Adaptive Fireworks Algorithm to solve 2D Inverse Heat Conduction Problem

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***Abstract*— A numerical method for coordinate and time-dependent Heat Transfer Coefficient estimation was developed. The main element of the developed estimation procedure is the Adaptive Fireworks Algorithm, which was used for solving the Inverse Heat Conduction Problem. A parallelized solution was implemented on graphic accelerator card to speed up the calculations and the Adaptive Fireworks Algorithm was compared with Genetic Algorithm based on their computation cost. In order to demonstrate the applicability of the method, Heat Transfer Coefficients, which appears during immersion quenching in an organic oil were estimated.**

Keywords—AFWA, immersion quenching, inverse heat conduction, GPU, heat transfer coefficient

I. Introduction

Several heat transfer phenomena are associated with manufacturing or operation process, which affects the outcome of the process itself. Typically, such a process like the heat treatment of metals. As its name suggest, it strongly depends on the temperature. During the immersion quenching of steels, high temperature (800-900°C) specimens are immersed in a coolant, thus the workpieces gain their expected properties as the result of rapid cooling. Typically, increased resistance to various mechanical loads. The rate of the heat transfer during the immersion depends on many parameters (coolant type, temperature, flow conditions, geometry, surface quality etc.). The advantageous properties can be reached safely if the characteristics of the coolant is known. The example shows that there is a growing need for numerical characterization of heat transfer today. The heat transfer processes that occur during immersion cooling training can be divided into three stages in terms of their cooling mechanism (if the surface temperature of the workpiece significantly exceeds the temperature of the refrigerant). These stages are sequentially the vapor blanket, nucleate boiling, and convection during the cooling process. The existence of these sections was supported by observations [1]. Shortly after the workpiece is placed in the refrigerant, a vapor film layer is formed on the surface of the workpiece, which due to its higher "heat resistance" acts as a kind of thermal insulator, i.e. it slows down the heat transfer. The heat leaves in the form radiation, or convection through the film layer. After the vapor film has thinned, at the Leidenfrost temperature, the vapor film rives and the medium starts to boil. The Leidentfrost temperature forms the boundary between the vapor film and the nucleate boiling stage. Once the surface temperature of the workpiece drops below the former temperature due to the boiling of the medium, the vapor film disappears completely at the so-called DNB (Departure of Nucleate Boiling) temperature. Up to the boiling point of the refrigerant, the heat flux density also decreases as the temperature decreases. Then the convection phase begins. This phase characterizes the surface heat transfer at temperatures which are below the boiling point. It can be concluded that surface heat transfer during training is a complex dynamic process, which complex mathematical description is still a frequent aim of several research [2] [3] [4] [5] [6] focusing on heat transfer. Thus, the goal of this research is to create a model for this process to help later analyzes of this process.

II. Methodology

A. Axially symmetric, cylindrical body heat transfer model

For the numerical experiments the heat transfer model was applied, which is described by the following differential equation, assuming central-symmetric heat transfer conditions for a cylinder of finite length L:

$$\frac{\partial}{\partial r}\left(\lambda\frac{\partial T}{\partial r}\right)+\frac{\lambda}{r}\frac{\partial T}{\partial r}+\frac{\partial}{\partial z}\left(\lambda\frac{\partial T}{\partial z}\right)+q_v=\rho C_p\frac{\partial T}{\partial t} \quad (1)$$

where t is the time, r is the polar coordinate, z is the coordinate along the "z" axis, T (r, z, t) is the temperature, the latent amount of heat (this value is zero during our research during the whole heat transfer process), ρ is the density, Cp is the specific heat, λ is the thermal conductivity. Using the initial boundary condition

$$T(r,z,0)=T_a \quad (2)$$

Due to the circularly symmetrical nature of the heat transfer to the cylinder shaft

$$\lambda\frac{\partial T}{\partial r}\bigg|_{r=0}=0 \quad (3)$$

connection is determined. On the three sub-surfaces delimiting the cylinder (where S_p is the mantle of the cylinder and S_a and S_v are the base and end plates of the cylinder), the heat transfer

$$\lambda\frac{\partial T}{\partial z}\bigg|_{z=0}=h_v\left[T_q-T(r,z=0,t)\right]$$

