USE OF GENETIQUE ALGORITHM TO IDENTIFY THERMOPHYSICAL PROPERTIES OF DEPOSITED FOULING IN HEAT EXCHANGER TUBES

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ABSTRACT. At high temperature, the circulation of fluid in heat exchangers provides a tendency for fouling accumulation to take place on the internal surface of tubes. This paper shows an experimental process of thermophysical properties estimation of the fouling deposited on internal surface of a heat exchanger tube using genetic algorithms (GAs). The genetic algorithm is used to minimize an objective function containing calculated and measured temperatures. The experimental bench using a photothermal method with a finite width pulse heat excitation is used and the estimated parameters are obtained with high accuracy.

NOMENCLATURE

a	Thermal diffusivity ($m^2.s^{-1}$)
C_p	Heat capacity ($J.kg^{-1}.K^{-1}$)
e	sample thickness (m)
h	Heat transfer coefficient ($W.m^{-2}.K^{-1}$)
P	Initial population
p	Laplace parameter (s^{-1})
$Q(t)$	Crenel excitation ($W.m^{-2}$)
R_c	thermal contact resistance ($W^{-1}.K.m^2$)
R_{foul}	fouling thermal resistance ($W^{-1}.K.m^2$)
T_1	Calculated temperature on the front face(K)
T_2	Calculated temperature on the rear face(K)
$T_2^*(t,\beta)$	Reduced temperature
$T_{measured}$	Measured temperature (K)
t_c	Heating time (s)

Greek letters

β	Vector of estimated parameters
θ_f	Laplace temperature on the front face of the sample ($K.s^{-1}$)
θ_r	Laplace temperature on the rear face of the sample ($K.s^{-1}$)
λ	Thermal conductivity ($W.m^{-1}.K^{-1}$)
ρ	Density ($Kg.m^{-3}$)
Ψ	Heat flux density ($W.m^{-2}$)

1. INTRODUCTION

Fouling generally exists in the nature and all kinds of industry process, especially in the heat transfer process. The harm is very huge; it causes losses to reach as high as the industrial production resultant 0.3 percent [Yang Shanrang 2004]. So many researches have been done in the past years. Researches on the heat exchanger fouling are progressing along three directions, that is, fouling prediction, fouling monitoring and fouling countermeasure [SUN Lingfang 2008]. And some investigation demonstrated that the fouling has been a major barrier to the wide application of enhanced surfaces, so there is an urgent need to determine its properties that affect the performance of heat exchange surfaces.

In this work, we present an experimental study allowing the identification of the thermophysical properties of the fouling deposited on heat transfer surfaces. In the literature, lots of researchers have used different optimization methods to identify thermophysical properties of materials. Among them, we mention Zied et al. [2008], Faugeroux et al. [2004], Mzali et al. [2003] and Jarny et al [1991]. Their identification procedures use classical optimization methods that generate a deterministic sequence of computation based on gradient-type method which has to evaluate derivatives of an objective function. The methods are applied to a single point in the search space. The point is then improved along the deepest descending direction gradually through iterations [Mitsuo Gen 2008]. This point-to-point approach embraces the danger of failing in local optima. Besides, when used with models that contain correlated or nearly correlated properties, these methods can show instabilities resulting in non-convergence. Indeed, correlation or near-correlation among parameters is known to be a limiting factor for the converged application of gradient-based estimation procedures [Garcia. S 1999]. In addition, in some cases, when we don't have an order of magnitude of thermophysical properties, gradient methods become incapable to estimate them.

For these reasons we investigate the feasibility of using genetic algorithms (GA) which are powerful means to handle correlation problems and to estimate parameters which are known with less accuracy, and whose operation does not require any knowledge of derivatives, or sensitivity study. In this work a genetic algorithm is used to estimate thermophysical properties of fouling deposited onto internal surface of a heat exchanger. The estimation procedure is based on the minimization of a fitness function that expresses the sum-square of the error between a measured temperature and a calculated one. The system under investigation is submitted to a finite width heat flux excitation using a photothermal method. The temperature response, during and after irradiation, is measured at the opposite face using a thermocouple. Results show the efficiency of the developed genetic algorithm to estimate all unknown thermophysical parameters of fouling without requiring information on their initial values.

