Analysis of different fouling predictive models in a Heat Exchanger from experimental data

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Abstract:

We present a methodology that incorporates the implementation and validation of experimental data analysis for the creation of a predictive tool of heat exchanger fouling effects. The goal is to determine a realistic fouling kinetics in order to develop an adapted maintenance practice for minimizing energetic and intervention costs. The test bench implemented is equipped with plate and gaskets heat exchanger provided with industrial plates sizes. Particles are injected into the cold fluid to simulate a fouling. A metrology device is used on heat exchanger in order to control thermal and hydraulic performance through usual parameters. Several realistic conditions are tested during a learning phase to establish predictive models based on these experimental data. Results are analyzed using: (i) the asymptotic fouling models of Kern and Seaton [1] (ii) several predictive models from a statistical approach by different methods (multiple linear regression, artificial neural network). For each of them, conclusions are made about the accuracy of the modes and their application limits.

Keywords:
Fouling,heat exchanger, data analysis, predictive method, experimental data, multiple linear regression, artificial neural network.

1. Introduction

Fouling in heat exchangers is since many years a real question that many contributions, from the scientific and industrial community, have allowed to understand the key mechanisms. The First works on the subject have begun in the late 50s with Kern and Seaton [1] by the establishment of a model that describe the growth of a particulate deposit to evaluate the fouling thermal resistance: They checks the asymptotic behaviour of the formation of a particle deposit on a surface. More or less at the same time, the fouling resistances of the TEMA [2] have been published on the basis of experience feedbacks (empirical) of fouling for a wide range of applications and heat exchangers.

These two approaches (theoretical and empirical) have formed the basis for most models of fouling in heat transfer for heat exchanger design.

Since, many studies have been conducted without allowing a significant advance forward in resolving this problem. In this framework, many works were carried out ([3], [4], [5], [6], [7], [8], [9], [10]) on the fouling problem in tubular or plate heat exchangers with various fluids. The research topics conducted were focused on the phenomenology description of fouling processes (under perfectly

controlled conditions in experimental laboratory benches) and also on the development of a specific metrology for detecting fouling.

Despite all these efforts, fouling in heat exchangers is always a problem and has a major impact on the energy efficiency of thermal installations and causes significant extra costs both on the investment in the design of the devices but especially during the operation thereof: these additional costs are mainly due to increased energy consumption, loss of production and maintenance costs [11]. According to different studies rather conservative, this additional cost may be estimated at 0.25% of the GNP of developed countries: estimate in 2000 to over 50 billion $ per year [11]. Also, note that these same studies also show that this surplus is responsible for about 2.5% of total anthropogenic carbon dioxide emissions [12].

The lack of numerical tools, protocol and methodology to predict the fouling kinetics and then to act effectively on the fouling effects of heat exchanger is the origin of this study. Through the realization of a test bench and using different detection techniques, we present a methodology that incorporates the implementation and validation of experimental data analysis methods. This methodology allows us to develop and validate a predictive tool of the fouling effects from to the knowledge of a reduced number of operating data. This tool should allow to determine a realistic fouling kinetics and to develop a tailored maintenance practice for minimizing energetic and intervention costs.

2. Test bench presentation

2.1. Thermal loop and his components

The test bench (Fig.1), with a thermal power of 5 kW, is composed of two circuits: a hot circuit and a cold circuit. They are interconnected by the heat exchanger subject to the test series. This exchanger is on a typical industrial range of a plates and gaskets heat exchanger (S_{exch} = 0.18m² / plate) with corrugations at an angle of 60°. The flow configuration is at counter-current with upward circulation of the cold fluid which represents the fouling fluid. The number of plates is 3 and corresponding to one channel per fluid. A storage tank (type DHW) with a volume of 100 liters coupled with an electrical resistance allows the production of hot water. A refrigerating group by compressing a refrigerant (R-407C) allows the cold production with the evaporator. This evaporator, helical coil type, is inserted into an 80 liters tank.