$$\lambda\frac{\partial T}{\partial z}\bigg|_{z=L}=h_a\left[T_q-T(r,z=L,t)\right]$$

$$\lambda\frac{\partial T}{\partial r}\bigg|_{r=R}=h_p\left[T_q-T(r=R,z,t)\right] \quad (4)$$

described by equations. In the above equations, T_q is the ambient temperature of the refrigerant, while

$$h_v = h_v(t, r) \ (z = 0)$$

$$h_a = h_a(t, r) \ (z = L)$$

$$h_p = h_p(t, z) \ (r = R) \quad (5)$$

T_s is the Heat Transfer Coefficient on the surface elements S_v, S_a and S_p, which also depends on the surface temperature and the surface coordinate. Smith's explicit Finite Difference Method was used to solve the thermal conductivity Fourier equation. [7]

B. The Inverse Heat Conduction Problem

The temperature of the specimen was measured at p points inside the boundary. As the result of the thermal field calculation, T_k^c is retrieved and was used to calculate the difference between T_k^c and T_k^m in (6). The solution of the inverse heat conduction problem can be reached by minimizing the this objective function.

$$S = \sum_{k=1}^{p} (T_k^m - T_k^c) \rightarrow min \quad (6)$$

C. Adaptive Fireworks Algorithm

Adaptive Fireworks Algorithm [8] was used to solve the optimization of the function defined in (6). The original algorithm is proposed for finding the global optimum of complex functions [9]. Since the release of the original algorithm, several variants have been published that have improved the inaccuracy of the first algorithm and modified the operators to achieve more accurate results, better convergence speed, and lower computational requirements.

D. Method of examination

The method developed for the estimation of the Heat Transfer Coefficient during time-varying heat transfer was examined on the basis of the following methodology:

1. Hypothetical Heat Transfer Coefficient functions $h_1^m(t), h_2^m(t) \,..\, h_n^m(t)$ were generated, which characterize the change of heat transfer as a function of time at different distances from the cylinder end face (1,2…n).
2. Cooling simulations were conducted using the hypothetical Heat Transfer Coefficients, taking into account the functions $h_1^m(t), h_2^m(t) \,..\, h_n^m(t)$ in the thermal boundary conditions of the mantle surface of a cylinder. The complex (time and coordinate dependent) function of the heat transfer coefficient was determined by bilinear interpolation of the $h_1^m(t), h_2^m(t) \,..\, h_n^m(t)$ functions and the distances measured from the base of the cylinder. As the result of the simulations, the cooling curves formed at a depth of 1 mm from cylinder component $T_0^m(t), T_1^m(t), T_2^m(t), T_3^m(t)$ were recorded.
3. With the usage of the developed estimation method, the Heat Transfer Coefficient functions $[\, h_1^c(t), h_2^c(t) .. h_n^c(t) \,]$ were calculated. For the calculations, the cooling curves were used which derived in the previous step $T_0^m(t), T_1^m(t), T_2^m(t), T_3^m(t)$ as a sample.
4. The developed estimation procedure was analyzed based on the comparison of the hypothetical $[h_i^m(t)]$ and the reconstructed $[h_i^c(t)]$ Heat Transfer Coefficient functions.

The following derived parameters were examined to qualify the prediction of the heat transfer coefficient:

- Maximum temperature difference, T_{diff}[°C] : maximum difference at any time of the calculated and measured temperature curves.
- To assess the accuracy of the estimate, total average deviation, E_{fa} and total relative deviation E_{fr} metrics were used which are defined with

$$E_{Fa} = \sqrt{\sum_{i=1}^{4} \frac{1}{t_{max}} \left(\sum_{t=0}^{t_{max}} [T_i^c(t) - T_i^m(t)]^2 \right)} \quad (7)$$

$$E_{Fr} = \sqrt{\sum_{i=1}^{4} \frac{1}{t_{max}} \left(\sum_{t=0}^{t_{max}} \left[\frac{T_i^c(t) - T_i^m(t)}{T_i^m(t)} \right]^2 \right)} \quad (8)$$

- Number of calculation steps required to estimate the Heat Transfer Coefficient, $N_{pred}[db]$: number of calculation steps performed until the condition for the value of the objective function $(S < 200) \wedge (T_{diff} < 10\ °C) \wedge (E_{fa} < 2.5\ °C) \wedge (E_{fr} < 0.03\ °C)$

The value of the largest temperature difference, T_{diff}[°C]: according to the sources found in the literature is 10 °C, so this value was considered as the acceptance limit in the research.

