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Abstract—A parallelized numerical method based on Fireworks Algorithm (FWA) has been developed to solve the Inverse Heat Transfer Problem. The Heat Transfer Coefficient functions obtained on the surfaces of an axisymmetric workpiece as a function of time are estimated by applying the novel technique. The objective function to be minimized by the FWA approach is defined by the deviation of a virtually acquired and the calculated temperatures. Numerical results have been demonstrated in 3 case studies.

Keywords—Fireworks Algorithm, IHCP, Heat Transfer Coefficients

I. INTRODUCTION

The knowledge of the thermal boundary conditions helps to understand the heat transfer phenomena took place during heat treatment processes. Heat Transfer Coefficients (HTC) describes the heat exchange between the surface of an object and the surrounding medium. The determination of HTC [1] faces a typical Inverse Heat Conduction Problem (IHCP). The IHCP methods are using the thermal samples acquired and predicted by simulations at a location of the work-piece. Several IHCP approaches are based on optimization methods, where the objective function that has to be minimized is determined as the difference of the recorded and calculated temperature data [2, 3]. Genetic algorithms [4, 5, 6] are applied successfully for solving many types of IHCP cases. The Fireworks Algorithm (FWA) became popular in recent years due to its ability to maintain a right balance between convergence and diversity [7, 8]. The efficiency of FWA technique in inverse heat conduction analysis was not analyzed yet before. We have shown that FWA can reduce the stability problems of the classical methods, for solving the inverse heat conduction problems.

In this work, an IHCP analysis of a time-dependent HTC(t) is presented. Cooling curves measured at the centerline of a cylinder have been used to obtain the inverse heat transfer computation. The objective function which is defined by the quadratic residual between the measurements and the calculated temperatures is minimized. The optimization techniques have been parallelized and implemented on a CPU architecture. Numerical results are demonstrated that HTC functions can be performed by using the proposed approach.

II. THE INVERSE HEAT TRANSFER PROBLEM

Assuming that the temperature on its surface is theoretical set during the heat transfer process, it is possible to solve the inverse heat conduction problem by determining the temperature variations of the thermal boundary conditions [1, 2, 3]. The temperature is given at *p* points in the solid region. Calling T_k^m, the theoretical set temperatures, and T_k^c, the calculated temperatures at those points, the solution of the present inverse problem can be obtained by minimizing the following fitness function

$$S = \sum_{k=1}^{p} (T_k^m - T_k^c)^2 = min \qquad (1)$$

The inverse problem is recast as an optimization problem. A variety of numerical and analytical techniques have been developed to solve the optimization problems.

III. THERMAL FIELD CALCULATION

A one-dimensional axisymmetric heat conduction model is considered to estimate the temperature distribution in a cylindrical work-piece. Both the thermal conductivity, density, and the heat capacity are assumed as functions of the temperature, respectively k(T), ρ(T) and C_p(T). The one-dimensional mathematical formulation of this nonlinear transient heat conduction problem can be described as follows:

$$\frac{\partial}{\partial r}\left(k\frac{\partial T}{\partial r}\right) + \frac{k}{r}\frac{\partial T}{\partial r} + q_v = \rho \cdot C_p \frac{\partial T}{\partial t} \qquad (2)$$

while initial and boundary conditions are

$$T(r, t = 0) = T_0 \qquad (3)$$

$$k\frac{\partial T}{\partial r} = HTC(t)\left[T_q - T(t)\right] \qquad (4)$$

where r is the radius, t is time, T_0 is the initial temperature, T_q is the temperature of the cooling medium and q_v stands for volumetric heat generation. It has to be noted that the phase transformations of the materials applied do not occur during the experiments. Therefore latent heat generation induced by phase transformations is not considered (q_v=0).

IV. FIREWORKS ALGORITHM

The basic FWA model [7] consists of fireworks and number of sparks (s) which are placed around firework. They are moving in the search space. For a N-dimensional search space, the position of the i^{th} spark is represented as $X_i = (x_{i1}, x_{i2}, \ldots, x_{iN})$. Each spark is a potential solution of the global optimum. In other words, each spark stands for a set of input parameters by its position (X_i) which could give the lowest fitness value (the global optimum) in the search space. There are more than one firework population is calculating in the space at the same time. At each generation, the new spark position is found by adding a displacement to the current position and leave intact the best fitness value of spark to memorize the best position. There are two types of sparks in the algorithm [9, 10, 11]. The first is the "explosion sparks", the second is the "gaussian sparks".

