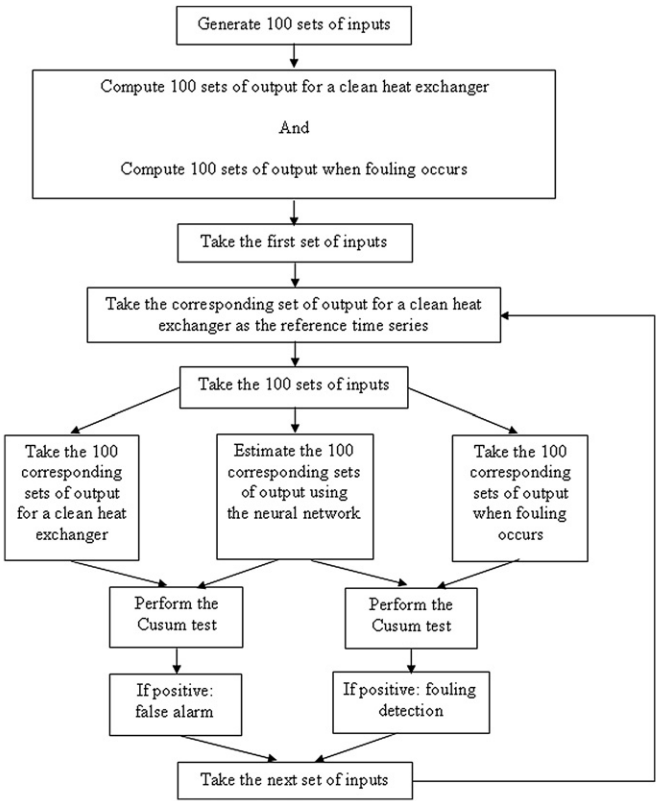

Fig. 7. Procedure to evaluate the detection technique.

5. Fouling detection

To simulate fouling, the overall convection heat transfer coefficient has been progressively decreased; the resulting fouling factor is shown in Fig. 6. The upper value of the fouling factor is then about 4.4×10^{-4} m^2 K/W. This falls within usual values taken into account for water, see e.g. [19,20]. The aim of the technique is to detect fouling before a limit value is reached. This value, the sizing value, is fixed to 3×10^{-4} m^2 K/W.

To test the efficiency of the detection technique, the following procedure has been used (Fig. 7). The great number of datasets and cross-tests will give results that are very strong statistically, which is necessary in order to make sure that the method is not prone to false alarms.

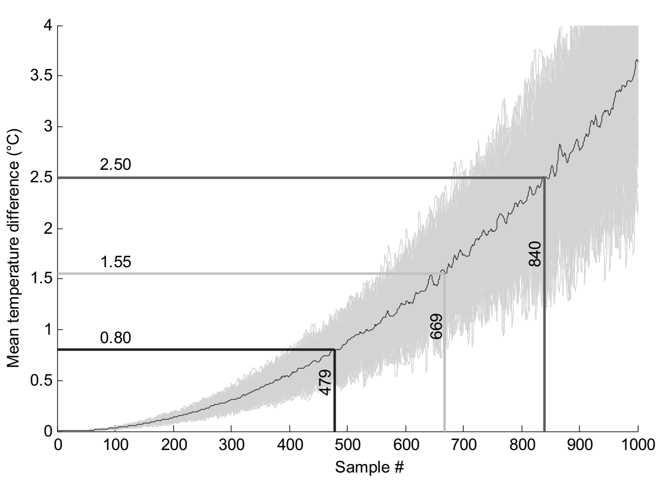

Fig. 8. Effect of fouling on the mean temperature difference.

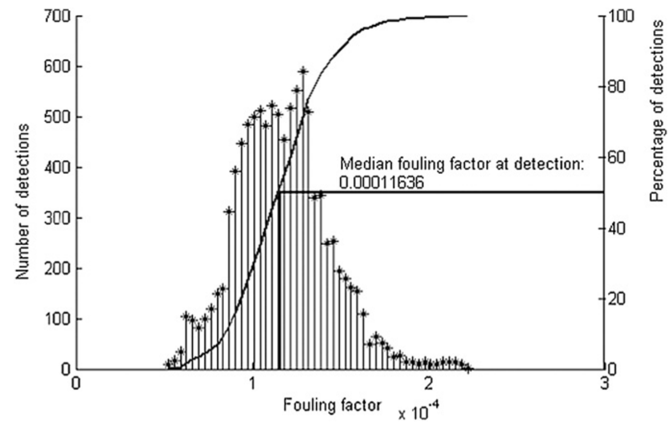

Fig. 9. Visualization of the distribution of the fouling factor at detection.

The Cusum test is a comparison between the moving average value of a time series and the average value of a reference time series. It is well documented in [21]. Due to the fact that fouling leads to the decrease of the estimated parameters, a one-sided test is sufficient (the second side – min operator– of the test would be necessary to detect an increase of the estimated parameters). This test is carried out in two steps:

1) compute the cumulative sum: $Cus(k) = \max(0,\ E[v_{\text{ref}}] - E[v] - g\ \sigma\ + Cus(k-1))$
2) check if $Cus(k) > h\ \sigma$; if so, then the drift is detected.

If g and/or h are too low, false alarms are encountered. If they are too high, the drift is not detected. It has been found that $g = 0.25$ and $h = 5$ are a good compromise. It leads to no false alarm and quite efficient fouling detection as shown hereafter.

To estimate if a simple temperature measurement could have been sufficient, the following average temperature difference has been computed over the hundred experiments:

$$E\Big[(T_{h,\text{o}} - T_{c,\text{o}})_{\text{fouling}} - (T_{h,\text{o}} - T_{c,\text{o}})_{\text{clean}}\Big]$$

Fig. 8 shows what would be this temperature difference at the minimum, average, and maximum detection sample number.

The light grey zone represents the temperature difference for the 100 experiments. It can be concluded that a simple test on the temperature difference would not have been as sensitive as the technique presented here.

To see if the goal of the technique is achieved, it is necessary to show that all detections occur before the upper limit of the fouling factor is reached. This is done in Fig. 9.

It can be concluded that the technique is quite sensitive, and that it could easily be implemented online as the computational time is quite low.

6. Conclusion

It has been shown that a neural network model of a cross-flow heat exchanger can be used to develop a fouling detection technique. It has been shown that the number of nonlinear neurons of the hidden layer of the neural network has to be increased compared to a simple tube-in-tube counter-flow heat exchanger.

It has also been shown that, once the neural network is well trained, there is no false alarm, and that fouling is detected quite early when it occurs. This has been carried out on a quite large database (100 experiments). Hence, although it is necessary to train the neural network offline, this technique could be implemented online in supervision systems so that the maintenance can be predictive instead of systematic, leading to a lower exploitation cost.

Future works will address fouling detection in actual heat exchangers. For that, a test rig is under construction in the LME, and measurements will be recorded in geothermal Icelandic power plants. Also, for small timescales the effect of the separating metal in the heat exchanger will affect the temperatures and therefore the simulation model will be revised to include the dynamic effects of the metal.

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