2. SYSTEM DESCRIPTION

Fouling of heat transfer surfaces is a serious problem that affects the design and efficiency of heat exchangers, and stills one of the unresolved problems in thermal science. It is generally defined as the accumulation of unwanted materials onto the heat transfer surface during the lifetime of the heat exchanger that may undergo a decline in its ability to transfer heat. In fact, the additional fouling layer has a low thermal conductivity that increases the resistance to heat transfer and reduces the performance of heat exchangers. Figure 1 shows a deposited fouling upon the internal surface of a heat exchanger:

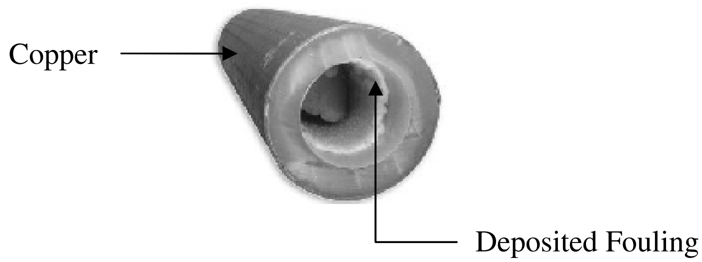

Figure 1. Fouling deposited onto a heat exchanger's internal surface

To determine the thermophysical properties of the added fouling layer of thickness e_1, a section of a heat exchanger with fouling is studied (figure 2):

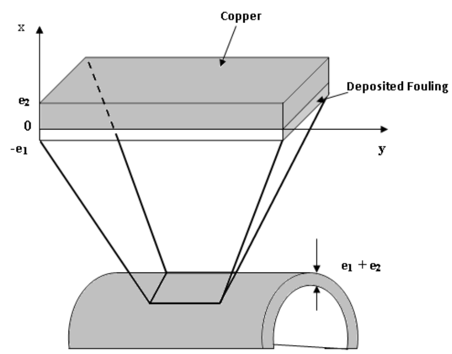

Figure 2. System under investigation

The system under investigation, composed of two layers of copper and the fouling deposited on of thickness e_2 and e_1 respectively, is submitted at t = 0 on the upper face to a finite width pulse heat flux Q(t) during a short time t_c as shown in figure 3. The sample is initially assumed at uniform temperature T_0. The expression of the heat flux excitation is given by the following equation:

$$Q\ (t) = \begin{cases} \Psi & 0 \le t \le t_c \\ 0 & t > t_c \end{cases} \tag{1}$$

The heat transfer on the two faces with the surrounding environment is taken into account and it is represented by two heat transfer coefficients h_1 and h_2.

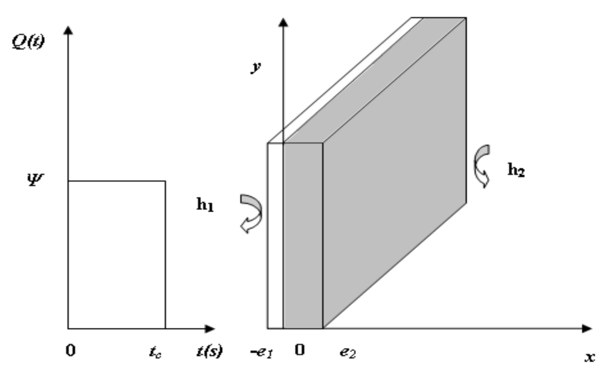

Figure 3. Principle of the finite width pulse heat flux method

In the one-dimensional experimental design shown in Fig. 4, the sides of the sample were insulated while an imposed heat flux was applied across the entire top surface:

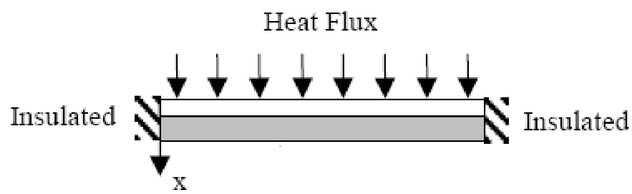

Figure 4. One dimensional boundary condition

3. MATHEMATICAL MODEL

The model assumes one-dimensional heat flux through a two-layer sample constituted by two materials of thickness e_1 and e_2. Their interface is characterized by an imperfect contact (thermal contact resistance R_c). The thermal properties and densities of both layers are assumed to be uniform and constant. The convective and radiative heat transfers on the two faces with the uniform environment are expressed by two heat transfer coefficients h_1 and h_2 [Albouchi 2005].