The explosion sparks displacement each dimension is calculated by

$$d_i = A_i \cdot r \qquad (5)$$

where r is a uniform distributed random number between -1 and 1. The Ai is the amplitude. The next position of spark is

$$X_i = X_i + d_i \tag{6}$$

The amplitude is calculated by

$$G = \sum_{N}^{i=1}(f(X_i) - y_{min}) \tag{7a}$$

$$A_i = \begin{cases} \hat{A} \cdot \frac{f(X_i) - y_{min}}{G}, & if\ G \neq 0 \\ 0, & if\ G = 0 \end{cases} \tag{7b}$$

where the Â constant to control the explosion amplitude. The y_{min} = min(f(X_i)) means the minimum value of fitness function. The f(X_i) the actual spark value of fitness function. Each spark has a minimum amplitude value which depends on the actual iteration and the highest iteration number (6)

$$A_{min} = A_{init} - \frac{A_{init} - A_{final}}{t_{max}} \cdot \sqrt{((2 \cdot N_{max} - n) \cdot n)} \tag{8}$$

where N_{max} is the maximum iteration number and n is the actual iteration number. The "gaussian spark" displacement is calculated by

$$d_i = g \cdot (X_k - X_i) \tag{9}$$

where the g is a Gaussian distributed random number. The X_k is also randomly selected firework position in the space, and the X_i is the spark position.

After iteration in every population, the best fitness value (F_{best}) and position (X_{best}) of spark are selected.

V. Computation Procedure for the Fireworks Algorithm

The inverse analysis aims to iteratively estimate the unknown HTCs using the FWA procedure which results in an acceptable difference between measurements taken at the given locations of the workpiece and temperatures estimated from the numerical model. The fitness function value of each spark at the n^{th} iteration is given by the difference between the theoretical set and calculated temperature curves, (4) at the position X_i^n. The computational steps of the FWA algorithm described above are given as follows:

- Step 1: Generate the initial sparks by random position, each spark are moving a dedicated population
- Step 2: Evaluate the fitness function of each spark.
- Step 3: Update the F_{best} and X_{best} for each population, if its fitness is smaller than the fitness of its previous best position.
- Step 4: Update the firework position as the best spark position.
- Step 5: Update each spark according to (4 - 9).
- Step 6: Repeat the loop until the stopping criteria or a predefined number of generations is reached (N_{max}).

It is strongly advised to parallelize the computational jobs in Step 2 because there are no need interferences between the iterations in each cycle as well as there is no communication between the sparks. The FWA algorithm process diagram can be shown on Fig. 3.

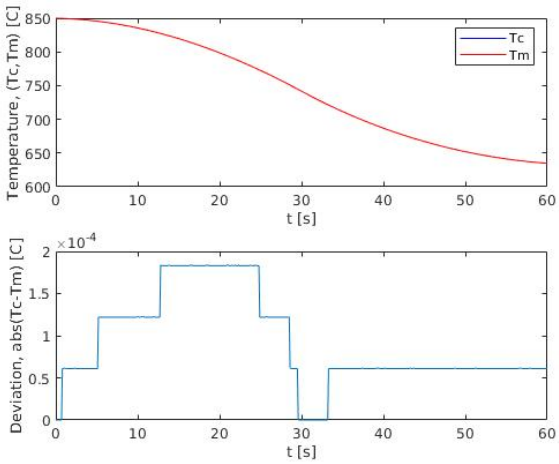
VI. Case Studies

The HTC obtained during immersion quenching of a cylindrical bar have been estimated by using the theoretical approach. The diameter of the cylindrical workpiece is assumed to 6.25 mm.

