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Optimization of the Temperature Fields Using the ABC Algorithm by Selecting the Kappa Parameter in Heat Conduction

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The goal of the study was to examine the distribution of temperature fields at each geometry point for heat conduction, using a type IV boundary condition at the point where the casting meets the casting mold. The focus was on comparing the temperature fields for reference calculations without disturbance and with 1% disturbance of reference temperatures. The artificial bee colony algorithm was used to optimize the kappa parameter value at the interface between the mold and the casting, which was a key element. Simulations were conducted for two different population sizes: 10 and 20 individuals. Each of these populations was tested with different numbers of iterations (4 and 8), and each iteration was run five times to ensure the reliability of the results. The ABC algorithm averaged the values of the calculated kappa parameter after five runs. We performed recalculations for 0% and 1% disturbances, using the obtained results to compare the actual temperature fields with the reference fields. We used the artificial bee colony algorithm in both cases to select the optimal value of the kappa parameter, thereby minimizing the differences between the actual and reference temperature field distributions. The analyzed system accurately represented the temperature distribution by partitioning the geometry of the mold and the casting into 1056 finite elements. The results allowed for a detailed analysis of the effect of disturbances on temperature distributions, as well as the artificial bee colony algorithm's effectiveness in optimizing the kappa parameter. Increasing the number of iterations and the number of individuals led to more accurate results, although this required more computational effort. The study showed that the ABC algorithm is an effective tool for optimizing thermal conductivity problems, especially in the context of varying boundary conditions. The study's final conclusions emphasize the importance of precise parameter selection in optimization algorithms, as well as the need to consider potential disturbances in simulation processes in order to obtain more reliable and accurate results on temperature distribution.

topics: heat transfer coefficient, temperature field, computer simulations, artificial bee colony (ABC) algorithm

1. Introduction

Heat conduction in materials is a fundamental problem in many fields of science and engineering, especially when industrial processes such as casting are involved. In general, modeling the temperature distribution in casting systems is significant for ensuring high-quality final products. Accurate prediction and control of the temperature at each point of the cast and mold geometry allows optimization of the manufacturing process, minimizing defects in the casts and increasing their mechanical properties [1].

The authors in [2] presented innovative approaches using finite element methods to solve inverse heat conduction problems. This research focuses on Robin-type boundary conditions and the use of artificial intelligence algorithms, which allow precise optimization of thermal process parameters. In foundry processes, solving inverse heat conduction problems under unstable heat fluxes at the system boundary is essentially a challenge for mechanical engineering. In the research presented in [3], the effectiveness of nature-inspired algorithms such as artificial bee colony (ABC) and ant colony optimization (ACO) in optimizing thermal parameters was demonstrated. These techniques allow

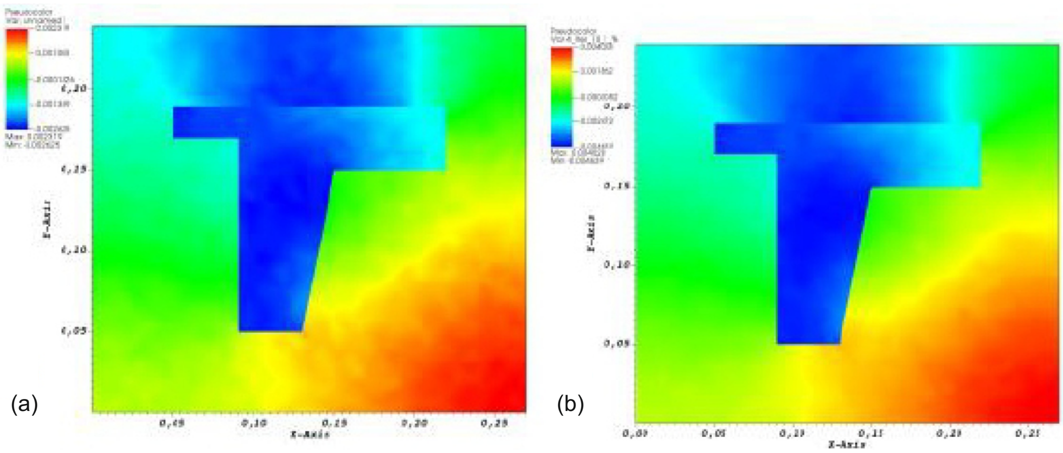

Fig. 1. Temperature field differences for 4 iterations, 10 individuals; (a) no disturbance, (b) 1% disturbance.

precise control of thermal processes in cylindrical castings, improving modeling accuracy and casting quality control. The implementation of such algorithms contributes to the effective management of variable boundary conditions, which is crucial to improving the efficiency and quality of industrial processes.

Modeling the distribution of temperature fields using the ABC algorithm is crucial to optimizing thermal parameters in casting processes. In industry, accurate temperature control minimizes defects in the cast, increases its mechanical properties, and increases production efficiency [4].

