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An inverse problem based on genetic algorithm to estimate thermophysical properties of fouling

A. Adili [a,*], N. Hasni [b], C. Kerkeni [a], S. Ben Nasrallah [c]

[a] Centre de Recherches et des Technologies de l'Energie, Laboratoire d'Energétique et des Procédés Thermiques, Route touristique de Soliman B.P. 95, Hammam-Lif 2050, Tunisie
[b] Institut National des Sciences Appliquées et des Technologies (INSAT), Centre Urbain Nord B.P. 676, Tunisie
[c] Ecole National d'Ingénieur de Monastir, Laboratoire des Etudes des systèmes Thermiques et Energétiques (LESTE), Avenue Ibn El Jazzar, Route de Kairouan, 5019 Monastir, Tunisie

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ABSTRACT

In the past few decades, the study on how to apply genetic algorithms to problems in the industrial engineering world has aroused a great deal of curiosity of many researchers in the area of management science, industrial operations and engineering systems. This paper shows an experimental process of thermophysical properties estimation of fouling deposited on internal surface of a heat exchanger tube using genetic algorithms. In brief, the deposits on heat exchanger tubes are caused by the presence of inorganic salts, of small quantities of organic materials and products of corrosion in the water. From thermophysical point of view, the deposited fouling has harmful effects on the heat exchanger efficiency. For these reasons the determination of its thermophysical properties became very important.

The experimental bench using a photothermal method with a finite width pulse heat excitation is used. The genetic algorithm is used to minimize an objective function containing a calculated and a measured temperature. This last is measured on the rear face of a bi-layer system composed of a section of a heat exchanger and the fouling deposited on during and after a finite width pulse heat excitation on its front face. The calculated temperature, that is a function of the unknown thermophysical properties of the bi-layer system, is calculated by the resolution of the one-dimensional linear inverse conduction problem, and by the use of the thermal quadrupoles formalism. The motivation in using genetic algorithms was their potential to overcome the restriction to the estimation of non-correlated parameters of gradient-based methods, and their powerful ability to work well for many complex problems which are very difficult to solve by conventional techniques. The results of the estimation procedure show on the one hand the efficiency and the stability of the developed genetic algorithm to estimate the thermophysical properties of fouling and the high accuracy of the obtained results on the other hand.

1. Introduction

The knowledge and the accurate estimation of thermophysical properties such as thermal diffusivity, conductivity, effusivity and heat capacity of materials are more and more important in industrial processes and quality. In this paper, we are interested to the identification of thermophysical properties of fouling deposited onto internal surface of heat exchanger. Fouling is a general term that includes any kind of deposit of extraneous material that appears upon the heat transfer surface during the lifetime of the heat exchanger. It reduces the cross sectional area for heat to be transferred and causes an increase in the resistance to heat transfer across the heat exchanger. This is because the thermal conductivity of the fouling layer is low. This reduces the efficiency of the heat exchanger. 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 [1]. 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. To determine these properties there are different research methods based on inverse analysis. During the last decades, several approaches have been suggested in the solution of the inverse parameter estimation problems. These approaches include the minimization of the residual of an objective function that expresses the sum-square of the error between a measured data and a calculated one by performing a mathematical model.

In practice, these research methods can be classified into two categories which are analytical research methods and heuristic

* Corresponding author.
E-mail address: ladiliali@yahoo.fr (A. Adili).

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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	Correlation matrix
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)
X_{ij}	Sensibility matrix
Z_β	Reduced sensibility matrix

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 ($kg\ m^{-3}$)
σ_n	standard deviation of the measurement errors (K)
Ψ	Heat flux density ($W\ m^{-2}$)

research methods. The first class is a guided algorithm based on gradient method that has to evaluate the derivatives of an objective function to identify the unknown parameters. In the literature, lots of researchers have used this kind of method to identify thermophysical properties of materials. Among them, we mention Cheheb et al. [2] who have identified thermal radiative and conductive properties of semitransparent materials using a photothermal crenel method, Faugeroux et al. [3] and Mzali et al. [4] theoretically have used the flash method to estimate thermal properties of samples which are assumed to be opaque and homogeneous and Albouchi et al. [5] have used the photothermal crenel technique to determine the effective thermophysical properties of a glass powder. These types of algorithms guarantee to find the optimal solution if it exists. However, they only guarantee to find a local optimal solution and not the global one [6]. Besides, when used with mathematical models that contain correlated or nearly correlated parameters, 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. Thus, application of gradient-based procedures for the simultaneous identification of the unknown parameters is therefore restricted to the identification of the uncorrelated parameters assuming the others to beknown [7]. In addition, in some cases, when we do not have an order of magnitude of the researched parameters, gradient methods become incapable to estimate them. For these reasons, we investigate the feasibility of using heuristic methods which are global search methods and powerful mean to handle correlation problems and to estimate parameters which are known with less accuracy, and whose operations do not require any knowledge of derivatives of the objective function. The most widely used heuristic algorithm is the genetic algorithm which is a probabilistic search technique that has its roots in the principles of genetics. In the GA, the solution is obtained with a random search process based on survival of the fittest concepts [8]. In this work, a genetic algorithm is developed and used to identify thermophysical properties of fouling deposited onto the internal surface of a heat exchanger. The identification procedure is based on the minimization of the residual between a measured temperature and a calculated one. The system under investigation, a bi-layer sample composed of a section of a heat exchanger with fouling deposited on, 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. Fouling 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. Fig. 1 shows a deposited fouling upon the internal surface of a heat exchanger:

To determine the thermophysical properties of the fouling added layer of thickness e_1, a section of a heat exchanger with fouling deposited on is studied (Fig. 2).

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

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

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.

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.

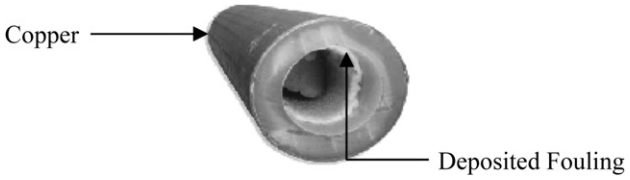

Fig. 1. Fouling deposited onto the internal surface of a heat exchanger.

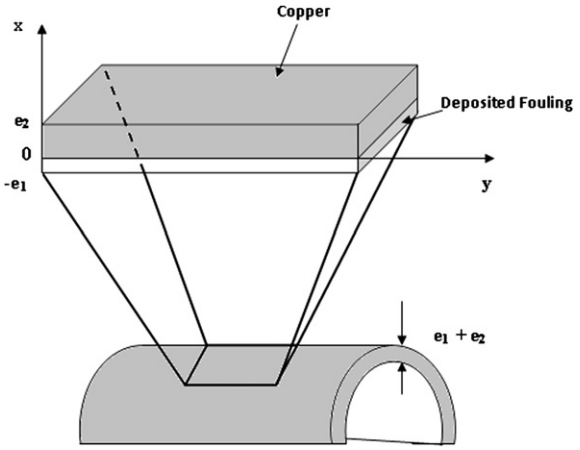

Fig. 2. System under investigation.

