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Heat Transfer Coefficient Optimization Using Artificial Intelligence Algorithms: Accuracy and Computational Efficiency Analysis

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This paper presents the results of a study on the reconstruction of the heat transfer coefficient under boundary conditions of the fourth kind, which is of key importance for casting processes. Understanding and optimizing this coefficient has a direct impact on the efficiency and quality of metallurgical production processes, which can contribute to significant material savings when reconstructing casting conditions. Using swarm algorithms, such as bee and ant algorithms, to estimate the coefficient is an innovative approach to the problem. These artificial intelligence methods are known for their efficiency in solving complex optimization problems, demonstrating the potential of implementing modern technology in traditional industries. The research includes a detailed analysis of how different levels of noise (0%, 1%, 3%, 6%) and algorithm parameters, i.e., the number of individuals $(20, 40, 60)$ or the number of iterations $(10, 14, 20)$, affect the accuracy of the results. This analysis improves our understanding of the impact of the aforementioned variables on the results and enables us to optimize them for improved accuracy and efficiency. Running the simulation six times for each iteration increases the reliability of the results, as it allows for estimating the variance and confidence in the results. This is an important aspect of scientific research that ensures the robustness and reproducibility of the results obtained. The study's findings provide concrete guidance for engineers and scientists involved in modeling thermal processes, which can lead to improved design and management of foundry processes. In this field, the application of artificial intelligence opens up new opportunities for innovation and improvement. The paper's authors raised important questions about the risks associated with increasing the number of iterations or individuals in a population. This is important for the practical application of results in real industrial settings, where computational and time resources are often limited. The results presented in the article provide important insights for engineers and scientists involved in modeling thermal processes in foundry operations, offering a new perspective on the use of advanced artificial intelligence techniques. Modern technologies and research methodologies can help the metallurgical industry advance technologically and economically.

topics: heat transfer coefficient, thermal conductivity modeling, computer simulations, swarm algorithms

1. Introduction

Artificial intelligence (AI) in thermomechanics is becoming increasingly popular, influencing the development of various industries and changing our lives and work. AI, a dynamically evolving field of computer science, supports and replaces human cognitive tasks with intelligent systems. Optimization, a key element of AI, finds application in science, engineering, and economics, requiring adaptive algorithms that are independent of the number of variables and the size of the space of solutions. Nature-inspired algorithms, such as genetic algorithms (GA) or swarm algorithms, for example, ant colony optimization (ACO) and artificial bee colony (ABC), have gained popularity because of their effectiveness. The first optimization algorithms, developed in the last century, are still of interest to researchers, particularly in the context of heat exchange optimization [1, 2]. Research in artificial intelligence and machine learning frequently involves comparisons with human intellect, facilitating a better understanding and advancement of these technologies [3]. Artificial intelligence derives patterns from the human brain and the collective intelligence of various species, such as bees, ants, and wolves. The heat transfer coefficient plays a key role in modeling thermal processes in the cast. Its precise reconstruction enables more accurate simulations of the cooling and solidification of metals, which directly affects the quality of final products. The literature indicates that the accuracy of modeling these processes is crucial for preventing defects in cast, such as cracks and porosity [4, 5].

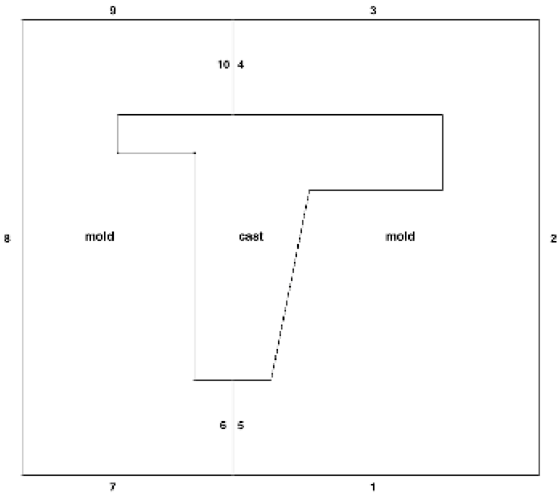

Fig. 1. Geometry of example shape of mold and casting with numbers of boundary edges in mold.