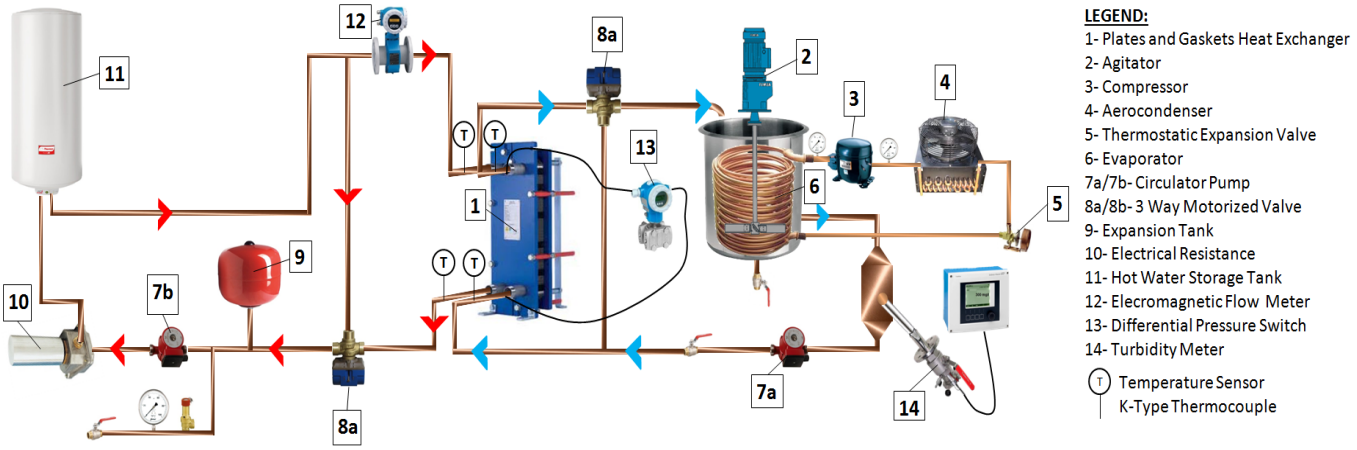

Fig.1.Schematic diagram of the facility

2.2. Fouling fluid

Anatase Titanium dioxide (TiO_2) particles are injected into the cold fluid (city water) to simulate a fouling fluid. An agitator is present in the cold fluid storage tank and permits to obtain a homogeneous suspension of the particles. These particles have an average diameter of 5 µm and have a low dispersion (Fig. 2) even after passing through the operating organs (agitator, pump) which can induce shear stress (Fig. 3).

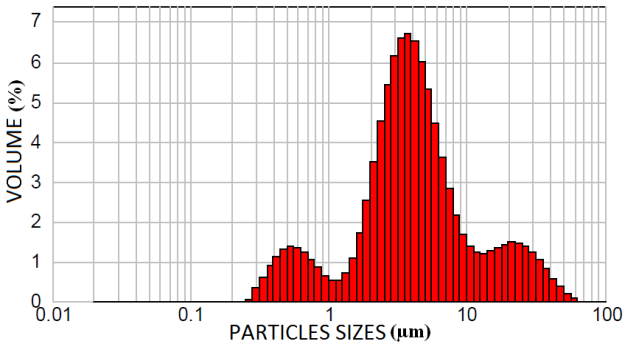

Fig.2.Size distribution of TiO2 powder – Measured on powderbefore injection in the cold fluid

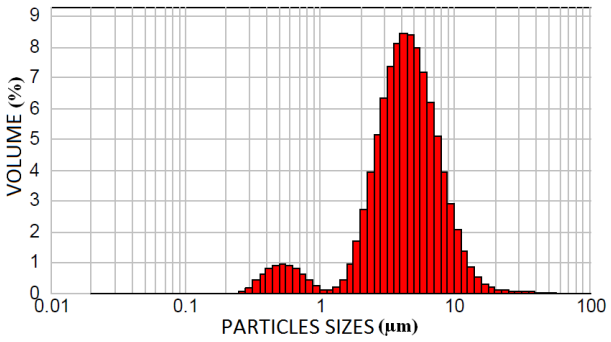

Fig.3. Size distribution of TiO2 powder - Measured after passing through the operating organs

2.3. Metrology

A metrology is placed at the terminals of the heat exchanger in order to control the thermal and hydraulic performance of the heat exchanger through usual parameters: volume flow rate of the clean fluid (hot fluid) with an electromagnetic flow meter, pressure drop on the fouling fluid (cold fluid) with two pressure ports connected to a differential pressure switch and four K-type thermocouples at the terminals of the exchanger (hot and cold inlet, hot and cold output). These measures enable us to establish the thermal balance and conservation in order to evaluate the thermal power ($\dot{Q}$), the mass flow of cold fluid ($\dot{m}_c$), the logarithmic mean temperature difference (ΔTml) and finally the overall heat transfer coefficient (U) using the three following equations:

$$\dot{Q} = \dot{m}_h \times Cp_{hc} \times \left(T_{i_h} - T_{o_h}\right) \quad (1)$$

$$\dot{Q} = \dot{m}_c \times Cp_c \times \left(T_{o_c} - T_{i_c}\right) \quad (2)$$

$$\dot{Q} = U \times S_{exch} \times \Delta T_{ml} \times F \quad (3)$$

F is a correction factor of the logarithmic mean temperature difference whose value is between 0 and 1. It allows to take into account, for heat exchangers whose flows are not perfect co-current or perfect counter-current, the two or three dimensional character of temperature profile (case of cross-currents or mixed configuration). In our case, F is equal to 1 (counter-current configuration).