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

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

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

$$T_i = 0 \text{ at } t = 0\,\text{s} \tag{3}$$

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

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

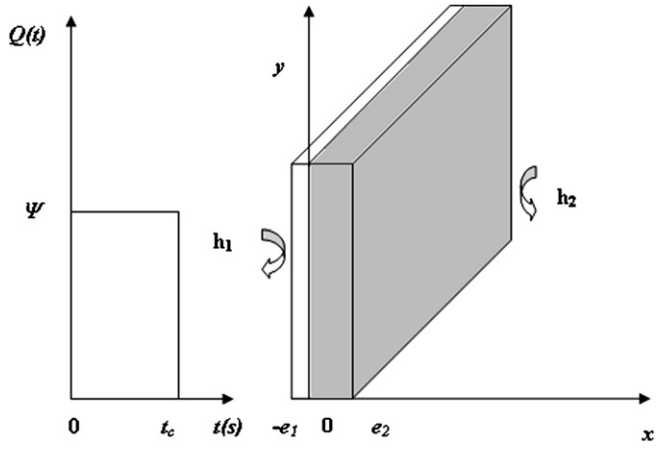

Fig. 3. Principle of the finite width pulse heat flux method.

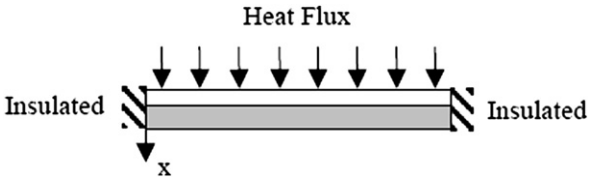

Fig. 4. One-dimensional boundary condition.

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

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

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

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

Here θ_f and θ_r are the Laplace transforms of the front and rear face temperatures of the sample, 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:

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

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

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

where Ψ is the density of the crenel heating flux (Fig. 3).

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

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

Due to the large number of parameters encountered in the mathematical model, this study is presented in dimensionless space with dimensionless parameters. The rear face temperature in Laplace space for a crenel heating excitation is given by:

$$\theta_r = \frac{\beta_4}{\beta_1^2 s_1^2} \frac{(1 - \exp(-s_1^2 t_c^*))}{(\delta + \varphi + \phi_1 + \phi_2)} \tag{12}$$

where

$$\delta = \left[s_1 \cdot ch(s_2) sh(s_1) + \beta_5 \cdot \beta_6 \cdot s_1^2 \cdot sh(s_2) sh(s_1) + \beta_6 \cdot s_1 \cdot ch(s_1) sh(s_2) \right] \tag{13}$$

$$\varphi = \beta_2 \beta_3 \left[\frac{1}{\beta_6 s_1} ch(s_1) sh(s_2) + \beta_5 \cdot ch(s_1) ch(s_2) + \frac{1}{s_1} sh(s_1) ch(s_2) \right] \tag{14}$$

$$\phi_1 = \beta_2[ch(s_1)ch(s_2) + \beta_5\beta_6 s_1 \cdot ch(s_1)sh(s_2) + \beta_6 sh(s_1)sh(s_2)] \quad (15)$$

$$\phi_2 = \beta_3\left[ch(s_1)ch(s_2) + \beta_5 s_1 \cdot ch(s_2)sh(s_1) + \frac{1}{\beta_6}sh(s_1)sh(s_2)\right] \quad (16)$$

The dimensionless parameters are defined by:

$$s_1 = \sqrt{\frac{p}{\beta_1}},\ \beta_1 = \frac{a_1}{e_1^2},\ s_2 = \sqrt{\frac{p}{a_2}}e_2,\ t_c^* = \beta_1 t_c,\ \beta_2 = \frac{h_1 e_1}{\lambda_1},$$
$$\beta_3 = \frac{h_2 e_2}{\lambda_2},\ \beta_4 = \frac{\psi}{\rho_1 C_{p1} e_1},\ \beta_5 = \frac{R_c\lambda_1}{e_1},\ \beta_6 = \left(\frac{\lambda_2\rho_2 C_{p2}}{\lambda_1\rho_1 C_{p1}}\right)^{1/2} \quad (17)$$

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 [5]:

$$T_2^*(t,\beta) = \frac{Ln(2)}{t}\sum_{i=1}^{n} V_i\theta_r\left(\frac{iLn(2)}{t}\right) \quad (18)$$

where V_i are the Graver–Stehfest's coefficients function, and $\beta = [\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]$ 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 global heat transfer coefficients (h_1 and h_2), and the contact resistance R_c between the fouling and the copper.

4. Sensitivity study

The aim of performing a sensitivity study before starting any estimation procedure is to evaluate the possibility to simultaneously estimate all unknown parameters. This depends on both magnitude of the parameters sensitivity coefficients and the correlation among the parameters. A sensitivity coefficient, X_{ij}, is defined as the effect that a change in a particular parameter β has on the variable state. The larger X_β, the more sensitive $T_{crenel}(t,\beta)$ is to β and the easier the estimation of this parameter. Mathematically, the sensitivity coefficients are defined as the first derivative of the measured variable with respect to the parameters of the model:

$$X_\beta = \left.\frac{\partial T_{crenel}(t,\beta)}{\partial\beta}\right|_{\beta_j\neq\beta} \quad (19)$$

where $\beta = [\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]$ and β_j are all parameters other than β that remain constant.

When performing a sensitivity study, it is meaningful to examine the reduced sensitivity $Z_{\beta j}$ which are obtained by multiplying the original coefficients by the parameter referred to [9]. These coefficients have the same unit as the state variable (temperature). Using the finite difference approximation, reduced sensitivity coefficients are written as:

$$Z_{\beta j} = \beta_j X_{ij} = \beta_j\frac{T_{icrenel}(t,\beta_j+\delta\beta) - T_{icrenel}(t,\beta_j)}{\delta\beta_j} \quad (20)$$

where $\delta\beta = (0,\ldots,0,\delta\beta_j,\ldots,0)$ is a small variation of the parameter β_j.