The transient temperature distribution in the sample can be obtained by solving the one dimensional heat equation for each layer:

$$\lambda_i \frac{\partial^2 T_i(x,t)}{\partial x^2} = \rho_i C_{pi} \frac{\partial T_i(x,t)}{\partial t}, \qquad i = 1,\ 2 \tag{2}$$

Where T_i is the temperature of layer i.
Coupled to initial and boundary conditions:

$$T_i = 0 \qquad\qquad at \quad t = 0 \tag{3}$$

$$-\lambda_1 \frac{\partial T_1(-e_1,t)}{\partial x} = Q(t) - h_1 T_1(-e_1,t) \quad at\ x = -e_1 \tag{4}$$

$$-\lambda_1 \frac{\partial T_1(0,t)}{\partial x} = \frac{1}{R_c}\left(T_1(0,t) - T_2(0,t)\right) \qquad at\ \ x = 0 \tag{5}$$

$$\lambda_1 \frac{\partial T_1(0,t)}{\partial x} = \lambda_2 \frac{\partial T_2(0,t)}{\partial x} \qquad at\ x = 0 \tag{6}$$

$$\lambda_2 \frac{\partial T_2(e_2,t)}{\partial x} = -h_2 T_2(e_2,t) \quad at\ x = e_2 \tag{7}$$

To solve the system of equations (2-7), the thermal quadrupoles formalism is used. The entire system can be described in Laplace space as:

$$\begin{bmatrix} \theta_f \\ \dfrac{\psi(1-\exp(-pt_c))}{p} \end{bmatrix} = \begin{bmatrix} 1 & 0 \\ h_1 & 1 \end{bmatrix} \begin{bmatrix} A_1 & B_1 \\ C_1 & D_1 \end{bmatrix} \begin{bmatrix} 1 & R_c \\ 0 & 1 \end{bmatrix} \begin{bmatrix} A_2 & B_2 \\ C_2 & D_2 \end{bmatrix} \begin{bmatrix} 1 & 0 \\ h_2 & 1 \end{bmatrix} \begin{bmatrix} \theta_r \\ 0 \end{bmatrix} = \begin{bmatrix} A & B \\ C & D \end{bmatrix} \begin{bmatrix} \theta_r \\ 0 \end{bmatrix} \quad (8)$$

Here θ_f and θ_r are the Laplace transforms of the sample's front and rear face temperatures, respectively. The coefficients A_i, B_i, C_i and D_i depend on the Laplace parameter p, on the thickness e_i of the layer i, and on the thermophysical properties of the material. Their expressions are given by the following equations:

$$A_i = D_i = \cosh\left(\alpha_i e_i\right)\ ,\ C_i = \lambda_i \alpha_i \sinh\left(\alpha_i e_i\right),\ B_i = \frac{1}{\lambda_i \alpha_i}\sinh\left(\alpha_i e_i\right)\ ,\ \alpha_i = \sqrt{\frac{p}{a_i}} \quad (9)$$

In the Laplace space, the rear face temperature is given by:

$$\theta_r(p) = \frac{\Psi}{pC}\left[1-\exp(-pt_c)\right] \quad (10)$$

Where Ψ is the density of the crenel heating flux (Figure 3).

With dimensional parameters, the rear face temperature, $\theta_r(p)$, is a function of several dimensional parameters given by the following expression:

$$\theta_r(p) = f(p,\ t_c,\ a_1,\ \lambda_1, \rho_1, C_{p1},\ e_1,\ h_1,\ a_2,\ \lambda_2,\ \rho_2, C_{p2},\ e_2,\ h_2,\ R_c,\ \Psi) \quad (11)$$

Due to the large number of parameters encountered in the mathematical model, this study is presented in dimensionless space with dimensionless parameters. Taking into account that we work at ambient temperature, we have used the approximation of equal heat transfer coefficient on the two sample faces ($h_1 = h_2 = h$). The rear face temperature in Laplace space for a crenel heating excitation is given by:

$$\theta_r = \frac{\beta_3}{\beta_1^2 s_1^2} \frac{\left(1-\exp(-s_1^2 t_c^*\right)}{\left(\delta + \varphi + \phi\right)} \quad (12)$$