2. Description of methods

2.1. Heat transfer

The heat transfer equation

$$\rho c \frac{\partial T}{\partial t} + \nabla \cdot (-\lambda \nabla T) = 0, \tag{1}$$

where ρ is the density [kg/m^3], λ is the thermal conductivity coefficient [W/(m K)], c is the specific heat [J/(kg K)], T is the temperature [K], and t is the time, with the assumed initial temperature field T_0 at initial time $t = 0$. The following boundary conditions are used in the model: (i) boundary condition of the third type, assuming heat exchange with the environment that is in temperature T_{env} with the heat exchange coefficient between the mold and the environment; (ii) the fourth type of boundary condition, describing the heat flow between cast and the mold with a layer separating these areas (no perfect contact)

$$\kappa = \lambda_p / \delta, \tag{2}$$

where λ_p is the heat transfer coefficient of the separating layer and δ is the thickness of this layer.

The equation (1) was solved using finite element method [5].

2.2. Artificial bee colony algorithm

The ABC algorithm, inspired by the technique of honey bees searching for food, is an efficient optimization technique that is applied to solve complex problems. It consists of three crucial components: working bees, observing bees, and scouting bees. Working bees transform existing solutions, creating new ones based on current solutions and random factors. Observing bees select solutions based on probabilities proportional to the quality of those solutions. Scout bees, if a solution does not improve after a fixed number of iterations, generate a new random solution. The ABC algorithm effectively finds global extremum in complex search spaces, so it can be used, among other things, in heat transfer coefficient reconstruction [6].

3. Research results

The purpose of this study was to investigate the distribution of temperature fields at each point in the geometry during heat conduction using a boundary condition of the fourth kind where the casting meets the casting mold.

The material properties are as follows: the density of the casting is 2984 kg/m^3, and that of the mold is 7500 kg/m^3; the specific heat of the casting is 1077 J/(kg K), and that of the mold is 620 J/(kg K); the heat conduction coefficient for the cast is 262 W/(m K), and that of the mold is 40 W/(m K). The initial temperatures for the cast were T_0 = 960 K, and for the mold, T_0 = 590 K. The cast and the mold were assumed to be separated by a boundary where the boundary condition of the fourth kind is valid with κ in the range of 900–1500 W/(m^2 K). Reference temperatures were obtained at κ = 1000 W/(m^2 K).

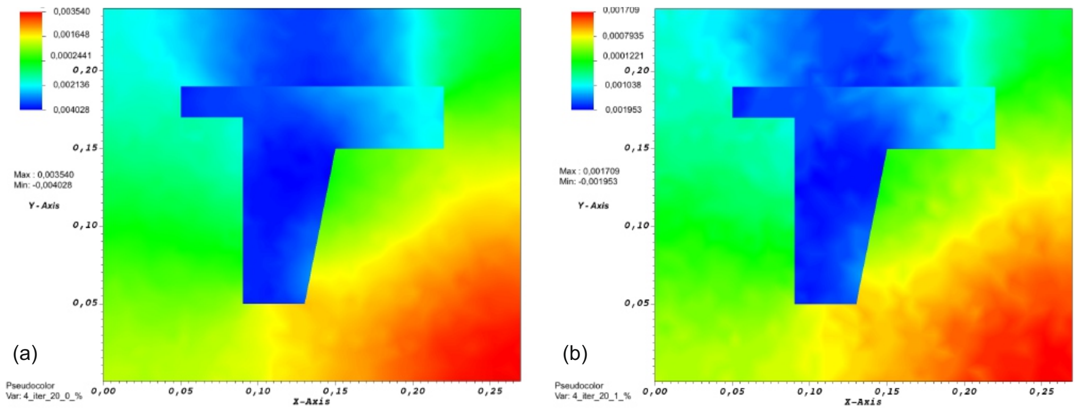

Fig. 2. Temperature field differences for 4 iterations, 20 individuals; (a) no disturbance, (b) 1% disturbance.

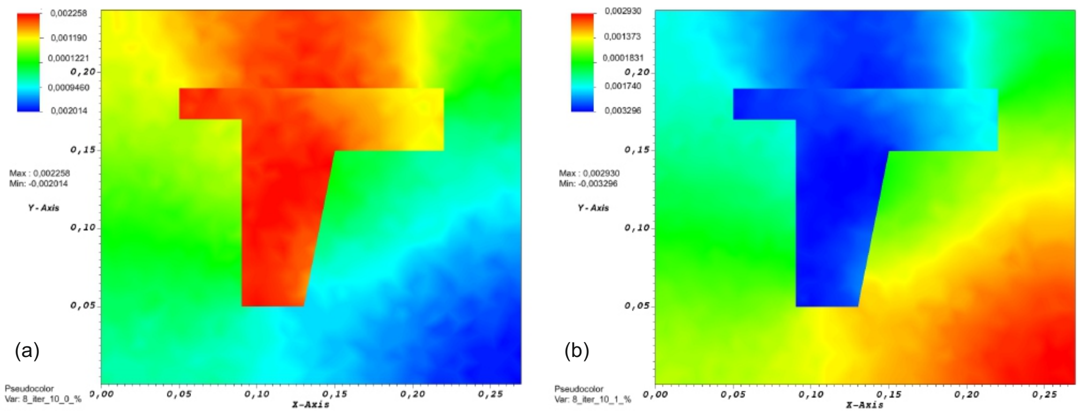

Fig. 3. Temperature field differences for 8 iterations, 10 individuals; (a) no disturbance, (b) 1% disturbance.