E. Graphics accelerator implementation

According to the preliminary tests, the prepared system is suitable for the original goal. It can estimate the value of the Heat Transfer Coefficient based on the temperature data. However, a serious disadvantage of the system is the resource requirements, which is a typical problem of methods using heuristics. The members of the population used in the search represent a Heat Transfer Coefficient function. To calculate the fitness value of individuals, we need to know how close the parameter is represented by the individual to what we are looking for: to do this, a full heat transfer simulation has to be run using known individual parameters, and then compared with actual values.

The part of the task that most influences the resource requirements is the fitness calculation itself and this subtask can be parallelized very effectively. This is because the fitness calculation of each individual is completely independent from each other, which raises the possibility that they should not be performed sequentially, but at the same time, in parallel. This is the reason why a parallel implementation was developed on graphic accelerator to enhance the calculation speed. In Fig. 1. can be seen, that as a result, a speed increase of up to 15x can be achieved. With this implementation, multi-day simulations can be completed in approximately 1-3 hours.

	CPU	***GPU***	
	Runtime (hour)	***Runtime (hour)***	***Fitness calculations***
100 individuals	20.42	1.34	2 227 662

Fig. 1. Comparison of the CPU and GPU implementation's runtime

III. Evaluation

Three tests were conducted. First, a test with constant Heat Transfer Coefficient functions to prove that the method is suitable for solving the Inverse Heat Transfer Problem. Secondly, complex Heat Transfer Coefficient functions were defined and compared based on the accuracy and computation cost with Genetic Algorithm (roulette wheel). Third, Temperature curves recorded during the cooling process of a cylinder in canola oil were reconstructed and the coordinate and time dependent Heat Transfer Coefficient was calculated using the estimation method, demonstrating the practical applicability of the developed calculation method.

A. Constant Heat Transfer Coefficient functions

Three types of functions $h_i^m(t)$ were defined for the tests performed under the constant Heat Transfer Coefficient condition [$h_1^m(t)$=300 $\frac{W}{(m^2 \cdot °C)}$, $h_2^m(t)$=1500 $\frac{W}{(m^2 \cdot °C)}$, $h_3^m(t)$ (t)=3000$\frac{W}{(m^2 \cdot °C)}$] for which it is assumed that the value of the Heat Transfer Coefficient is constant over the entire 0-170 second time period. The values of the metrics calculated for testing are shown in Fig. 3. The results of the tests show that after the evaluation of the objective function, the difference between the measured and calculated temperature cycles for each Heat Transfer Coefficient is very small [0.93°C; 0.76°C; 0.46 °C]. This difference is acceptable according to the literature, and it can be concluded that the AFWA algorithm is suitable for reliable estimation of constant Heat Transfer Coefficients.

B. Complex Heat Transfer Coefficient functions

Hypothetical Heat Transfer Coefficient functions [$h_i^m(t)$] were defined. The complex Heat Transfer Coefficient functions for the cylinder surfaces was generated based on the bilinear interpolation of the functions [$h_i^m(t)$] and the coordinates belonging to the thermocouples on Fig. 2.

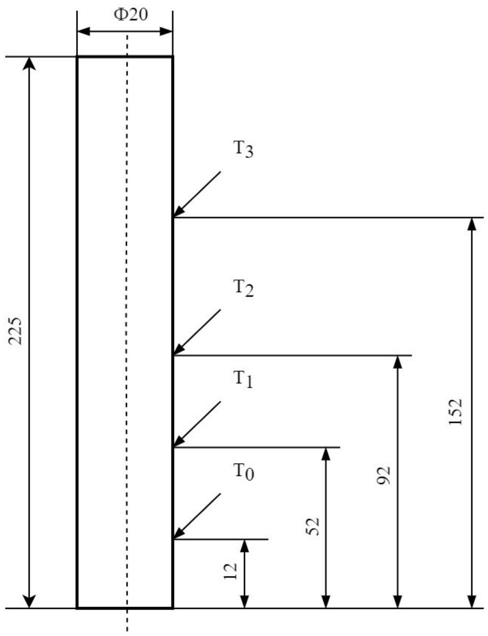


Fig. 2. Location of the thermocouples on the specimen (mm)

