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Influence of the Control Points Position on the Accuracy of Heat Transfer Coefficient Selection

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The presented paper focuses on investigating the influence of the control points position on the accuracy of the heat transfer coefficient selection. In the presented study, the main focus is on determining the heat transfer coefficient in a layer separating two bodies. Such a situation occurs, for example, in solidification problems where a cast is held inside a mold and heat transfer takes place from the cast to the mold. The authors use swarm intelligence algorithms to the task of determining the heat transfer coefficient. In the presented study, two different swarm intelligence algorithms are employed, i.e., artificial bee colony and ant colony optimization. The numerical model is based on the authors' own implementation of the transient heat transfer solver that uses the finite element method to solve the appropriate differential equation. The study presents the results of the selection of the heat transfer coefficient in the computational domain of one quarter of a square casting inside a square mold. Both swarm intelligence algorithms were run for sets of 10, 15, and 20 individuals with 2 and 6 iterations. The study also takes into account possible inaccuracies in reference temperatures in the form of 1%, 2%, and 5% noise. For both algorithms, three different sets of control points were used: one with points directly on the contact boundaries and two sets with increasing distance from the boundaries. The results obtained in this work show that the location of control points has an impact on the quality of the results obtained in the coefficient selection.

topics: inverse problems, artificial bee colony, ant colony optimization, heat transfer

1. Introduction

A common problem in engineering simulations is the need to calibrate the model or select the coefficients used in the simulation so that the results match the experimental results as much as possible. Traditionally, these types of problems were solved using gradient optimization methods such as inverse problems [1]. Even though solving inverse problems has been mastered for many years, they are still difficult to solve. Example applications include determining the vibration damping value in wind turbines [2] or the heat conduction coefficient in sounding rockets [3].

Due to their difficulty, many techniques have been developed to solve inverse problems. In addition to the previously mentioned gradient methods, there are methods based on statistical techniques such as linear regression or Bayesian regression [4].

Currently, solutions to inverse problems are also being sought using artificial intelligence methods, such as neural networks or machine learning. For example, Ameya et al. [5] used physics-informed neural networks to solve the inverse problem of supersonic compressible flow that arises during the design of space vehicles. Additionally, there are many examples of the use of neural networks in computed tomography image reconstruction [6].

A separate issue is the use of inverse swarm intelligence algorithms in problems such as the artificial bee colony algorithm or the ant colony optimization algorithm. The principle of their operation is based on defining a population, i.e., a set of potential solutions to the problem, an objective function, update rules specifying how individuals in the population modify their position in the solution space, and communication rules between individuals when exchanging information. Early work on describing this class of algorithms were made by Karaboga et al., who presented an artificial bee colony (ABC) algorithm in [7]. Currently, there are many works that use swarm algorithms, for example, [8] or [9].

In the presented work, we would like to deepen the knowledge on the factors influencing the results obtained in the reconstruction of model coefficients from results, in particular by examining the impact of the arrangement of temperature measurement points on the subsequent results. A specific example was the determination of the heat conduction coefficient of the layer separating two areas with different material properties in the simulation of heat conduction in a cooling casting.

2. Heat transfer model

The casting cooling model is based on the heat transfer equation

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

where ρ is the density, c is the specific heat, T is the temperature, 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) the third type boundary condition, assuming heat exchange with the environment, which is at temperature T_{env} with the heat exchange coefficient α; (ii) the fourth type of boundary condition, describing the heat flow between two areas Ω_1 and Ω_2 with a layer separating these areas (no perfect contact),

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

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

Equation (1) was solved using finite element method (FEM).

3. Swarm intelligence algorithms

3.1. Artificial bee colony

The operation of the artificial bee colony (ABC) algorithm is based on mathematical modeling of the behavior of bee colonies when they search for food.

The execution of the algorithm begins with initialization, i.e., creating an initial population P, consisting of a specific number of SN individuals. Each individual is assigned a potential solution to the optimization problem x_i, where $i =, \ldots, SN$, also called a nectar source.