Where:

$$\delta = [s_1.ch(s_2)\,sh(s_1) + \beta_4.\beta_5.s_1^2.sh(s_2)\,sh(s_1) + \beta_5.s_1.ch(s_1)\,sh(s_2)] \quad (13)$$

$$\varphi = \beta_2{}^2[\frac{1}{\beta_5 s_1} ch(s_1)sh(s_2) + \beta_4.ch(s_1)ch(s_2) + \frac{1}{s_1} sh(s_1)ch(s_2)] \quad (14)$$

$$\phi = \beta_2[2ch(s_1)ch(s_2) + \beta_4\beta_5 s_1.ch(s_1)sh(s_2) + (\beta_5 + \frac{1}{\beta_5})sh(s_1)sh(s_2) + \beta_4 s_1.sh(s_1)ch(s_2)] \quad (15)$$

The dimensionless parameters are defined by:

$$s_1 = \sqrt{\frac{p}{\beta_1}},\ \beta_1 = \frac{a_1}{e_1^2},\ s_2 = \sqrt{\frac{p}{a_2}}e_2,\ t_c^* = \beta_1 t_c,\ \beta_2 = \frac{he_1}{\lambda_1},\ \beta_3 = \frac{\psi}{\rho_1 C_{p1} e_1},\ \beta_4 = \frac{R_c \lambda_1}{e_1},\ \beta_5 = \left(\frac{\lambda_2 \rho_2 C_{p2}}{\lambda_1 \rho_1 C_{p1}}\right)^{1/2} \quad (16)$$

The variation of the reduced temperature $T_2^*(t,\beta)$ with time in the usual space domain is calculated using the numerical algorithm proposed by Graver-Stehfest of θ_r [F. Albouchi 2005] :

$$T_2^*(t,\beta) = \frac{Ln(2)}{t}\sum_{i=1}^{n} V_i \theta_r\left(\frac{iLn(2)}{t}\right) \tag{17}$$

Where V_i are the Graver-Stehfest function's coefficients, and $\beta = [\beta_1, \beta_2, \beta_3, \beta_4, \beta_5]$ is the vector of the unknown parameters to be estimated using an inverse problem based on genetic algorithm.

The identification procedure of all parameters β_i allows us to calculate the unknown thermophysical properties of the first layer of fouling which are the thermal diffusivity a_1, the thermal conductivity λ_1, the volumetric heat capacity ($\rho_1 C_{p1}$), the heat transfer coefficient (h), and the contact resistance R_c between the fouling and the copper.

4. PARAMETERS ESTIMATION: USE OF GENETIC ALGORITHM

The parameters β_i, to be estimated, are regarded as unknown while the measured temperature profile at a set of discrete points is available [Swati Verma 2007]. The unknown parameters are estimated from adjusting the theoretical temperature history obtained from the mathematical model $T^*_2(t,\beta)$ to the measured temperature history $T_{measured}$. This can be achieved from the minimization of the fitness function S which calculates the sum-square of the gap between the measured and the calculated temperature as shown below:

$$\min(S(\beta)) = \sum_{i=1}^{N} (T_{measured} - T_2^*(t,\beta))^2 \tag{18}$$

To minimize this fitness function there are many methods, among them we mention the gradient methods which are the most used by many researchers. The principle of these methods requires the evaluation of the derivatives in the fitness function and may also need information on an initial solution vector β for the searched parameters. In these approaches, the use of a bad starting point may result in the solution getting trapped in a local optimum [M. Tamer Ayvaz 2007]. Besides, when the parameters to be estimated are correlated or nearly correlated, the minimization of the fitness function S using a common gradient-based method such us the Gauss linearization method, the Gauss-Newton method or the Levenberg-Marquardt method becomes very difficult [S. Orain 2001].

Therefore, in the solution of the inverse problems, heuristic algorithms are usually preferred due their ability of finding global or near global optimum solutions without the necessity of working with gradients, as well as requiring information on an initial solution. The most widely used heuristic algorithm is the genetic algorithm, which is a stochastic global search procedure based on the mechanics of natural selection and natural genetics [Holland 1975, Goldberg 1989].

For the present study, a genetic algorithm is used to search for optimal values of the vector β composed of five unknown parameters [$\beta_1, \beta_2, \beta_3, \beta_4, \beta_5$], called chromosomes or individuals, of the model $T_2^*(t,\beta)$.