The graphs show how the differences in temperature fields between reference temperatures and those found in simulations with the recovered κ are spread out over different iterative conditions and geometrical arrangements.

Two main cases were analyzed, i.e., with and without disturbance. Simulations were performed for four different cases. For calculations where four iterations and 10 individuals were considered, assuming 1% disturbance, the results show a larger difference between temperatures (Fig. 1b). The values range from -0.004639 to 0.004028, with the dominant blue color suggesting lower temperatures in the central part of the disturbance. For the same number of iterations and number of individuals without disturbance (Fig. 1a), the temperature distribution is more uniform, with values ranging from -0.002625 to 0.002319, indicating more stable thermal conditions.

The analysis of the temperature field differences for four iterations and 20 individuals (Fig. 2b) shows that the disturbance is more pronounced in the temperature distribution, which is consequently evident by the larger temperature differences (from -0.001953 to 0.001709). In contrast, without disturbance, greater thermal stability is seen (Fig. 2a). The range of temperature differences is from -0.004028 to 0.003540, suggesting that without the presence of the disturbance, thermal conditions are more stable. With eight iterations and 10 individuals, the effects of disturbance are less intense but still apparent (Fig. 3b). In this case, the range of temperature differences is from -0.002258 to 0.002930. The analysis of the case without disturbance (Fig. 3a) shows that the distribution is more uniform relative to the case with disturbance, with values ranging from -0.002502 to 0.002808. In contrast, without disturbance, the temperature distribution is more uniform, suggesting more stable thermal conditions, with values ranging from -0.003235 to 0.002808. The analysis shows that a higher number of iterations leads to a more uniform temperature distribution, reducing the impact of disturbance. Larger disturbances lead to larger

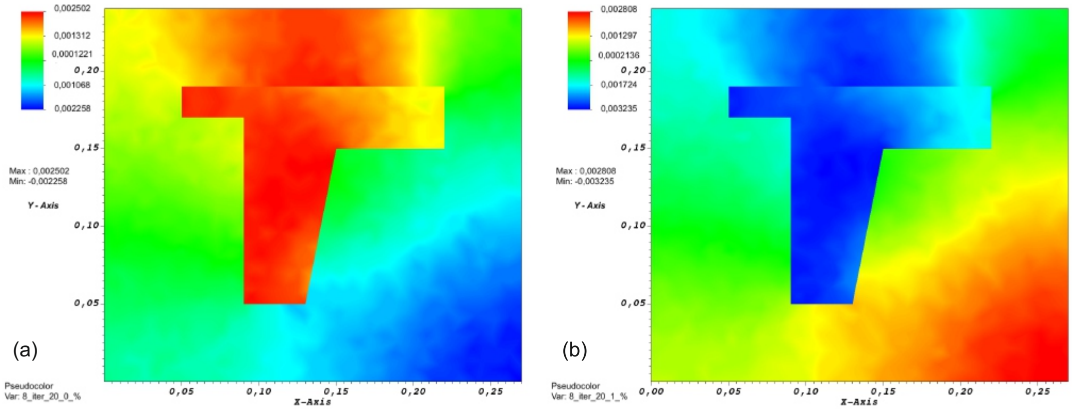

Fig. 4. Temperature field differences for 8 iterations, 20 individuals; (a) no disturbance, (b) 1% disturbance.

temperature differences, especially in the central areas of disturbance. Calculations without disturbance show greater thermal stability, which is particularly evident with a larger number of iterations. For processes requiring stable thermal conditions, it is recommended to minimize disturbance and increase the number of iterations in the analysis. In processes liable for perturbations of the initial conditions, it is necessary to constantly monitor and compensate for the effects of these perturbations on the temperature distribution. It is also worth conducting further studies for different configurations of boundary conditions and different materials to better understand the effects these factors have on temperature distribution. The analysis shows how important it is to choose the appropriate boundary conditions and the number of iterations in heat conduction analyses. The presented results can serve as a basis for further research and optimization of industrial processes related to heat transfer.

4. Conclusions

In the paper, it was shown that a larger number of iterations leads to a more uniform temperature distribution while reducing the impact of disturbances. With a higher number of iterations for the undisturbed case, the test results show greater thermal stability. To ensure stable thermal conditions, it is recommended to minimize disturbances and increase the number of iterations in the calculation.

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