In general, these sensitivity coefficients must be large. The simultaneous identification of many parameters using a based gradient method is possible only if different $Z_{\beta j}$ are uncorrelated in the course of time. The degree of correlation among all parameters is obtained by computing the off-diagonal elements of the correlation matrix:

$$r(\beta_i,\beta_j) = \frac{\mathrm{cov}(\beta_i,\beta_j)}{\sqrt{\mathrm{var}(\beta_i)\mathrm{var}(\beta_j)}} \quad (21)$$

where the variance–covariance matrix (cov (β_j, β_i)) is given by the following equation:

$$\mathrm{cov}(\beta_i,\beta_j) = (X^T X)^{-1}\sigma_n^2 = \sigma_n^2\begin{bmatrix} \mathrm{var}(\beta_1) & \mathrm{cov}(\beta_1,\beta_2) & \cdot & \mathrm{cov}(\beta_1,\beta_6) \\ \mathrm{cov}(\beta_2,\beta_1) & \cdot & \cdot & \cdot \\ \cdot & \cdot & \cdot & \cdot \\ \mathrm{cov}(\beta_6,\beta_1) & \cdot & \mathrm{cov}(\beta_6,\beta_5) & \mathrm{var}(\beta_6) \end{bmatrix} \quad (22)$$

We notice that the variance–covariance matrix is related to the standard deviation of the errors measurement that is assumed to be uncorrelated, additive, normally distributed with zero mean and constant standard deviation σ_n equal to 9.3×10^{-3} K.

The correlation matrix is a bridge over which we measure the degree of interrelationship among two parameters which tells us whether if they vary together perfectly, near perfectly, or there is no correlation between them. It provides a way of an easily comparison of correlation factors and a determination of clusters of parameters that co-vary. The estimated parameters can be considered correlated when the correlation coefficients are near from the unity [10], and uncorrelated when they are near from zero. The correlation matrix corresponding to the six preceding parameters is given in Table 1. To be compared, the table is calculated from the reduced sensitivities. Since the correlation $r(\beta_i, \beta_j)$ between β_i and β_j is the same as $r(\beta_j, \beta_i)$ between β_j and β_i, only the top triangular portion of the matrix is given. The diagonal terms are equal to the unity because each parameter is completely correlated with itself and the off-diagonal terms are between −1 and 1.

From the correlation matrix and according to Figs. 5(a), (b) and 6, one notes primarily that β_1 is correlated to β_2 and β_3 especially for long times ($t > 90$ s) when the sensitivity coefficients of β_1, β_2 and β_3 are linearly dependent. Secondarily we remark from Figs. 5(c) and 6 that in most cases β_2 and β_3 are linearly, positively and perfectly correlated. This remark can be emphasized by the value of the correlation coefficient between β_2 and β_3 which is near from the unity. Thirdly, Fig. 5(d) and (e) show that β_2 and β_3 are correlated to β_6. In fact, the correlation coefficients $r(\beta_2, \beta_6)$ and $r(\beta_3, \beta_6)$ are higher than 0.908 and according to Fig. 6 for $t > 45$ s the reduced sensitivity coefficients have the same shape. Fourthly, on the one hand, it can be seen from the correlation matrix, Figs. 5(f), (g) and 6 a good correlation in the earliest time between β_4 and β_5 and between β_4 and β_6 on the other hand. Fifthly, Fig. 6 shows that the reduced sensitivity coefficients of β_5 and β_6 have the same forms and their maxima are reached almost at the same time. Besides Fig. 5(h) shows that these two parameters are strongly correlated. Finally, we have to mention that the other coefficients correlation $r(\beta_i, \beta_j)$ measure a significant interrelationship between the different parameters which are in most cases higher than 0.41.

Table 1
Correlation matrix.

	$r(\beta_i, \beta_1)$	$r(\beta_i, \beta_2)$	$r(\beta_i, \beta_3)$	$r(\beta_i, \beta_4)$	$r(\beta_i, \beta_5)$	$r(\beta_i, \beta_6)$
$r(\beta_1, \beta_j)$	1	−0.95	−0.96	0.7	−0.58	−0.41
$r(\beta_2, \beta_j)$		1	0.99	−0.69	0.79	0.91
$r(\beta_3, \beta_j)$			1	−0.65	0.75	0.908
$r(\beta_4, \beta_j)$				1	−0.93	−0.98
$r(\beta_5, \beta_j)$					1	0.97
$r(\beta_6, \beta_j)$						1