A genetic algorithm is a stochastic search algorithms based on the survival mechanism of the fittest concepts. It, differing from conventional search techniques, starts randomly with an initial generated solution population of n individuals satisfying boundary and system constraints.

$$Population = P = \begin{bmatrix} \beta_1^1 & \beta_2^1 & \beta_3^1 & \beta_4^1 & \beta_5^1 \\ \beta_1^2 & \beta_2^2 & . & . & \beta_5^2 \\ . & . & . & . & . \\ . & . & \beta_3^j & . & . \\ \beta_1^n & \beta_2^n & \beta_3^n & \beta_4^n & \beta_5^n \end{bmatrix} = \begin{bmatrix} \beta^1 \\ \beta^2 \\ . \\ . \\ \beta^n \end{bmatrix} \tag{19}$$

Each row in the population is called a chromosome or individual, representing a solution to the problem at hand. Optimal parameters are obtained by exchanging genetic information between individuals to reproduce improved solutions from one generation to the next by three genetic operators, which are selection, crossover and mutation (Figure 5):

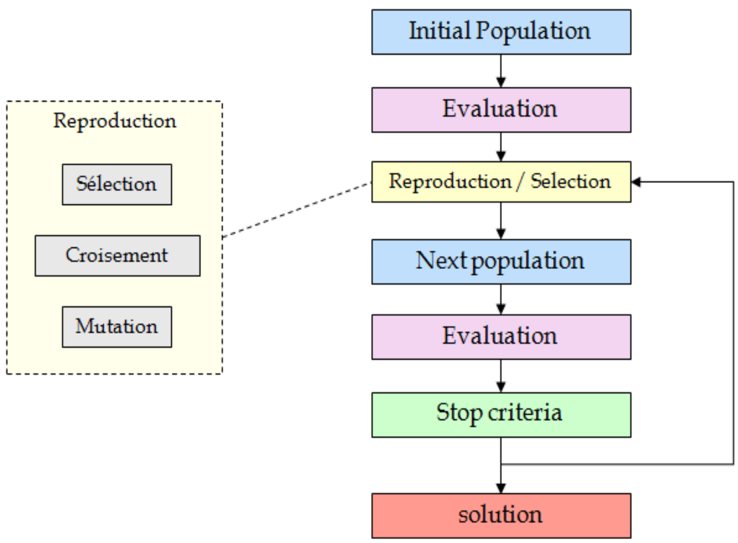

Figure 5. Genetic algorithm flowchart

The chromosome evolves through successive generations. During each generation, every chromosome is evaluated by measuring its fitness in the population and assigning to it a score. To create the next generation, new chromosomes, called offspring, are formed by either merging two chromosomes from the current generation using a crossover operator or modifying a chromosome using a mutation operator. The crossover operator takes two selected individuals and combines them about a crossover point thereby creating two new individuals. The mutation operator randomly modifies the genes (β_i^j) of a chromosome, introducing further randomness into the population. A new generation is formed by selection, according to the fitness values, some of the best parents and offspring are kept, the others are rejected to keep the population size constant. Fitter chromosomes have higher probabilities of being selected. After several generations, the algorithms converge to the best chromosome, which hopefully represents the optimum or suboptimal solution that gives the most minimal fitness function.

5. EXPERIMENTAL SETUP AND RESULTS

The experimental apparatus is schematically shown in Fig. 6**.** It involves a stabilized power, a heat source, a sample to be characterized, a thermocouple, a data acquisition system and a computer.

The investigated sample, composed of two layers, is a section of a heat exchanger with fouling deposited on. The first layer of fouling has a thickness e_1 of 0.1 mm; the second layer is the copper of the heat exchanger of thickness e_2 equal to 1mm.

In order to be put under the conditions of the one dimensional heat transfer, the sample's sides were insulated (Fig. 4) while an imposed heat flux with a finite width was applied across the entire top surface using a halogen lamp, which provides a uniform heat flux equal to 1kw.m^{-2}, during 15 s.

The thermal characterization consists in analyzing the temperature evolution measured by a K-type thermocouple, located on the central rear face of the sample, immediately after the absorption of the heat flux density delivered by the halogen lamp. The measurement is performed for 250s, and the sampling interval is set as 0.25s throughout the entire temperature recording. After the thermal excitation, the temperature reaches a maximum and then decreases due to the heat diffusion. The electrical signal, being proportional to the temperature variation $T_{measured}$, and depending on the various thermophysical properties to be identified is read and recorded with a data acquisition unit (Agilent 34970A) which allows transferring data to a computer via an RS-232 interface.