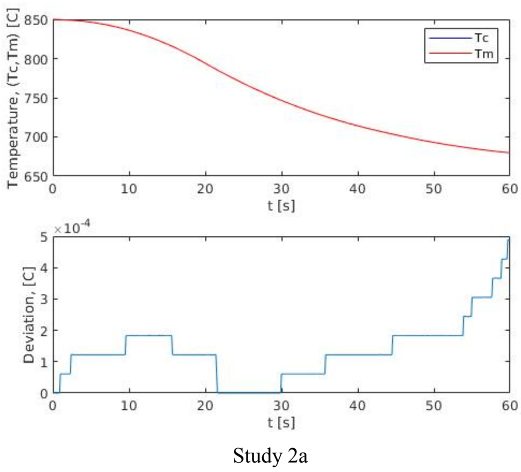
The workpiece has been heated up to 880°C and immersed in cooling material without agitation at 20°C temperature. The cooling time is 60 sec.

A 1D axisymmetric heat transfer model was applied to calculate the temperature distribution during the cooling process. Inverse computations have been carried out by including FWA algorithm, to predict the HTC(t) functions. The calculation process in each FWA stopped when the relative deviation of the fitness value was less than 0.1.

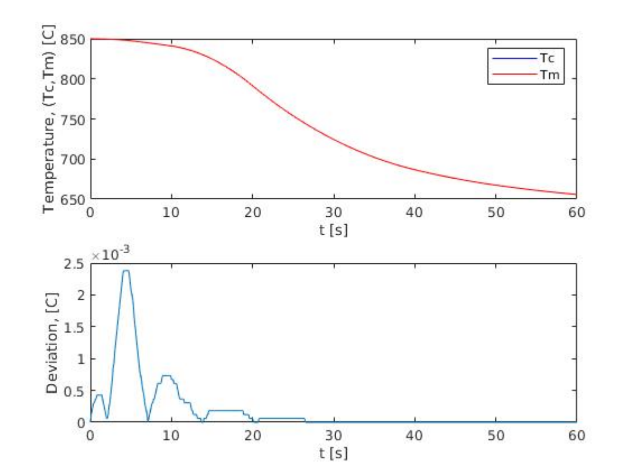
The theoretical HTC function in the first study has 3 values: (500, 5000, 800) W/(m^2K), the second study has 5 values: (200, 500, 4000, 2000, 800) W/(m^2K)) and the third study has 10 values: (100, 300, 800, 1000, 6000, 5000, 4000, 2000, 1200, 800) W/(m^2K).



Study 1a



Study 2a



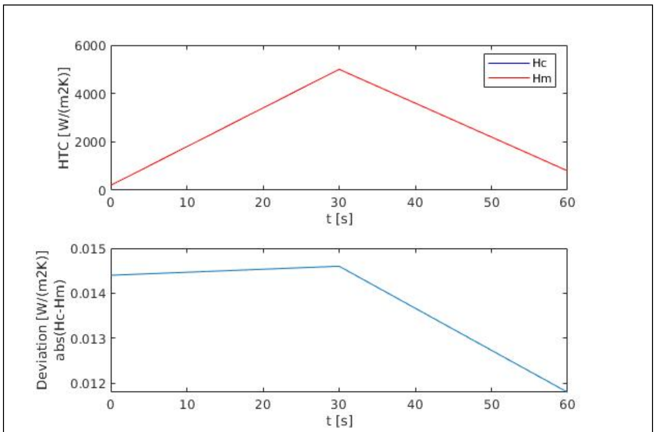
Study 3a

Fig. 1. The cooling curves of the theoretical set T_k^m, and the predicted T_k^c samples and their deviations (Study 1a, Study 2a, Study 3a)

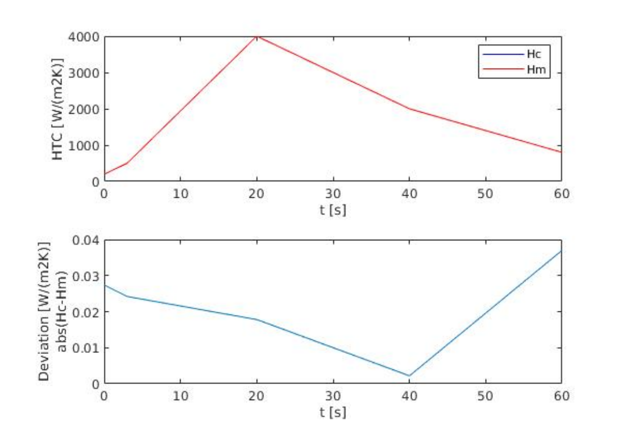
The theoretical set T_k^m, and the reconstructed T_k^c cooling curves are shown in Fig. 1 Satisfactory agreement of the original and the predicted cooling curves can be observed. The difference between the theoretical set and estimated samples as a function of time is shown in the charts of Fig. 1. In the study 1b the HTC function has only three values. In the study 2b the HTC function has five values, and in the study 3b the HTC function has ten values. The theoretical and the reconstructed HTCs and their deviations are shown in Fig. 2.