Subsequent phases take place iteratively. During the search phase, scout bees randomly search for new nectar sources in the search space. Worker bees exploit nectar sources in accordance with a given quality criterion (objective function).

During the selection phase, worker bees inform observer bees about the best sources based on the quality of the nectar sources. Observer bees select the best source among them and recruit worker bees to further exploit it. The probability of assigning a bee to a food source, p_i, is based on a value of fit_i, which is the value of the objective function.

In the next step, the coordinates of the food sources are updated.

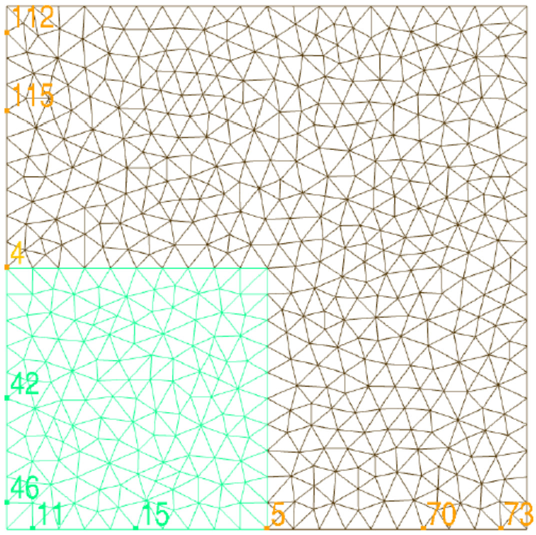

Fig. 1. Computational area with position of control points visible.

4. Ant colony optimization

The ant colony optimization (ACO) algorithm is a metaheuristic inspired by the foraging behavior of real ants, mainly used to solve the problem of finding the best path in a graph. In nature, ants leave a pheromone trail on their way to food. This scent fades over time if the road is not frequently traveled by ants, which tend to choose a shorter (more optimal) route.

The following rules are used to implement the algorithm. In the first phase, an ant k from the set of ants ($k = 1, \ldots, M$), where M is the number of ants, chooses a path randomly, with the probability affected by values of the heuristic function η and constants that determine the influence of pheromones α, and heuristic values on the ant's choice of the appropriate path β. For the selected path, the value of the objective function J_E is determined. If the chosen path turned out to be better than the previous one, it is remembered. A single ant k leaves along the way an amount of pheromone equal to $\Delta\tau_{ij}^k$.

The above steps are performed until a specific stopping criterion is met, namely the maximum number of iterations is reached or a solution of satisfactory quality is found.

5. Results

The task of the calculations was to determine the value of the thermal conductivity coefficient κ of the separating layer of an aluminum alloy casting from a steel mold. The view of the FEM mesh is presented in Fig. 1, where the green area is the area of cast. The sizes of the computational area

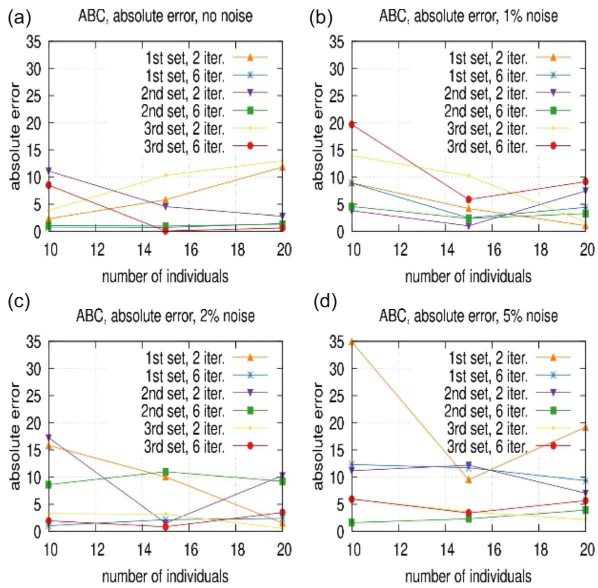

Fig. 2. Absolute error between the true κ value ($1000\ \mathrm{W/(m^2K)}$) and the one recovered by the ABC algorithm under different conditions.