Constants	*T_{diff}[°C]*	*S*	*E_{Fa}*	*E_{Fr}*
$h_1^c(t) = 300\frac{W}{(m^2 \cdot °C)}$	0.93	12.39	0.15	0.0007
$h_2^c(t) = 1500 \frac{W}{(m^2 \cdot °C)}$	0.76	15.68	0.19	0.0016
$h_3^c(t) = 3000 \frac{W}{(m^2 \cdot °C)}$	0.46	8.86	0.1075	0.0017

Fig. 3. Test results: with constant Heat Transfer Coefficient functions

Using the developed numerical method, the Heat Transfer Coefficient functions were reconstructed by describing the time-varying Heat Transfer Coefficient functions $h_i^m(t)$ assigned to the locations determined by each thermocouple with polynomials of different degrees. On one hand, the different degrees determined the accuracy of the estimation, since at low degrees the estimation of the functions that can be described by a complex topology can be performed only within certain limits. On the other hand, since the sum of the degrees of the polynomials (the sum of the degrees of the four polynomials) is equal to the number of the dimension of the optimization problem space, the computation time also increased as the degree increased. The research was extended to apply another population-based optimization procedure and then compared it with the AFWA method. The computational efficiency of the Genetic Algorithm (GA) was examined based on roulette wheel selection to solve the same inverse thermal conduction problem. [9] The algorithm can also be used to solve complex problems such as breast cancer screening [10], controlling heliostat field of solar power tower plants [11] or production strategy selection [12].

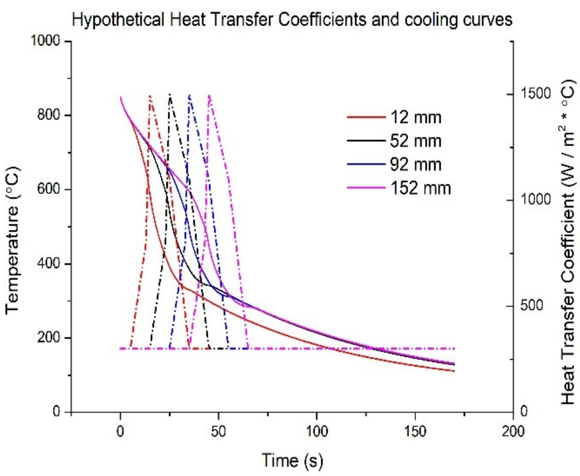
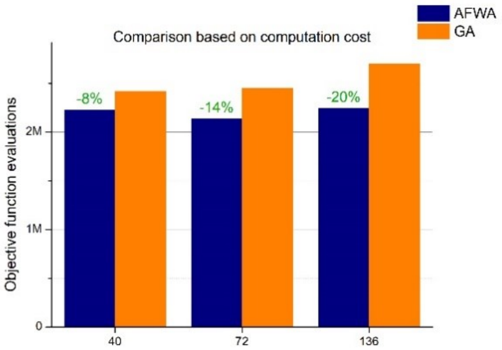


Fig. 4. Hypothetical Heat Transfer Coefficient functions and cooling curves



	Parameter number		
	40	72	136
AFWA	2 227 662	2 137 080	2 243 833
GA	2 419 890	2 457 435	2 701 980

Fig. 5. Comparison of AFWA and GA computation cost

The results of the first test are shown in the first two columns in Fig. 5. Here the functions were defined with a polynomial of degree 5, which means 2·5·4 = 40 data must be reconstructed during the optimization. At this parameter number, the AFWA method was able to reach the stop condition in 8% fewer calculation steps than the GA method. When reconstructing 72 unknown parameters, the number of calculation steps is 14% less. In this case, the functions were "coded" in the form of a polynomial of degree 9. Finally, for functions defined by 17 pair of numbers (a polynomial of degree 17), in which case the dimension number of the optimization problem space is 136, the AFWA optimization method called the objective function 20% less times. Since the Adaptive Fireworks Algorithm required less objective function evaluation for all three simulations compared to the Genetic Algorithm, it can be concluded that the AFWA optimization procedure should be applied to this task.