To quantify the magnitude of deviation between the theoretical set and the recovered temperature samples the mean, standard deviation and maximum value of the difference of cooling curves in each study were calculated (Table 1).

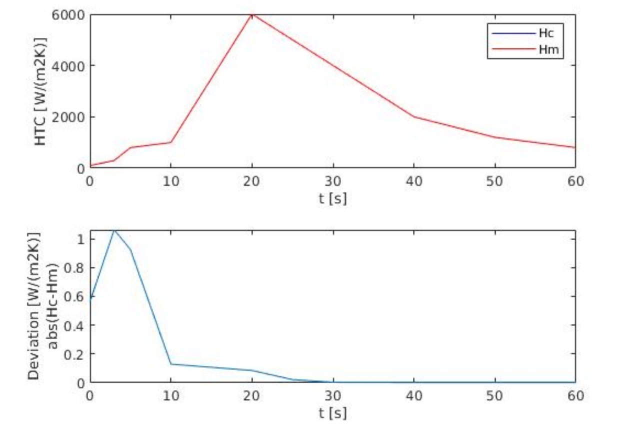
Using the FWA algorithm for estimating the HTC function in a one-dimensional axisymmetric model could be precise in the examined cases between calculated and theoretical cooling curves. On the other hand, the deviation of HTC functions not as same as accurate as the deviation of cooling curves. More investigations need to determine a modified procedure of FWA algorithm to more complex HTC functions could be calculated less or equal of calculated deviations such as one- or two-dimensional axisymmetric cases (Fig. 1, 2).



Study 1b



Study 2b



Study 3b

Fig. 2. Theoretical and predicted HTC functions and their the deviations (Study 1b, Study 2b, Study 3b)

TABLE I. THE STATISTICAL INFORMATION OF DEVIATIONS BETWEEN THEORETICAL SET T_K^M, AND THE RECONSTRUCTED T_K^C COOLING CURVES

Study	Mean deviation [°C]	Standard deviation, [°C]	Maximum deviation, [°C]
1	3.8e-05	0.0001	0.0002
2	4.0e-05	0.0001	0.0004
3	6.3e-05	0.0004	0.0024

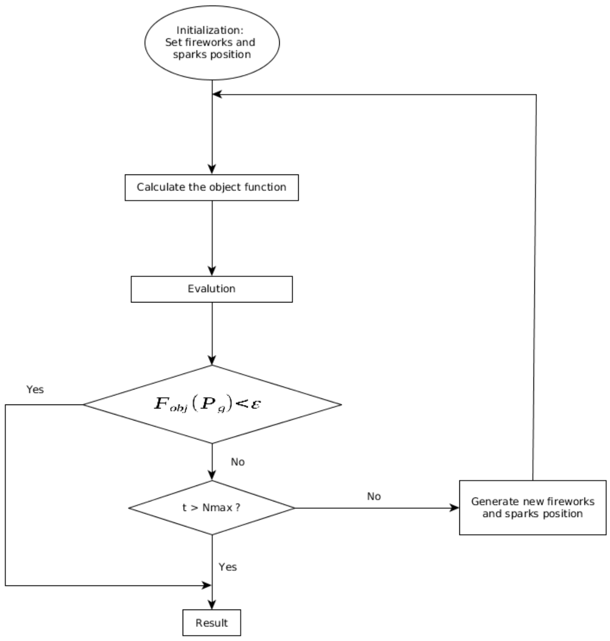


Fig. 3. The FWA algorithm process diagram

VII. CONCLUSIONS

An inverse thermal analysis using Fireworks Algorithm has been presented to estimate the Heat Transfer Coefficient in a one-dimensional heat conduction problem. The HTC obtained on the surfaces of a cylindrical work-piece was considered as functions of local coordinates and time/temperature. The temperature signals acquired during immersion quenching experiment have been applied for the inverse method. The obtained results underline the feasibility of the procedure and the capabilities for the FWA technique to predict a complex Heat Transfer Coefficients without using any prior information of the unknown transient functions.