3. Fouling evaluation methods and experimental results

3.1. Fouling evaluation method

The fouling resistance is evaluated by two methods:

1- On one hand, the performance of the heat exchanger is measured trough the evaluation of the overall heat transfer coefficient Uo in a clean initial state (Uo = constant) and compared to the performance drop between the clean operating state and the fouling operating state any throughout the evolution of the test. This calculation is possible using equations (1) to (3) using data from the instrumentation present on the test bench. We will call this reference value Uo-measured.

2- On the other hand, the value of Uo is not a constant (as Uo-measured) but it is calculated using the empirical correlation (4) [6] to determine the hot and cold partial heat exchange coefficient (h).

$$Nu = 0.291 \times Re^{0.7} \times Pr^{1/3} = \frac{h \times D_h}{\lambda} \quad (4)$$

Then, with the thermal resistances additivity rule, we can determine an overall heat transfer coefficient Uo which varies depending on operating conditions (flow, temperature, pressure, thermo-physical properties ... etc.). We will call this reference value Uo-correlation.

In all cases, the final calculation is the same and consists in quantify the decrease of the overall heat exchange coefficient between U and Uo and evaluate the Rf value by (5):

$$Rf(t) = \left(\frac{1}{U}\right) - \left(\frac{1}{U_o}\right) \quad (5)$$

The use of the empirical correlation (4) established by experimentation in [6] implies a difference between Uo-measured and Uo-correlation which generates a difference of fouling resistance values evaluated in all cases with (5).

Measurement time step is two minutes and an average is done every ten minutes to smooth curves and minimize the number of data for future analysis. The duration of the tests is significant (> 650h), in particular to check the asymptotic fouling resistance behaviour. The first test (test n°1) represents an ideal situation (no unexpected events) and the second one (test n°2) has the same kinetics but with two impromptu events. For each of them, we observe the fouling kinetics difference between the two methods mentioned above.

3.2. Experimental results

Similar test conditions allows us to obtain, as shown in Fig. 4, repeatable fouling kinetics at any point until the appearance of the first impromptu event during the test n°2. Indeed, the test n°1 is our reference and highlights the asymptotic behaviour of the fouling kinetics (Fig.5). Still regarding test n°1, we can observe in Fig.5 an inflection point of the fouling kinetics. A re-entrainment by packet of the depot due to fluid shear stress could have caused this inflection [6]. The test n°2 (Fig.6) has two impromptu events (caused by shocks on the heat exchanger) which constituting three phases with three different developments: before the shock, the detachment and a sudden re-entrainment of a part of the depot.

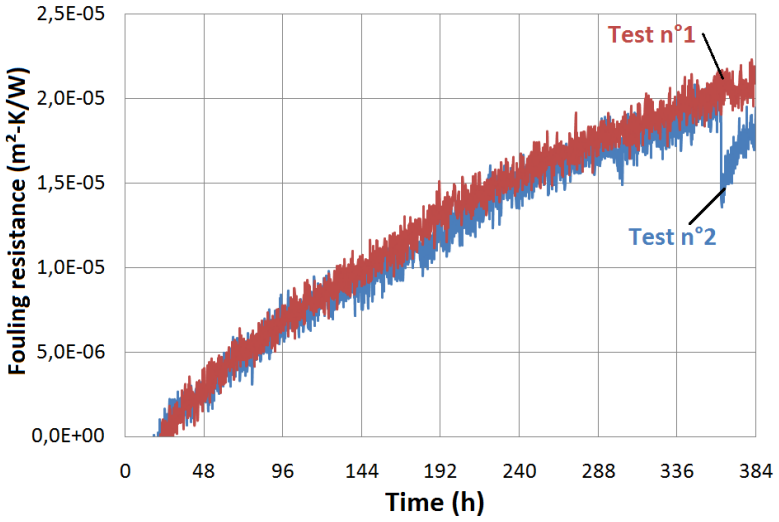

Fig.4.Kinetic fouling with Uo-correlation for test n° 1 and test n° 2– Repeatability

Observation of Uo-measured curves on Fig.5 and Fig.6 shows a zero initiation period while the Uo-correlation curve shows an initiation period of about 24 hours. The measured value of Uo (Uo-measured) is more accurate (compared of the use of empirical correlation) and thereof ensures a rapid detection of the performance drop. For the operator, this rapid detection enables to initiate more quickly cleaning procedures. However, this value being constant, it imposes mistakes that may be more or less injurious due to variations in operating conditions.