C. *Heat Transfer Coefficients estimation based on measured data*

Using the specimen shown in Fig. 2, immersion quenching experiments were performed in an organic coolant. [13] The cylindrical specimen was placed in a standing (vertical position) 30 ℃ canola oil from an initial temperature of 850 ℃. This temperature inhomogeneity can be explained by the fact that the kinetics of heat removal in the organic medium on the surface of the cylinder in the vertical position take place differently.

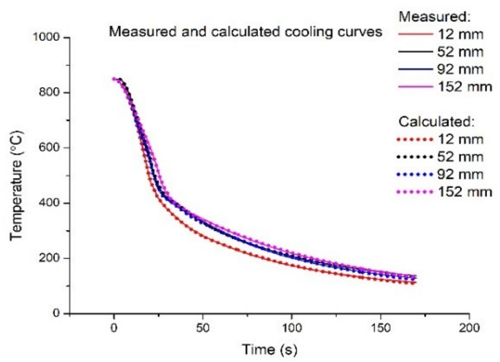


Fig. 6. Estimation of the measured cooling curves

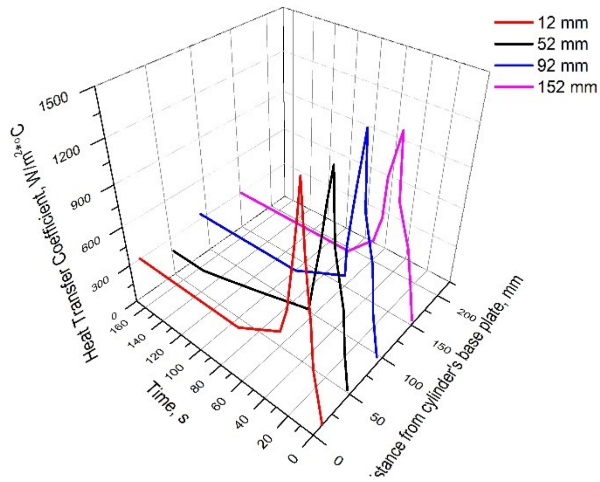


Fig. 7. Estimated Heat Transfer Coefficients

Using the cooling curves and the developed inverse estimation method, the Heat Transfer Coefficient functions were generated. The measured cooling curves and the curves resulting from the inverse calculations are illustrated in Fig. 6. As shown in the figure, the difference between the measured and calculated curves at the same locations is small. The Fig. 7. shows the estimated Heat Transfer Coefficients.

IV. Conclusion

The aim of the research was to develop a calculation method which is suitable for estimating the Heat Transfer Coefficients that change under time and coordinate under the heat transfer conditions with rapid temperature change. Achieving this objective presupposed the solution of an Inverse Heat Transfer Problem. A mathematical model and calculation method were developed to solve the Inverse Heat Transfer Problem (IHCP), in which the swarm-based, robust Adaptive Fireworks Algorithm (AFWA) optimization procedure was used. A mathematical method was implemented in a framework, which allows the estimation of the Heat Transfer Coefficient formed on the surface of a cylindrical body based on the 2-dimensional axisymmetric heat transfer model. By implementing the system on a graphical accelerator, multiple speed increase was achieved. This latter development meant more than fifteen-fold increase in computing speed.

To investigate the applicability of the developed numerical method, a methodology was developed which uses temperature samples generated using hypothetical heat transfer coefficients as input data to check the accuracy of the method. The estimation procedure "reconstructs" the Heat Transfer Coefficient function. Then the adequacy of the prediction can be assessed on the basis of a comparison of the hypothetical original and the numerically estimated Heat Transfer Coefficient functions. Using this methodology, the estimation procedure was examined using the AFWA method. In estimating the Heat Transfer Coefficient, which varies in time and space, the test results confirmed the accuracy of the prediction. The computational efficiency of AFWA was compared with a Genetic Algorithm (with roulette wheel selection, elitism). Based on the numerical calculations, it can be concluded that with the AFWA algorithm, the Heat Transfer Coefficients can be estimated with fewer calculation steps than with the GA optimization procedure.

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