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REFERENCES

[1] Beck J. V; Blackwell B; St Clair Jr. C.R: Inverse Heat Conduction, Wiley, New York, 1985. DOI: 10.1002/zamm.19870670331

[2] Alifanov O.M.: Inverse Heat Transfer Problems, Springer, Berlin/Heidelberg, 1994.

[3] Özisik M.N.; Orlande H.R.B.: Inverse Heat Transfer: Fundamentals and Applications, Taylor & Francis, New York, 2000

[4] Verma S.; Balaji C: Multi-parameter estimation in combined conduction radiation from a plane parallel participating medium using genetic algorithms, International Journal of Heat and Mass Transfer 50, 1706-1714., 2007 DOI: 10.1016/j.ijheatmasstransfer.2006.10.045

[5] Kim K.W.; S.W. Baek: Inverse surface radiation analysis in an axisymmetric cylindrical enclosure using a hybrid genetic algorithm, Numerical Heat Transfer Part A e Applications 46 (4) 367-381., 2004 DOI: 10.1080/10407780490478533

[6] Felde I.: Estimation of Thermal Boundary Conditions by Gradient Based and Genetic Algorithms, MATERIALS SCIENCE FORUM 729: pp. 144-149. (2012) DOI: 10.4028/www.scientific.net/MSF.729.144

[7] Y. Tan, C. Yu, S. Zheng, and K. Ding, “Introduction to fireworks algorithm,” International Journal of Swarm Intelligence Research (I-JSIR), vol. 4, no. 4, pp. 39–70, 2013.

[8] Y. Tan and Y. Zhu, “Fireworks algorithm for optimization,” in Advances in Swarm Intelligence, pp. 355–364, Springer, 2010.

[9] S. Zheng, A. Janecek, and Y. Tan, “Enhanced fireworks algorithm,” in Evolutionary Computation (CEC), 2013 IEEE Congress on, pp. 2069–2077, IEEE, 2013.

[10] J. Liu, S. Zheng, and Y. Tan, “The improvement on controlling exploration and exploitation of firework algorithm,” in Advances in swarm intelligence, pp. 11–23, Springer, 2013.

[11] J. Li, S. Zheng, and Y. Tan, “Adaptive fireworks algorithm,” in Evolutionary Computation (CEC), 2014 IEEE Congress on, pp. 3214–3221, IEEE, 2014

[12] Felde I.: Estimation of Thermal Boundary Conditions by Gradient Based and Genetic Algorithms, MATERIALS SCIENCE FORUM 729: pp. 144-149. (2012) DOI: 10.4028/www.scientific.net/MSF.729.144

[13] Y. Tan, C. Yu, S. Zheng, and K. Ding, “Introduction to fireworks algorithm,” International Journal of Swarm Intelligence Research (I-JSIR), vol. 4, no. 4, pp. 39–70, 2013.

[14] Y. Tan and Y. Zhu, “Fireworks algorithm for optimization,” in Advances in Swarm Intelligence, pp. 355–364, Springer, 2010.

[15] S. Zheng, A. Janecek, and Y. Tan, “Enhanced fireworks algorithm,” in Evolutionary Computation (CEC), 2013 IEEE Congress on, pp. 2069–2077, IEEE, 2013.

[16] J. Liu, S. Zheng, and Y. Tan, “The improvement on controlling exploration and exploitation of firework algorithm,” in Advances in swarm intelligence, pp. 11–23, Springer, 2013.

[17] J. Li, S. Zheng, and Y. Tan, “Adaptive fireworks algorithm,” in Evolutionary Computation (CEC), 2014 IEEE Congress on, pp. 3214–3221, IEEE, 2014