Conversely, the calculated value Uo-correlation is less accurate (because it is an empirical correlation) and imposes an initiation period and consequently a late detection of the performance drop of the heat exchanger. However, it allows the advantage to adapt with changes of operating conditions because the value of Uo-correlation is not constant (because the variation of the local heat exchange coefficients evaluated with (4), among others, depending on the thermo-physical properties which also vary depending on the temperatures and operating conditions).

We also denotes a significant difference on the asymptotic values of fouling resistance, in part due to the presence of unexpected events (with Uo-correlation : $Rf_{testn°1}{}^{*} = 3.05.10^{-5}\ \mathrm{m^2.K.W^{-1}}$ and $Rf_{testn°2}{}^{*} = 4.25.10^{-5}\ \mathrm{m^2.K.W^{-1}}$).

We also note that, despite the presence of events that take off and take away a part of the deposit in the test n°2, the final asymptotic fouling resistance is stronger than test n°1. This phenomenon is explained by the fact that, during the extraction of the deposit, a part of it is re-entrained directly into the fluid and a part is also moved in dead zones (less thermally active zones as recirculation zones or distribution). But the extraction of the deposit leaves micro-roughnesses on the heat exchange area which promotes, later, a faster and stronger adhesion of new particles [6]: we see this phenomenon by the significant increase of the originally slope that characterizes the deposition flux (Fig.6).

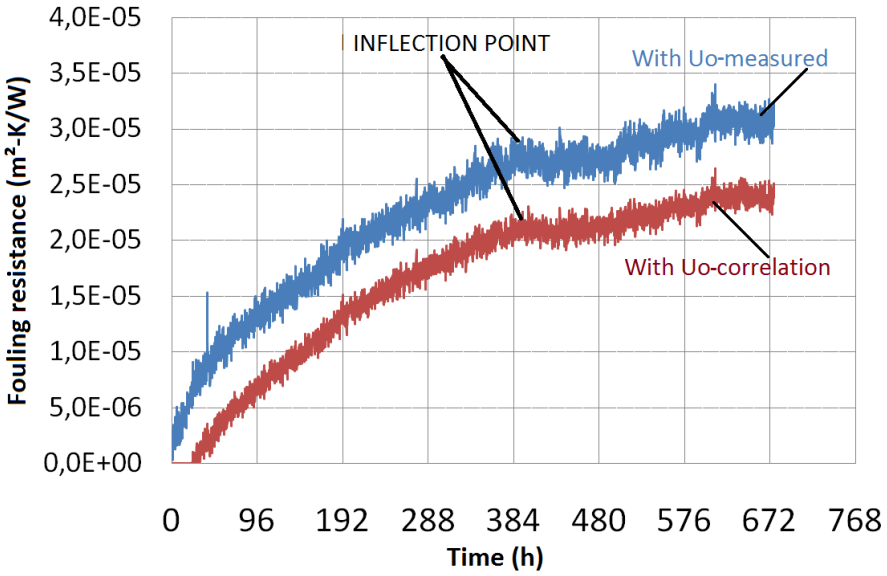

Fig.5. Fouling kinetic with Uo-measured and Uo-correlation for the test n°1

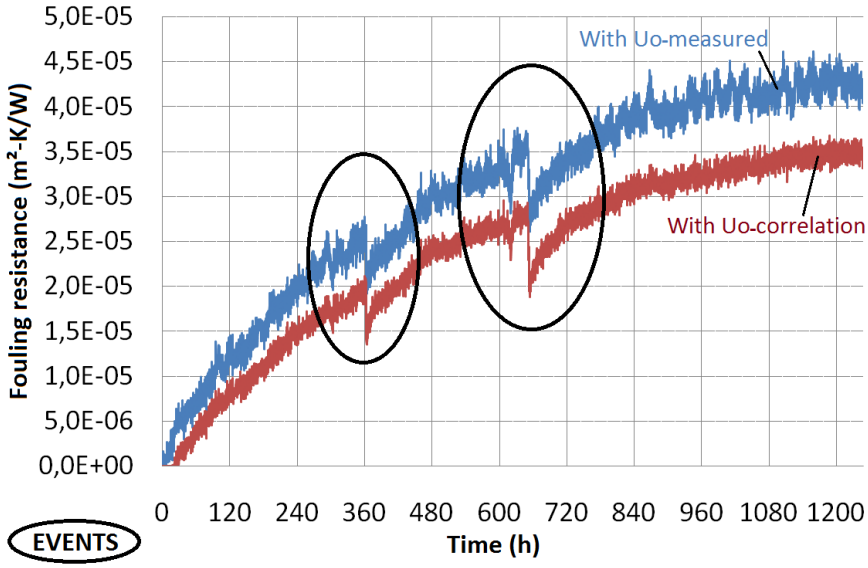

Fig.6. Fouling kinetic with Uo-measured and Uo-correlation for the test n°2

4. Prediction models

From the experimental data obtained previously, several predictive models are developed. We analyse the results of these different models (deterministic and statistical) to evaluate their precision compared to experimental data but also the influence on the accuracy of the model of various parameters such as the number of preachers and the sample size.