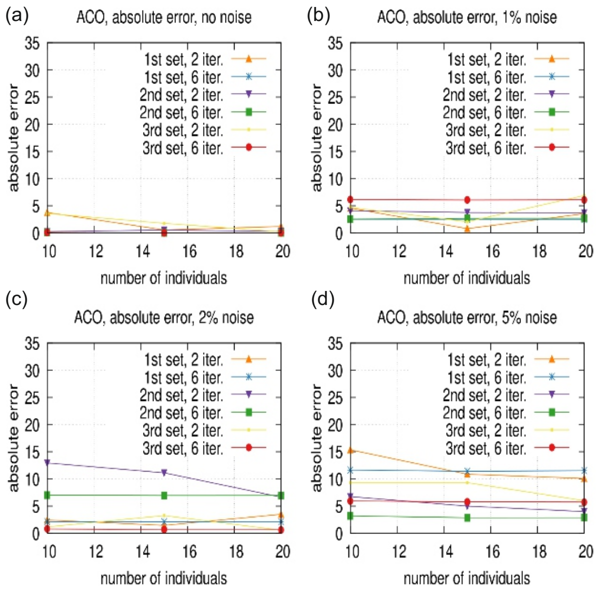

Fig. 3. Absolute error between the true κ value ($1000\ \mathrm{W/(m^2K)}$) and the one recovered by the ACO algorithm under different conditions.

are 0.04 m for mold and 0.02 m for cast. It is assumed that left and bottom sides are the axes of symmetry, while the top and right sides have the third type boundary condition imposed on them (with $\alpha = 100\ \mathrm{W/(m^2\ K)}$ and $T_{env} = 300$ K). The material properties are as follows: density of casting $2984\ \mathrm{kg/m^3}$, of mold $7500\ \mathrm{kg/m^3}$, specific heat of casting 1077 J/(kg K), of mold 620 J/(kg K), heat transfer coefficient of casting 262 W/(m K), of mold 40 W/(kg K). The initial temperatures were $T_0 = 960$ K for cast and $T_0 = 590$ K for mold. It was assumed that the cast and mold areas were separated with the boundary condition of the fourth type with a κ value in the range of 900–1500 $\mathrm{W/(m^2\ K)}$. Reference temperatures were obtained with $\kappa = 1000\ \mathrm{W/(m^2K)}$.

The calculations were performed for three different sets of control points: the first set with control points located in finite element (FE) mesh nodes 2, 3 (cast) and 4, 5 (mold) (the location of nodes 2, 3 is the same as nodes 4, 5), the second set with nodes 15, 42 (cast) and 70, 115 (mold); and the third set with nodes 11, 46 (cast) and 112, 73 (mold). The locations of all control points are presented in Fig. 1.

Both algorithms used population sizes equal to 10, 20, 30 bees/ants and number of iterations equal to 2 or 6 iterations. Additionally, in each case, noise of 0%, 1%, 2%, and 5% of reference temperatures was also considered.

As for the results (presented in Figs. 2 and 3), it can be observed that ACO gives better results than ABC algorithm and there is a reduction of error with increasing number of iterations and population size for both algorithms.

In terms of the location of the control points, we observe that usually the first set gave a worse result than the other two sets. The difference is not huge, but noticeable. The average absolute error for the first set was equal to 7.59 (ABC) or 4.42 (ACO), while the other two sets had error values of 5.82 (ABC, second set), 4.02 (ACO, second set) and 5.68 (ABC, third set), 3.59 (ACO, third set).

6. Conclusions

The paper has shown that the precision of the recovered thermal conductivity coefficient of the separating layer is at least satisfactory, regardless of the used parameters values of the chosen algorithms. However, with carefully chosen points it is possible to obtain slightly better results.

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