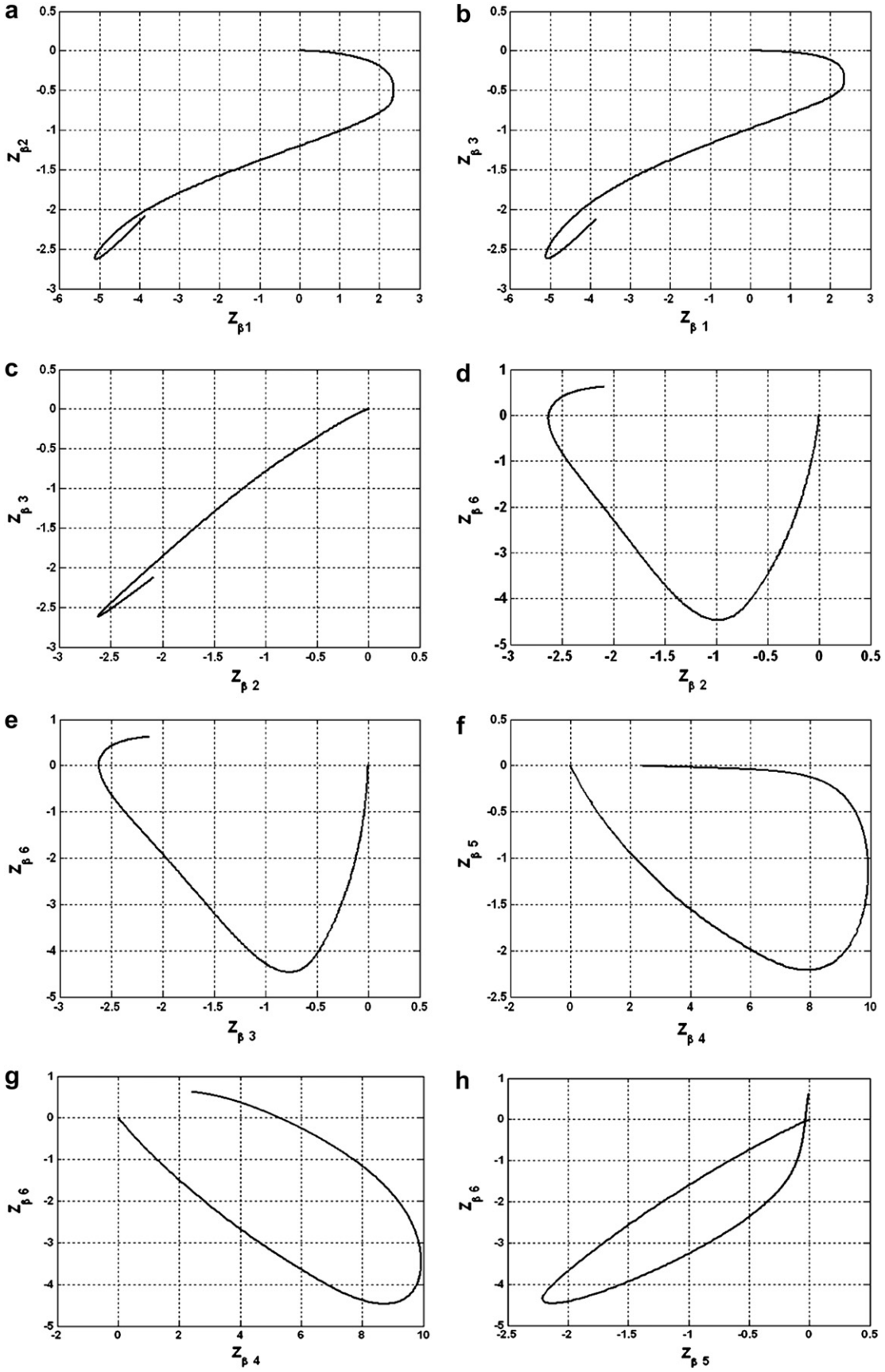

Fig. 5. Linear dependence between the dimensionless sensitivity coefficients of: $Z_{\beta 1}$ and $Z_{\beta 2}$: 5(a), $Z_{\beta 1}$ and $Z_{\beta 3}$: 5(b), $Z_{\beta 2}$ and $Z_{\beta 3}$: 5(c), $Z_{\beta 2}$ and $Z_{\beta 6}$: 5(d), $Z_{\beta 3}$ and $Z_{\beta 6}$: 5(e), $Z_{\beta 4}$ and $Z_{\beta 5}$: 5(f), $Z_{\beta 4}$ and $Z_{\beta 6}$: 5(g), $Z_{\beta 5}$and $Z_{\beta 6}$: 5(h).

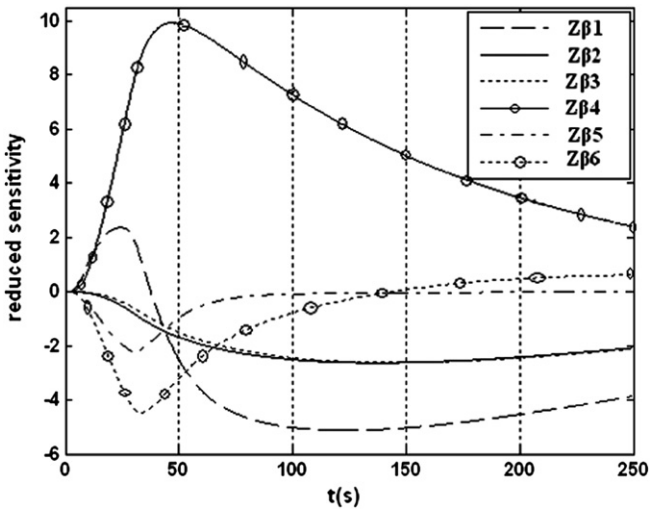

Fig. 6. The variation of reduced sensitivity coefficients of the reduced model.

The sensitivity study has shown that more than two parameters are correlated and some other parameters are nearly correlated. Therefore, the use of a traditional method like gradient methods or analytical methods to estimate thermophysical properties of the deposited fouling becomes very difficult. In fact, these methods are incapable to estimate correlated or nearly correlated parameters simultaneously and they need to define a rapport between them to be estimated. For these reasons we have adopted a heuristic search based on genetic algorithms to estimate thermophysical properties of the deposited fouling.

5. Parameters estimation: use of genetic algorithm

The basic idea of the inverse problem considered in this study is regarded as a parameter estimation problem. It is about determining the vector of parameters β that minimizes a fitness function $S(\beta)$ that corresponds to the gap between the measured temperature T_{measured} and the mathematical model output $T_2^*(t,\beta)$, and to improve estimated parameters until the mathematical model output is sufficiently close to the measurements as written in the following equation:

$$\min(S(\beta)) = \sum_{i=1}^{N}\left(T_{\text{measured}} - T_2^*(t,\beta)\right)^2 \tag{23}$$

To minimize this fitness function there are many methods, among them we mention the gradient methods which are largely used by many researchers in different domains. Although these techniques are well developed, they maintain significant drawbacks. Their principle requires the evaluation of the derivatives of the fitness function $S(\beta)$ by differentiating equation (23) with respect to each of the unknown parameters β_j ($j = 1,\ldots,6$) and then setting the resulting expression equal to zero yielding to the following set of algebraic equation:

$$\sum_{i=1}^{n} 2*\frac{\partial T_{\text{crenel}}(t,\beta)}{\partial \beta_j}[T_{\text{crenel}}(t,\beta) - T_{\text{measured}}] = 0 \tag{24}$$

From their principle, we note that gradient methods can be applicable only for derivable functions. Furthermore, employing gradient search methods mechanism need to start from an initial guessed solution near to the exact solution. In these approaches, the use of a bad starting point may result in the solution getting trapped in a local optimum [8]. 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 genetic algorithm which is implemented in this study to search for optimal values of the vector β composed of six parameters $[\beta_1, \beta_2, \beta_3, \beta_4, \beta_5, \beta_6]$, called chromosomes or individuals, and they represent the unknown parameters of the model $T_2^*(t,\beta)$. In the genetic algorithm, the solution is obtained with a random search process based on the principles of natural selection and survival of the fittest from natural evolution which were first described by Darwin. Genetic algorithm in particular became popular through the work of John Holland in the early 1970s, and particularly his book "Adaptation in Natural and Artificial Systems" (1975). Genetic algorithm is categorized as global search heuristics [11,12].

Genetic algorithm is implemented as a computer simulation in which a population of abstract representations (called chromosomes) of candidate solutions (called individuals) to an optimization problem evolves toward better solutions. Mathematically, the population is a matrix of p parameters and n individuals satisfying boundary and system constraints.

$$\text{Population} = P = \begin{bmatrix} \beta_1^1 & \beta_2^1 & \beta_3^1 & \ldots & \beta_p^1 \\ \beta_1^2 & \beta_2^2 & \cdot & \ldots & \beta_p^2 \\ \cdot & \cdot & \cdot & \ldots & \cdot \\ \cdot & \cdot & \beta_3^j & \ldots & \cdot \\ \beta_1^n & \beta_2^n & \beta_3^n & \ldots & \beta_p^n \end{bmatrix} = \begin{bmatrix} \beta^1 \\ \beta^2 \\ \cdot \\ \cdot \\ \beta^n \end{bmatrix} \tag{25}$$

Each row in the population is called an individual representing a solution to the problem at hand. Traditionally, solutions are represented in binary as strings of zero and one, but integers and floating point numbers can also be used. Optimal parameters are obtained by exchanging genetic information between individuals to reproduce improved solutions from one generation to the next by four genetic operators, which are evaluation, selection, crossover and mutation as shown in the following flowchart (Fig. 7).

The evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, every chromosome is evaluated by measuring its fitness function $S(\beta)$ in the population and assigning to it a score. Based upon their fitness, multiple individuals are stochastically selected from the current population to form a new population of $n/2$ individuals. To create the next generation, new individuals, 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. The cycle restarts by the formulation of a new generation 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. The algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached.

5.1. Selection

According to Darwin's evolution theory, the selection is the operator that select best individuals (chromosome) according to their fitness function $S(\beta)$ to survive and create new children. The selection of the parents can occur in many ways, but all selection methods have the same objective of preserving good individuals

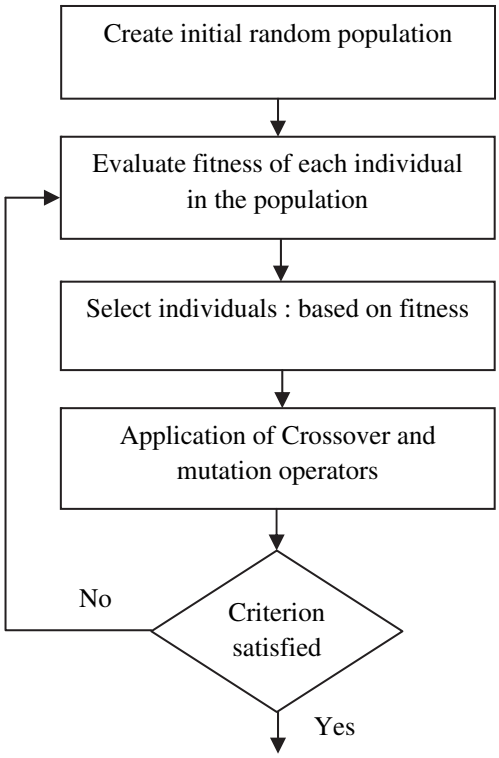

Fig. 7. Genetic algorithm flowchart.

and discarding the less fit ones. There are a number of different selection methods, such as roulette wheel selection, rank selection, elitism selection, etc. The roulette selection is one of the traditional selection techniques. The commonly used reproduction operator is the proportionate reproductive operator where a string is selected from the mating pool with a probability proportional to the fitness [13]. The principle of roulette selection is a linear search through a roulette wheel with the slots in the wheel weighted in proportion to the individual's fitness values like in the following figure.

The better the chromosomes are, the more chances to be selected they have. The previous selection will have a problem when the fitness values differ very much. As shown in Fig. 8 where chromosome 2 has a fitness higher than 63%, so its circumference occupies 63% of the roulette wheel, and then other chromosomes have too few chances to be selected. For this disadvantage the rank selection is used. It ranks the population and every chromosome receives fitness from the ranking as described in the following principle: the worst chromosome has fitness 1, the second worst fitness ***2*** and the best has fitness *n* (number of chromosomes in the population). It results in slow convergence but prevents too quick

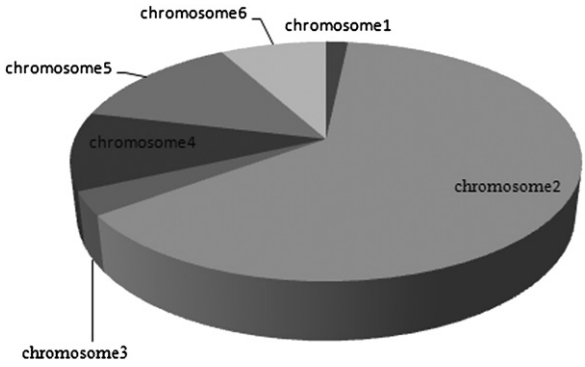

Fig. 8. Principle of the roulette wheel selection (*graph of fitnesses*).

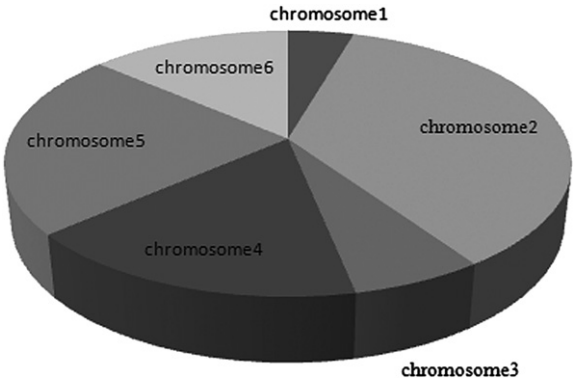

Fig. 9. Situation after ranking (graph of order numbers).

convergence. It also keeps up selection pressure when the fitness variance is low. It preserves diversity and hence leads to a successful search. We can see in Fig. 9, how the situation changes after changing fitness to order number.

After ranking, all the chromosomes have a chance to be selected. But this method can lead to slower convergence, because the best chromosomes do not differ so much from other ones. In these approaches, we used an elitist selection. Elitism preserves the best chromosomes in the next generation, and the rest are removed. This ensures that the chromosomes of the most highly fit member of the population are passed on to the next generation without being altered by genetic operators. Using elitism ensures that the maximum fitness of the population can never be kept from one generation to the next. Elitism usually brings about a fast convergence of the population [14]. In some cases, elitism improves the chances of trapping in a local optimum, while in others it reduces it [14], besides chromosomes with bed fitness might contain some genes (parameters) that can lead to a more rapid convergence. For this reason, we used in this work an elitist selection based on the following principle: eighty percent of the new population is chosen from the best chromosomes that have the minimum fitness, and the other twenty percent is chosen from the chromosomes that have the maximum fitness of the old population. This ensures that selective operator maintains the genetic diversity and reduces the chance to be trapped in a local optimum.

5.2. Crossover

Taking a cue from nature, genetic algorithms do not use mutation very often. The primary mechanism in genetic algorithms to create new individuals is crossover. In its simplest form, crossover randomly chooses two individuals from the pool that were selected to be parents, and exchanges segments of their two chromosomes around a chosen point as shown in Fig. 10.

The result of the crossover is two new individuals, each with a segment of chromosome from each parent. There are several types of crossovers, including single-point crossover, multi-point

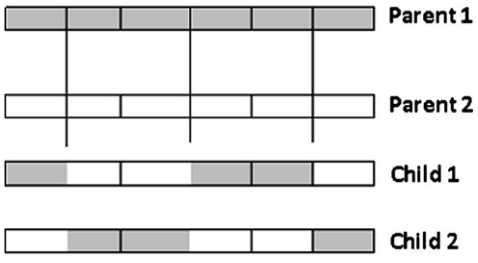

Fig. 10. Principle of the crossover operator.