Accuracy of the model is evaluated using following indicators: the standard deviation σ of the relative error ε, the average relative error and the coefficient of determination R^2 (the square of the sample correlation coefficient of Pearson) with the following definitions:

$$\sigma = \sqrt{\frac{\sum(x - \bar{x})^2}{n - 1}} \tag{7}$$

$$\varepsilon = \left(\frac{Rf_{mod} - Rf_{re}}{|Rf_{re}|}\right) \times 100 \tag{8}$$

$$R^2 = \left[\frac{\sum(x - \bar{x}) \times (y - \bar{y})}{\sqrt{\sum(x - \bar{x})^2 \times \sum(y - \bar{y})^2}}\right]^2 \tag{9}$$

4.1. Kern & Seaton Model – Asymptotic model

One of the first correlative models for the characterization of the fouling kinetic is the Kern and Seaton [1] model:

$$Rf(t) = Rf^* \times (1 - e^{-t/\tau}) \tag{10}$$

The evaluation of the asymptotic fouling thermal resistance Rf^* and the time constant τ strongly influence the accuracy of the model so, if these constants are correctly evaluate this model gives quite satisfactory results. Analysis of the experimental data of the test n°1 gives us the results of the two constant Rf^* and τ. These values have permitted to realize the curves of Fig.7.

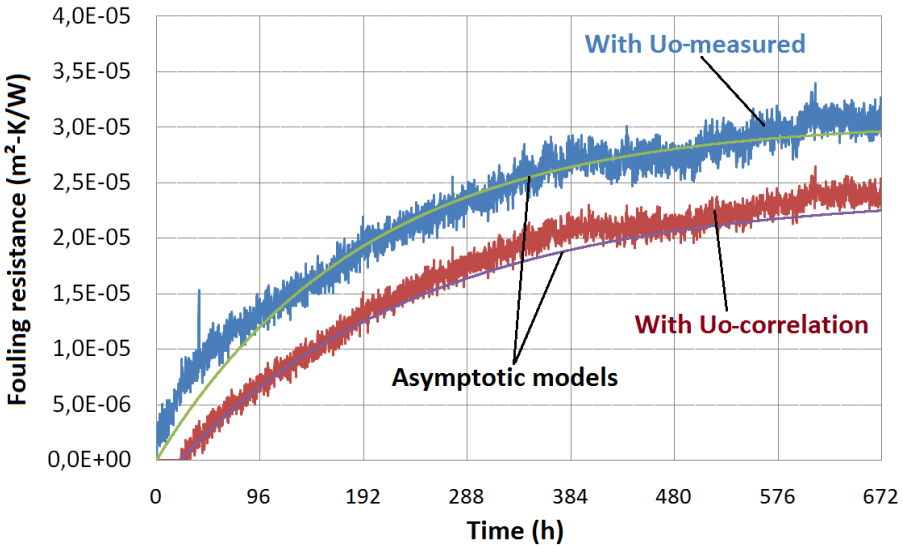

Fig.7. Fouling kinetic of the test n°1 (with Uo-measured and Uo-correlation) and associated asymptotic models

The asymptotic model is quite faithful to the experimental data with coefficients of determination R^2 near to 1, a standard deviation and an average relative error quite low (Table 1).

	Test n°1 - *Rf* measure with Uo-measured	Testn°1 - *Rf* measure with Uo-correlation
R^2	0.972	0.988
σ	14.49	13.74
ε average (%)	-5.02	-4.96

Table 1.Results of precision indicators (R^2, σ, ε average) for the asymptotic model

Regarding test n°2, the presence of two events that involve sharp declines of the fouling resistance, the asymptotic model evaluate from the test n°1 cannot be applied (Fig 8).