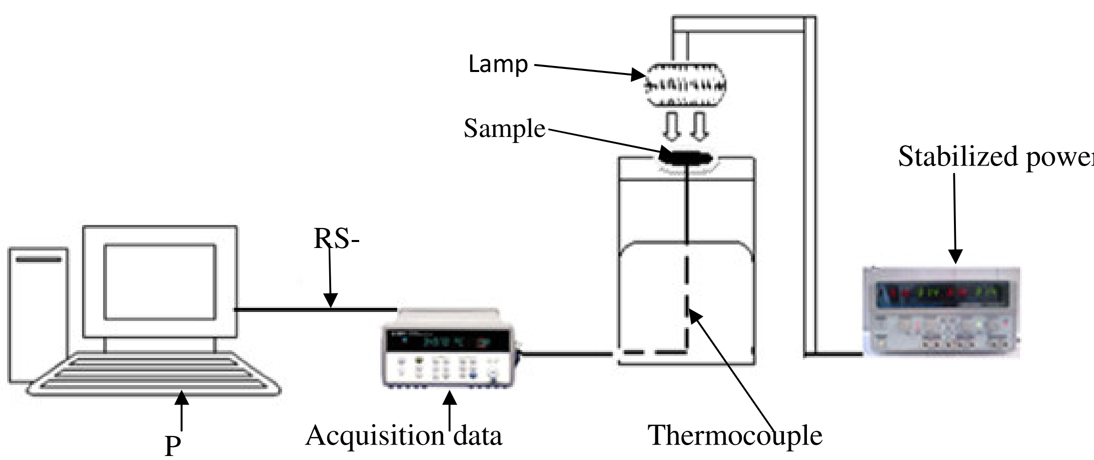

Figure 6. Experimental device

In this parameters' estimation, the thermophysical parameters of the second layer of copper are fixed. Its thermal diffusivity a_2 and thermal effusivity $\sqrt{\lambda_2 \rho_2 C_{P2}}$ are fixed at known values of 1.16 10^4 m^2.s^{-1} and 37.039 Kw.m^{-2}.k^{-1}s$^{-1/2}$, respectively.

The estimation was carried on with a genetic algorithm with a population of 100 chromosomes, each one of five genes (five parameters), and in 250 generation steps with the same procedures. The initial population defined above is generated in a large domain. Each parameter β_i is delimited by an upper and a low bound, that is $\beta_1 \in [0, 200\ s^{-1}]$, $\beta_2 \in [0,1]$, $\beta_3 \in [0, 50]$, $\beta_4 \in [0, 10]$, $\beta_5 \in [1, 100]$.

Figure 7 shows a comparison between measured temperature and the calculated one using ten chromosomes of the initial population. According to this figure, we notice that these initial chromosomes are not potential solutions but the importance is that they must just provide an answer until this stage, even bad.

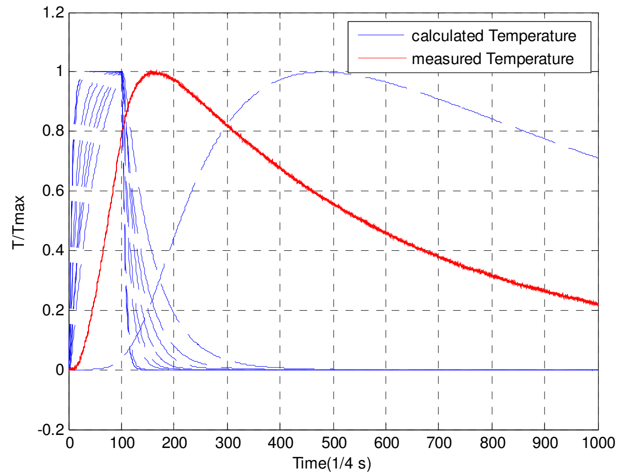

Figure 7. Comparison between measured temperature and calculated temperature for the initial population

The rank-based selection is used in this algorithm. The new population is chosen from the old based on the rank, the highest fitness member in the old population is rank #1, the second-best solution is rank #2, etc. Seventy five percent of the new population is chosen from the top thirty percent of the old population, and the other twenty five percent chosen from the bottom seventy percent. This ensures that selective operator maintains the genetic diversity.

Two-point crossover is used; its technique is illustrated in Fig 8. Two points are chosen along the length of the chromosome, and the parameters between those two points are then swapped on each parent chromosome to make the two children.