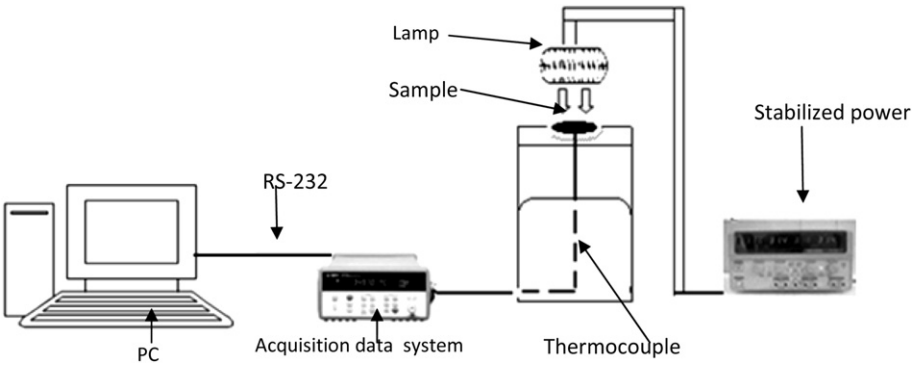

Fig. 11. Experimental device.

crossover, and uniform crossover [15]. In this work, we applied a three-point crossover as shown in Fig. 10. Child 1 and child 2 are different from parent 1 and parent 2, but save some character of parents.

5.3. Mutation

Finally, to satisfy the diversity of the population every individual is subject to a random change in the population by using a mutation operator. In contrast to crossover operators, mutation operators focus more on local search because they can only modify properties of individuals but cannot recombine properties from deferent parents.

6. Experimental setup and results

The experimental apparatus is schematically shown in Fig. 11. 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 0.5 mm; the second layer is the copper of the heat exchanger of thickness e_2 equal to 1 mm. 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 1 kw 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 250 s, and the sampling interval is set as 0.25 s 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 34970 A) which allows transferring data to a computer via an RS-232 interface.

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 six genes (six parameters), and in 200 generation steps with the same procedure. The initial population is generated in a large domain. Each parameter β_i is delimited by an upper and a low bound, that is $\beta_1 \in [0, 200\ s^{-1}]$, $\beta_2 \in [0, 1]$, $\beta_3 \in [0, 1]$, $\beta_4 \in [0, 50]$, $\beta_5 \in [0, 10]$, $\beta_5 \in [1, 100]$.

Fig. 12 shows a comparison between measured temperature and the calculated one using six chromosomes of the initial population.

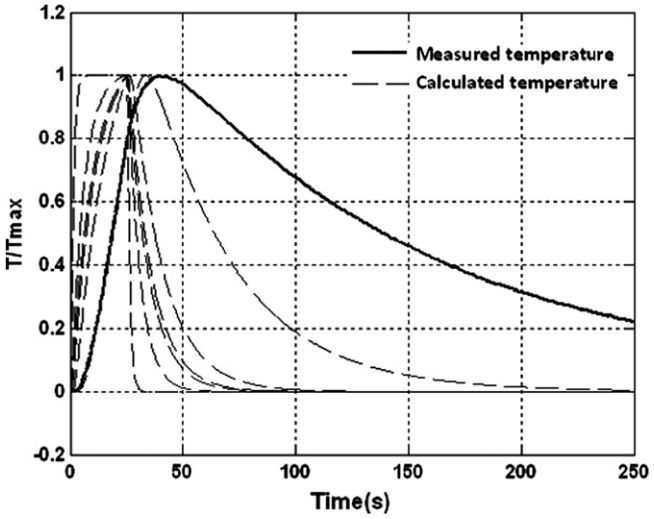

Fig. 12. Comparison between measured temperature and calculated temperature for the initial population.

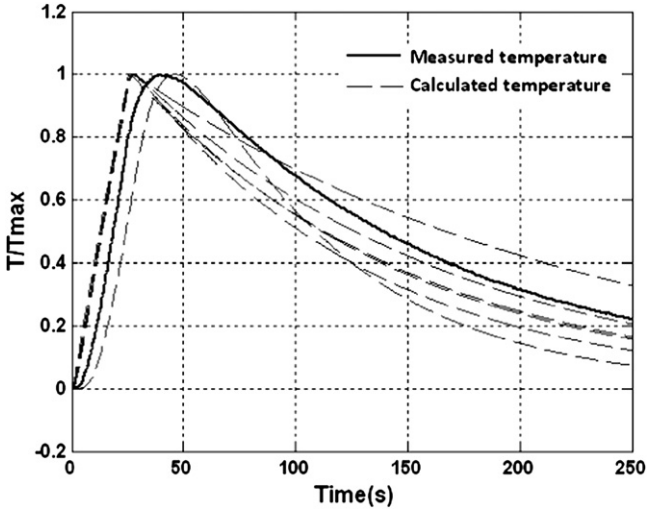

Fig. 13. Comparison between the measured and the calculated temperature at the tenth generation.