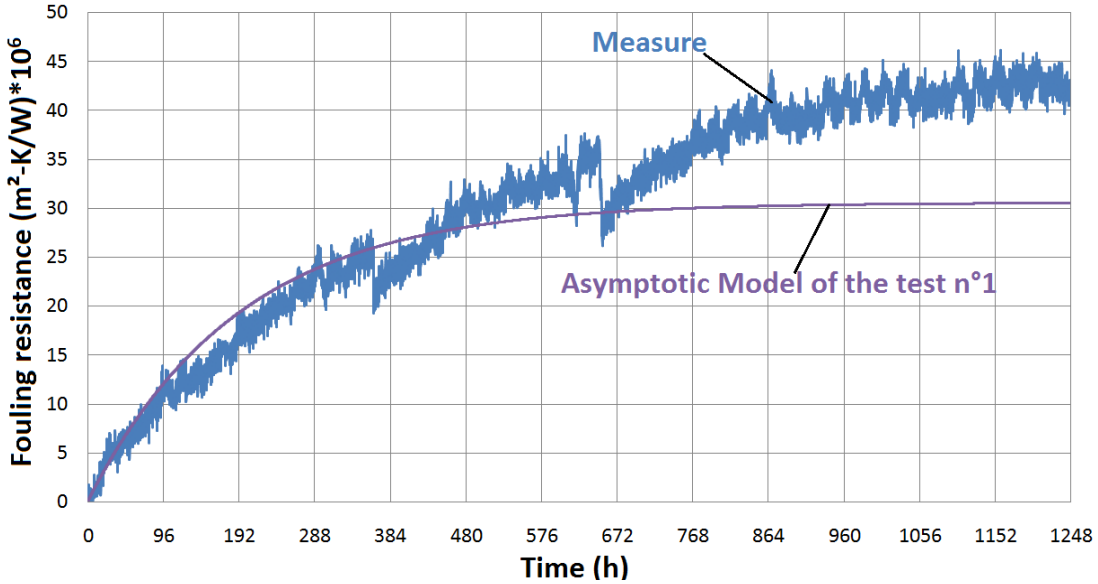

Fig.8. Fouling kinetic of the test n°2 (with Uo-measured) and asymptotic model evaluated by the test n°1

To apply it more accurately, it is essential to break down the kinetic of test n°2 in three distinct phases and determine three different kinetics with different values of asymptotic resistances and also time constants: this involve a very different model compared to the model established with the test n°1. We can conclude that the performance prediction with the use of a simple model like Kern & Seaton is limited to stable and constant operating conditions.

4.2. Multiple Linear Regression modelling

In the framework of modelling by Multiple Linear Regression (MLR), we carry out a study regarding accuracy of the model according to the number of variables used and also depending on the sample size. The goal is to know if the use of a model based on experimental data (test n°1) will be able to predict, with good accuracy, the data of the test n°2, while ensuring the use of a minimum of variables and data.

The analysis of correlation coefficients allows us to eliminate many measured or calculated variables and therefore significantly reduce the model. Table 2 shows the results with MLR model with three different sizes of samples (25% of the first data of the test n°1, 50% and 100%) and taking into account the 8 independent variables (and 10 dependent variables): time, hot and cold fluid volume flow rate, inlet and outlet temperature of each fluids, temperature difference of each of fluids, the Reynolds and Prandtl numbers for the hot and cold fluid, flow velocity of the hot and cold fluid, logarithmic mean temperature difference, thermal power and finally pressure drop on the cold fluid. Table 3 shows, in connection with the reduction of the model, the same results with the use of 100% of the data of test n°1, but at first time with only five independent variables (time, volume flow rate of the cold and hot fluid, inlet and outlet temperature of the hot fluid) and then in a second time with the use of only 3 independent variables (time, inlet and outlet temperature of the hot fluid).

	Modelling of *Rf* of the test n°2 with 25% of the first data of the test n°1	Modelling of *Rf* of the test n°2 with 50% of the first data of the test n°1	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1
R^2	0.9958	0.9934	0.9989
σ	59.896	80.846	30.995
ε average (%)	1.357	5.567	0.117

Table 2. Results of precision indicators (R^2, σ, ε average) for the modelling by MLR (Multiple Linear Regression)-Models with 18 variables

	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1- Modelling with 5 variables	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1- Modelling with 3variables
R^2	0.962	0.9635
σ	28.101	222.379
ε average (%)	-16, 712	40.955

Table 3. Results of precision indicators (R^2, σ, ε average) for the modelling by MLR (Multiple Linear Regression)-Models with 5 variables and with 3 variables

R^2 indicator is still very high ($R^2 > 0.96$, Table 2 and Table 3) and is therefore not a discriminating indicator: this is especially due to of the very large sample sizes. Our comparison is therefore focused on the two other indicators. Modelling by MLR gives satisfactory results when many variables are used to build the model. Indeed, the use of the entire sample data test of test n°1 provides a mean relative error of 0.117% while it is 1.357% using 25% of the data and finally to 5.567% by using 50% of the raw data. Therefore, more the sample size is important and more the relative error and standard deviation seem reduced.