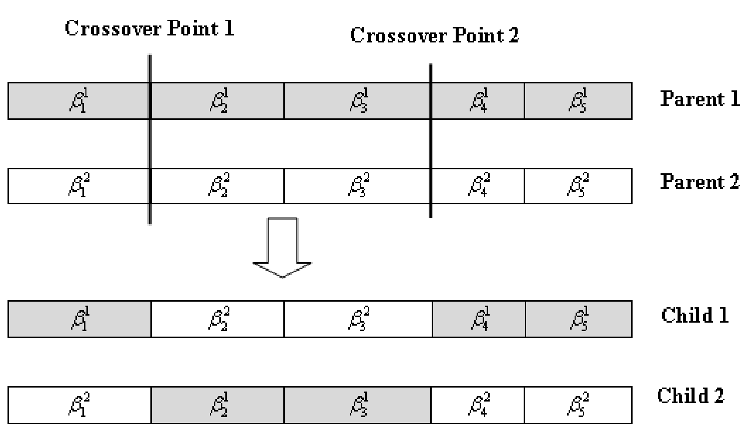

Figure 8. Principle of the crossover operator

Finally, to satisfy the diversity of the population every individual is subject to random change by using a mutation operator.

The performance of the genetic algorithm was performed averaging five runs with different initial populations; the genetic algorithm converges to the average parameters given in table 1:

Table 1. Estimated paramaters

Parameters	β_1	β_2	β_3	β_4	β_5
Estimated values	87	$9{,}44\ 10^{-04}$	4,83	0,36	19,18
Standard deviation $\sigma_{\beta i}$	$2.44\ 10^{-2}$	$1.57\ 10^{-6}$	$5.23\ 10^{-2}$	$9.76\ 10^{-3}$	0.23
Relativeuncertainty %	0.0723	0.428	2 .79	6.98	3.09

Using the definition given in equation (16), the unknown dimensional parameters of the fouling can be calculated. These parameters are the thermal diffusivity (a_1), the thermal conductivity (λ_1), the volumetric heat capacity ($\rho_1 C_{p1}$), the heat transfer coefficient (h), and the contact resistance R_c ; their values are given in Table 2. The results in table 2 clearly indicate that the genetic algorithm allows the simultaneous estimation of all the unknown parameters β_i.

Table 2. Calculated dimensional parameters

Parameters	$a_1(m^2.s^{-1})$	$\rho_1 C_{p1}$ (KJ/m^3.K)	$\lambda_1(W.m^{-1}.K^{-1})$	h $(W.m^{-2}.K^{-1})$	R_c $(W.m^{-2}.K^{-1})$
values	$0.87\ 10^{-6}$	2070	1.8	17	$2\ 10^{-5}$
Relative uncertainty %	2.072	4.790	6.862	8.29	14.842

The quality of the estimation is analyzed, by comparing the experimental response and the calculated temperature using the best chromosomes estimated by the genetic algorithm. Figure 9 presents comparisons between the measurements and the optimal model using the estimated parameters. The figure shows a good agreement between the measured and calculated temperatures.

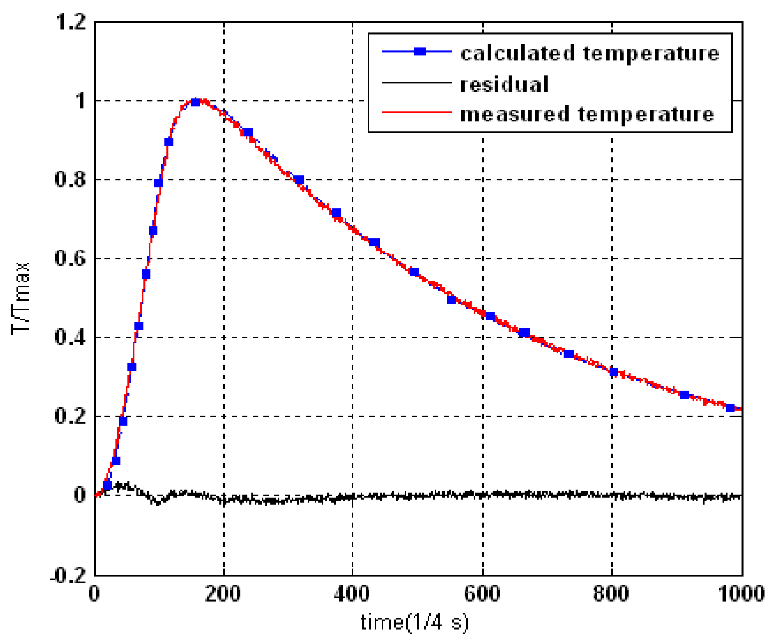

Figure 9. Comparison between measured and calculated temperature at the convergence of the GA

These results show that the proposed solution algorithm is effective in the determination of the unknown thermophysical of the fouling accumulated onto the internal surface heat exchanger. It should be emphasized that one of the advantages of the proposed solution algorithm is that there is no need to define an initial solution to start the optimization process.