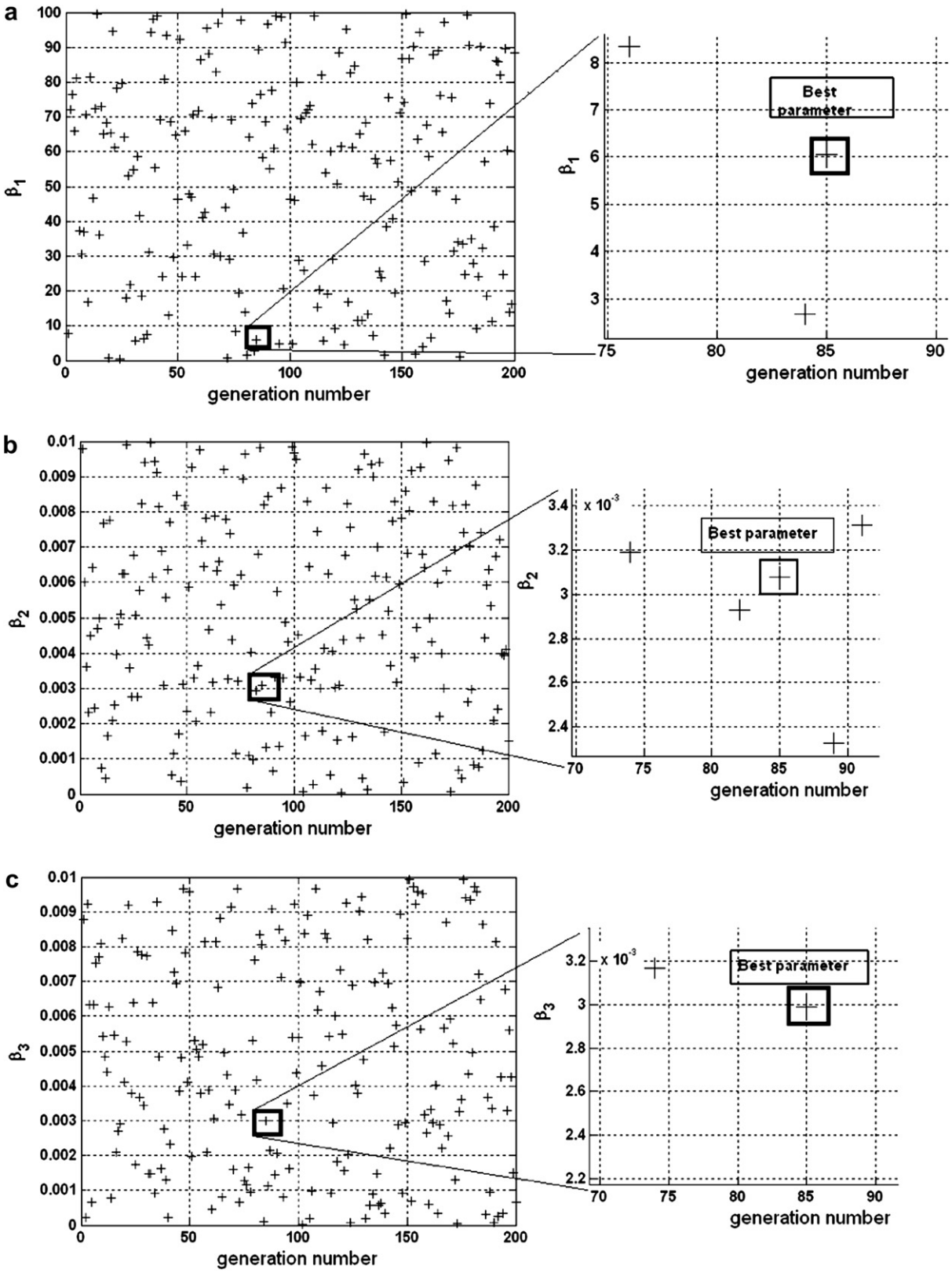

Fig. 14. Evolution, along the successive generations (left), of parameter β_i and the best so-far parameter (right): (a) β_1, (b) β_2, (c) β_3, (d) β_4, (e) β_5, (f) β_6.

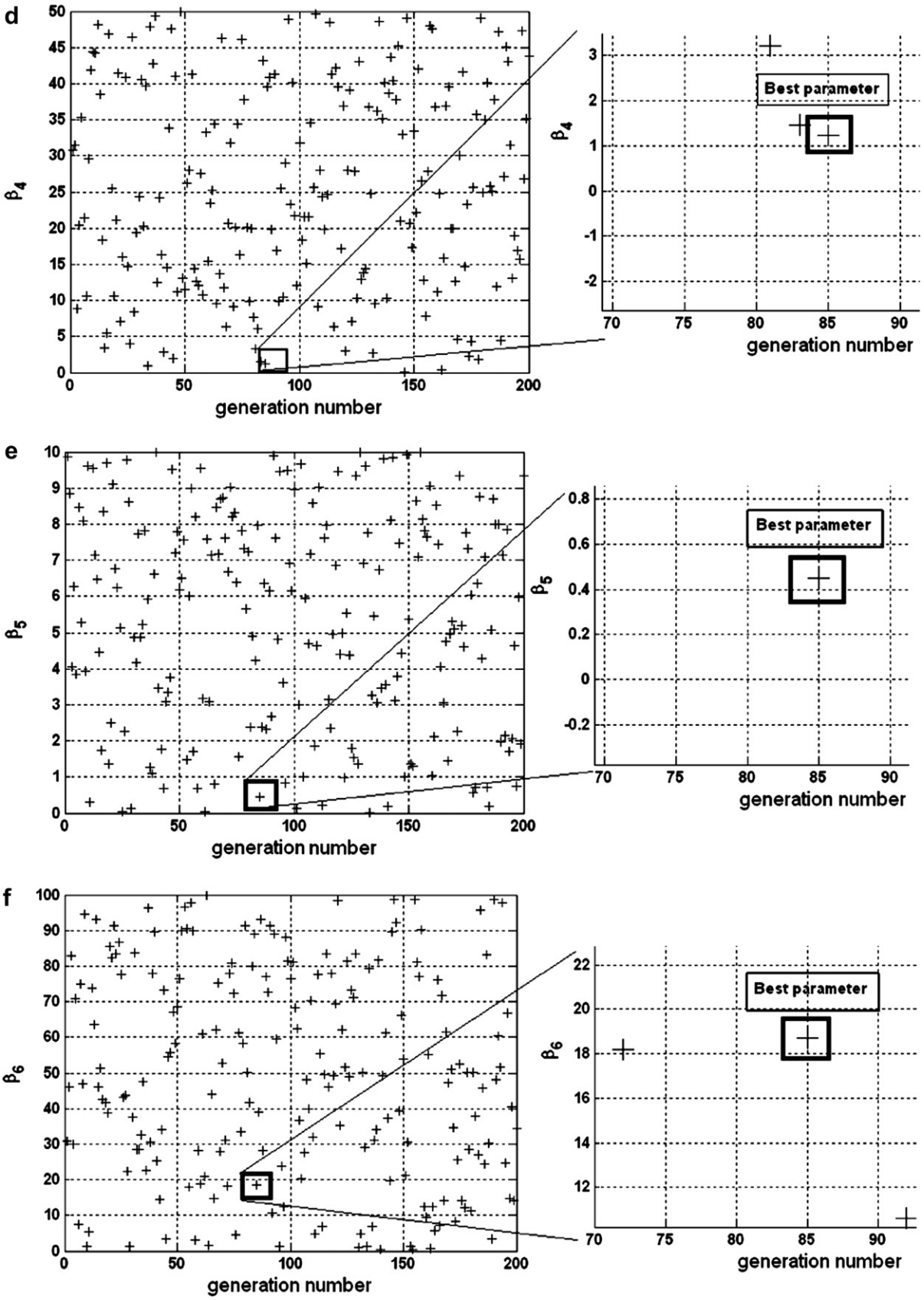

Fig. 14. (*continued*).

Table 2
Estimated parameters.

Parameters	β_1	β_2	β_3	β_4	β_5	β_6
Estimated values	6.09	3.19×10^{-03}	2.98×10^{-03}	1.24	0.45	18.6
Standard deviation $\sigma_{\beta i}$	0.11	1.36×10^{-4}	6.36×10^{-5}	1.63×10^{-2}	1.86×10^{-2}	0.32
Relative uncertainty %	1.19	4.28	2.13	1.31	4.17	1.70

Table 3
Calculated dimensional parameters.

Parameters	a_1 ($m^2\ s^{-1}$)	$\rho_1 C_{p1}$ ($kJ/m^3\ K$)	λ_1 ($W\ m^{-1}\ K^{-1}$)	h_1 ($W\ m^{-2}\ K^{-1}$)	h_2 ($W\ m^{-2}\ K^{-1}$)	R_c ($W\ m^{-2}\ K^{-1}$)
Values	0.97×10^{-6}	2010	1.96	15.7	14.6	9.12×10^{-5}
Relative uncertainty %	3.88	3.31	7.20	12.47	10.33	12.36

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.