However, the inflection point (Fig. 5) being part of the sampling which use 50% of the data of test n°1 false this tendency because, during this inflection point, the normal trend of the fouling kinetics is modified and the associated model is impacted: this results on a less good global accuracy of the model. The analysis of correlation coefficients allowing the reduction of the variable number of the model gives significantly less good results with, at a same sample size, a significant increase in the standard deviation and relative error. Indeed, the use of five variables implies an average relative error of about 16% while this one is greater than 40% by using the modelling with only 3 variables.

4.3. Artificial Neural Networks modelling

A same approach for modelling performed by multiple linear regressions is used with an Artificial Neural Networks (ANN) approach. Results are summarized in Tables 4 and 5.

	Modelling of *Rf* of the test n°2 with 25% of the first data of the test n°1	Modelling of *Rf* of the test n°2 with 50% of the first data of the test n°1	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1
R^2	0.841	0.960	0.997
σ	39.183	10.395	4.186
ε average (%)	-16.997	-3.807	-1.579

Table 4. Results of precision indicators (R^2, σ, ε average) for the modelling by ANN (Artificial Neural Network)-Models with 18 variables

	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1- Modelling with 5 variables	Modelling of *Rf* of the test n°2 with 100% of the first data of the test n°1- Modelling with 3variables
R^2	0.974	0.976
σ	66.058	145.298
ε average (%)	-2, 377	19.494

Table 5 Results of precision indicators (R^2, σ, ε average) for the modelling by ANN (Artificial Neural Network)-Models with 18 variables

R^2 coefficient is very high, however a value of about 0.86 is obtained through the use of 25% of the data with 8 independent variables (and 10 dependant variables): ANN needs a very important size of data sample. The other results from the models with 8 independent variables and larger samples sizes tend to the values of the mean relative error and standard deviation to those obtained with modelling by MLR.

Regarding the reduction of the model, although less accurate, a modelling using 5 variables then 3 variables allow us to obtain to much more satisfactory values of standard deviation and mean relative error values with ANN than MLR. Indeed, the use of 5 variables implies an average relative error of about 2.4% while that resulting from the modelling with only 3 variables do not exceed 20% (instead of 40% with MLR).

We can visualize the prediction kinetics obtain with MLR and ANN modelling with 5 variables and with 3 variables respectively in Fig.9 and Fig.10.

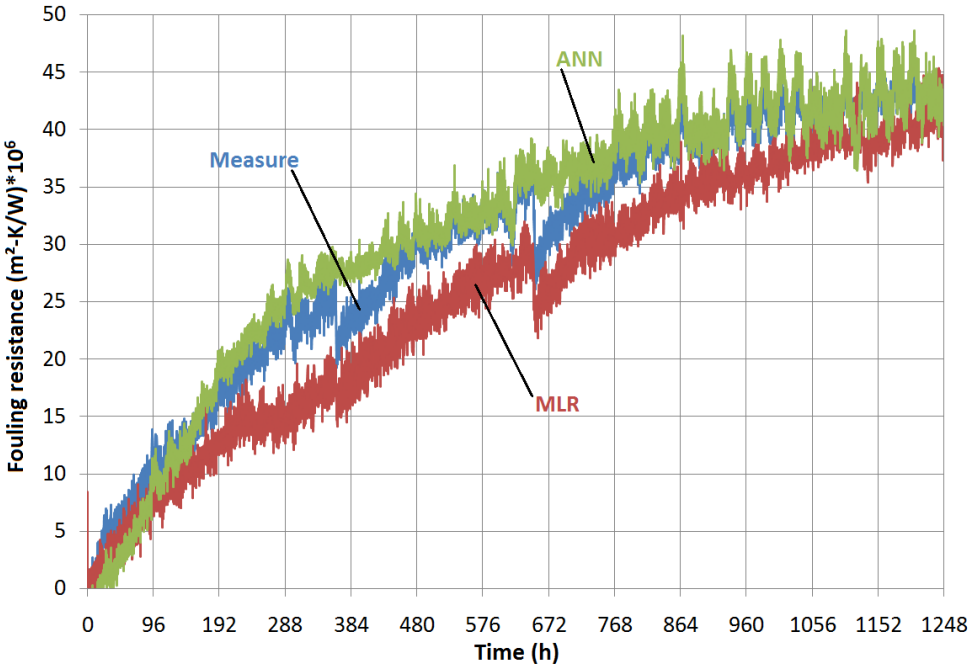

Fig.9. Fouling kinetics of the test n°2 (with Uo-measured) and associated prediction models by MLR and ANN using sample size of 100% (of the data test of the test n°1) and 5 variables