6. EFFECT OF THE DEPOSITED FOULING ON THE HEAT TRANSFER

Whatever the cause or exact nature of the fouling, an additional resistance to heat transfer is introduced and the operational capability of the heat exchanger is correspondingly reduced. If we knew both the thickness and the thermal conductivity of the fouling, we could treat the heat transfer problem simply as another conduction resistance in series with the wall as shown in Fig 10.

In general, we know neither of these quantities, but in the present work we have identified experimentally all thermophysical properties of the deposited layer which allows us to know its additional thermal resistance.

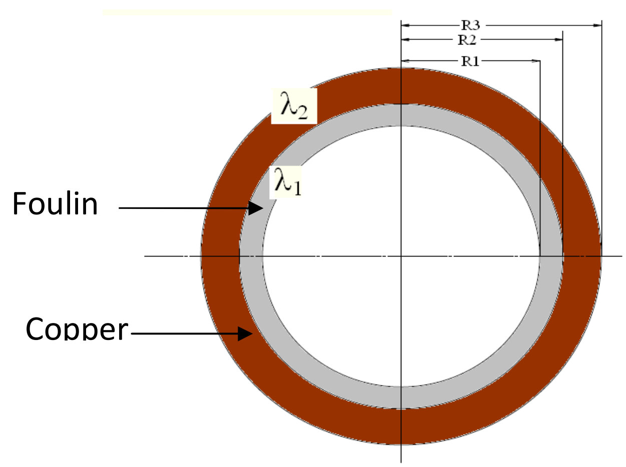

Figure 10. Schematic view of the fouling thermal resistance

The fouling thermal resistance can be expressed as a function of the thickness of the fouling layer (e_1) and its thermal conductivity (λ_1):

$$R_{foul} = \frac{1}{2\pi\lambda_1 L} Ln(\frac{R_2}{R_1}) \tag{20}$$

Where $R_2 - R_1 = e_1$ is the thickness of the fouling layer and L is the length of the heat exchanger tube.

Let's recall that, before the accumulation of fouling deposits and without circulation of any coolant, the thermal resistance is equal to the one of metal (copper) that constitute the heat exchanger:

$$R_{copper} = \frac{1}{2\pi\lambda_2 L} Ln(\frac{R_3}{R_2}) \tag{21}$$

Where R_2 and R_3 are the inner and the outer tube radius of the heat exchanger, respectively, and L is its length.

As mentioned above the first layer of fouling has a thickness e_1 of 0.1mm, the second layer is the copper constituting the heat exchanger of thickness e_2 equal to 1mm and knowing that the heat exchanger outer radius tube is equal to 7mm and its thermal conductivity is equal to 398 $W.m^{-1}.K^{-1}$, we remark thus during the operational lifetime the thermal resistance increases until one hundred and fifteen times of its initial value as shown in Eq (22):

$$\frac{R_{foul}}{R_{copper}} = \frac{\lambda_2}{\lambda_1} \frac{Ln(\frac{R_2}{R_1})}{Ln(\frac{R_3}{R_2})} \approx 115 \tag{22}$$

Thus the designer of a heat exchanger must take into account the effect of fouling upon heat exchanger efficiency during the operational lifetime and make previsions in his design for a sufficient extra capacity to insure that the heat exchanger will meet process that will perturb its primordial role. So, the designer has to select which material that does not readily corrode or produce much deposit of corrosion products such as copper-bearing alloys which can minimize chemical fouling and eliminate biological one.

7. CONCLUSION

In this study, an estimation procedure of thermophysical properties of the fouling deposited on internal surface of heat exchangers tube is presented. This procedure is based on a stochastic method using genetic algorithm. The experimental results show, on the one hand, the capability of the genetic algorithm to identify a large number of unknown parameters with high accuracy, on the other hand, it allows us to determine the deposited fouling's thermal properties. It has been shown the harmful effects of the fouling thermal resistance that reduces the efficiency of the heat exchanger which impose the necessity of the maintenance of heat exchanger tubes.

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