After the creation of the initial population, chromosomes are evaluated and the best are selected according to their fitness by the use of an elitist selection as described above, then the three-point crossover and the uniform mutation are applied. Since these four genetic operators have been applied, we plotted in Fig. 13 the response of the calculated temperature using the six best individuals at the tenth generation. We notice that, along the evolution generation, the responses of the mathematical model have the tendency to come closer of the experimental response.

This iterative process (evaluation, selection, crossover and mutation) continues until one of the following possible termination criteria is met: if a known optimal or acceptable solution level is attained; or when the fitness for the best so-far chromosome does not change significantly from iteration to iteration; or if a maximum number of generations have been performed. When the last condition is chosen, genetic algorithms are typically iterated for anywhere from 10 to 500 or more iterations [7]. In this work, the stop criterion is met when the fitness $S(\beta)$ of the best chromosome is lower then $10^{-3}\ K^2$ and the algorithm achieves 200 generations. Fig. 14 illustrates the different parameters evolution from the initial to the final generation and stresses the efficiency of the genetic algorithm. This figure shows that the convergence is reached at the generation number eighty five.

The performance of the genetic algorithm was performed by averaging five runs with different initial populations; the genetic algorithm converges to the average parameters given in Table 2.

The results shown in Table 2 clearly indicate that the genetic algorithm allows the simultaneous estimation of highly correlated parameters. As one would expect, the estimation procedure is more accurate as the sensitivity coefficients are high, as outlined in Fig. 6. These results confirm the sensitivity study.

Using the definition given in equation (17), the unknown thermophysical properties of the fouling and the global heat transfer coefficients can be easily 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 coefficients h_1 and h_2 on the front face and the on rear face of the sample, and the contact resistance R_c; their values are given in Table 3.

The relative uncertainties on calculated parameters are obtained using the following expressions:

$$\frac{\Delta a_1}{a_1} = \frac{\Delta \beta_1}{\beta_1} + 2\frac{\Delta e_1}{e_1}$$

$$\frac{\Delta \rho_1 C_{p1}}{\rho_1 C_{p1}} = \frac{\Delta \beta_3}{\beta_3} + \frac{\Delta \Psi}{\Psi} + \frac{\Delta e_1}{e_1}$$

$$\frac{\Delta \lambda}{\lambda} = \frac{\Delta a_1}{a_1} + \frac{\Delta \rho_1 C_{p1}}{\rho_1 C_{p1}}$$

$$\frac{\Delta h}{h} = \frac{\Delta \beta_2}{\beta_2} + \frac{\Delta \lambda}{\lambda} + \frac{\Delta e_1}{e_1}$$

$$\frac{\Delta R_c}{R_c} = \frac{\Delta \beta_4}{\beta_4} + \frac{\Delta \lambda}{\lambda} + \frac{\Delta e_1}{e_1}$$

The thickness of the deposited fouling and the heat flux density are known with an accuracy of 1%. One can easily observe from these results (Table 3) that the genetic algorithm succeeds in identifying the correlated thermophysical properties of fouling with reasonable errors. 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. Fig. 15 presents comparison between the measurements and the optimal model using the estimated parameters. This figure shows a good agreement between the measured and calculated temperatures.

These results show that the proposed solution algorithm is effective in the determination of the unknown thermophysical properties of the fouling accumulated onto the internal surface of the 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.

To qualify this evaluation, the residual between measured and calculated temperatures is represented in Fig. 16. We remark that it is a centered residual on zero and has a constant standard deviation equal to 9.75×10^{-3} K. We can thus consider that these estimations are completely acceptable.

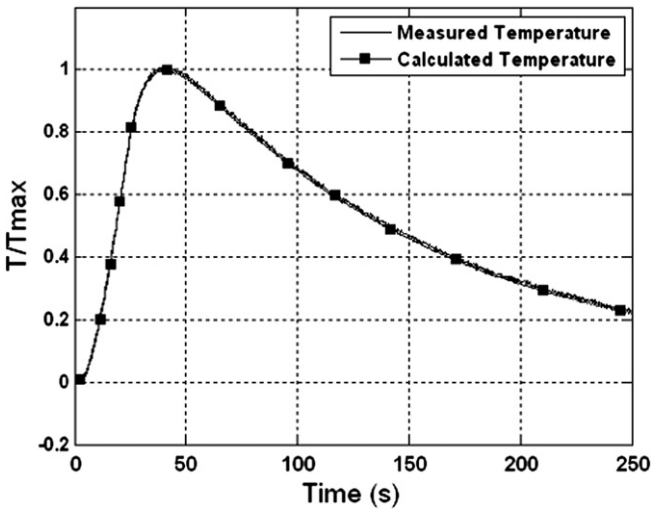

Fig. 15. Comparison between measured and calculated temperature at the convergence of the GA.

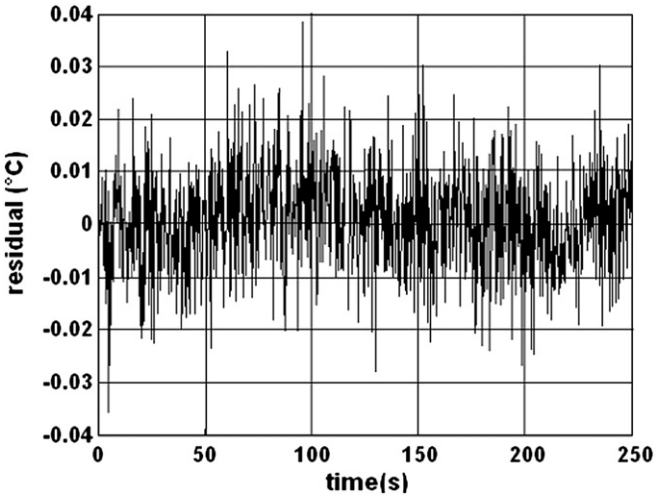

Fig. 16. Residual between calculated and measured temperatures.

7. Conclusion

An estimation procedure presented in this paper allows the estimation of thermophysical properties of fouling deposited onto internal surface of heat exchanger. This procedure is based on a stochastic method using genetic algorithm whose chromosomes code the unknown model parameters. The non-gradient nature of genetic algorithm has been exploited to handle problems of the initialization solution and the degree of correlation between parameters. The estimation method consists in minimizing an objective function which computes the sum of squared errors between a measured temperature and a calculated one which is developed using the quadrupoles formalism. The experimental results show, on the one hand, the capability of the proposed estimation approach to identify a large number of unknown parameters even in presence of a strong correlation between them. On the other hand, this study allows us to determine the thermal resistance of the deposited fouling which has a harmful effect on the thermal efficiency of heat exchanger.

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