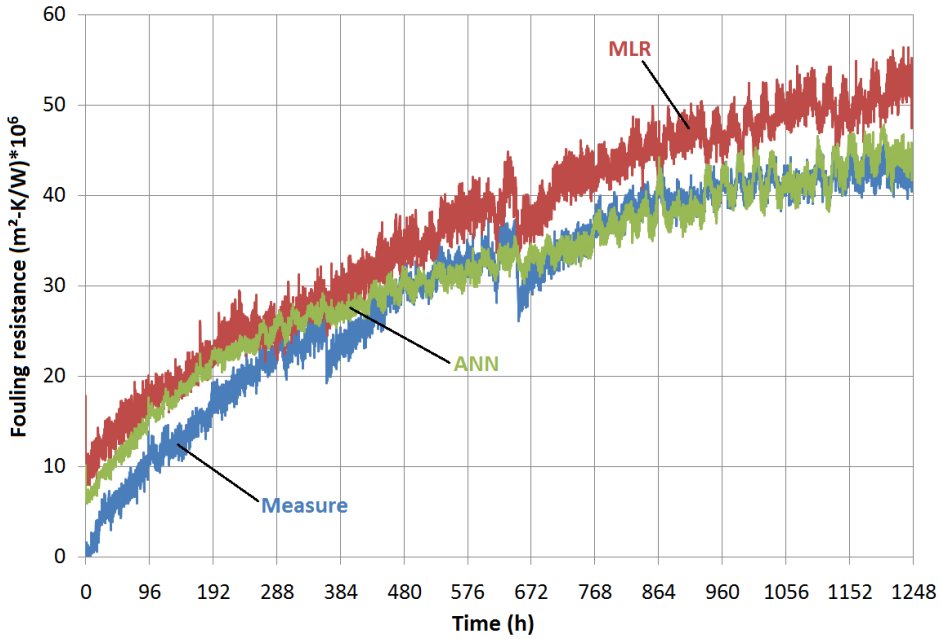

Fig.10. Fouling kinetics of the test n°2 (with Uo-measured) and associated prediction models by MLR and ANN using sample size of 100% (of the data test of the test n°1) and 3 variables

5. Conclusions

The test bench has allowed to measure the decrease of the thermal performance of a heat exchanger due to the presence of a fouling fluid. This decrease was evaluated by the measure of the overall heat exchange coefficient. We have realized two tests with the same operating conditions except that one has undergone two unexpected events which have drastically modified the fouling kinetics. The goal of the modelling work was to model the fouling kinetics of the test with unexpected events only with the experimental data of the test without these events.

Firstly, we have observed that the use of a high accuracy correlation to evaluate Uo-correlation could allow us to have a quickly detection of fouling effects and so, subsequently, help us to implement preventive maintenance practices significantly adapted.

Secondly, we have verified that the classical model of Kern & Seaton which describes the fouling kinetics is not applicable if unexpected events appear. Indeed, the increase of asymptotic value (due to the events) cannot be simulated with this model and this has as consequence a bad evaluation of the performance decrease.

Then, we can say that modelling by the use of ANN is, in this case study and in comparison with modelling by MLR, very interesting especially in framework of model reduction (good results on the indicators characterizing accuracy) but it seems however essential to use a large data samples in order to increase the accuracy. The model reduction is very interesting for industrial situations. Indeed, in industrial operating conditions, we often search to reduce the number of measurement because metrology is generally expensive and especially on the fouling fluid.

The improvement of the efforts on the learning phase, with other tests that take into account other unexpected events representative of usual industrial situations (e.g. sudden increase of the mass flow, sudden On/Off of the test bench due to electrical failure) will permit a better use ofthe ANN models

capabilities and finally to obtain a high accuracy model with a high adaptation capacity that can allow to anticipate the maintenance practices.

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Nomenclature

Dh	hydraulic diameter, m
F	corrective factor
h	partial heat exchange coefficient, W/(m².K)
$\dot{m}$	mass flow, kg/s
n	number of observation
Nu	Nusselt number
Pr	Prandtl number
$\dot{Q}$	thermal power, W
Rf	fouling resistance, m².K/W
Re	Reynolds number
S	heat exchange area, m²
T	temperature, K
t	time, s
U	global heat exchange coefficient, W/(m².K)
V	flow velocity, m/s
x,y	value of sample data
$\bar{x}, \bar{y}$	arithmetic average value of x and y

Greek symbols

Δ	difference between two values
ε	relative error, *%*
λ	thermal conductivity, W/(m.K)
σ	standard deviation, -
τ	time necessary to obtain 63.2% ofR_f^*, *s*

Subscripts and superscripts

c	cold
exch	exchange
h	hot
i	inlet
ml	logarithmic mean
mod	model
o	outlet, origin
re	real
*	asymptotic value

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