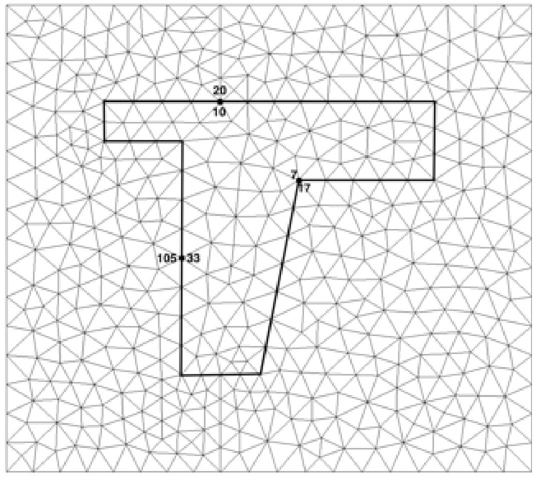

Fig. 2. Fine element mesh with denoted nodes.

The metallurgical industry, particularly the casting sector, is constantly striving to optimize production processes to increase productivity and improve product quality. A key factor affecting the quality of casts is the control and optimization of the heat transfer coefficient under various boundary conditions.

A precise understanding and reproduction of this coefficient directly affects the efficiency of metallurgical processes, which can lead to material and energy savings.

2. Description of methods

2.1. Heat transfer

Heat conduction is one of the key physical processes occurring during metal casting. This study focuses on the reconstruction of the heat transfer coefficient under fourth-kind boundary conditions. The problem of heat conduction has been formulated as an inverse mathematical problem, wherein the objective is to reconstruct the heat transfer coefficient based on measured temperature data [6].

2.2. Artificial intelligence algorithms

Inspired by the foraging behaviors of honeybees, the ABC algorithm serves as an efficient optimization method to solve complex problems. It comprises three main phases: the employed bee phase, the onlooker bee phase, and the scout bee phase. Employed bees modify existing solutions, creating new ones based on current solutions and random factors. Onlooker bees select solutions based on a probability proportional to the quality of the solutions. If a solution remains unimproved after a specified number of iterations, the scout bee phase generates a new random solution. The ABC algorithm is effective in finding global extrema in complex search spaces, which makes it useful for reconstructing the heat transfer coefficient.

Algorithm ACO emulates the behavior of ants, which use pheromones to find the shortest paths to food sources. In ACO, artificial ants explore the solution space in search of optimal results. Initially, pheromones are evenly distributed, and each ant starts with a random solution. Ants build their solutions step by step, selecting paths based on the amount of pheromone and heuristic information. Ants update their pheromones to reinforce good solutions once they have constructed all solutions. The ACO algorithm is effective in exploring the solution space and avoiding local extrema, making it suitable for the heat transfer coefficient reconstruction [6, 7].

3. Research results

The objective of the calculations was to determine the value of the thermal conductivity coefficient κ for the layer separating an aluminum alloy cast from the mold (Fig. 1). The finite element method (FEM) mesh is depicted in Fig. 2. It was assumed that boundaries 1, 2, 3, 9, 8, and 7 are subject to third-kind boundary conditions (with $\alpha = 100$ W/(m^2 K) and $T_{env} = 300$ K). Ideal thermal contact was assigned to boundary pairs 10 and 4, as well as 6 and 5. The material properties are as follows: the density of the cast is 2984 kg/m^3, and of the mold 7500 kg/m^3; the specific heat capacity of the cast is 1077 J/(kg K), and of the mold 620 J/(kg K); the thermal conductivity coefficient for the cast is 262 W/m^{2}K, and for the mold, it is 40 W/(m K). The initial temperatures were $T_0 = 960$ K for the cast and $T_0 = 590$ K for the mold.

TABLE I

The reconstructed coefficient κ value for 20 individuals using ABC and ACO algorithms.

20 bees/ants	No. of iter.	κ ABC	κ ACO	Time [min] ABC	Time [min] ACO
0% noise	5	1000.291059	999.996794	12.13	7.48
	10	999.655194	999.999999	20.96	16.10
	14	1000.043579	1000.000000	25.99	22.27
	20	999.989570	1000.000002	37.68	33.09
1% noise	5	1001.561974	1002.269180	23.87	8.33
	10	1002.100594	1002.256785	45.13	16.59
	14	1002.236314	1002.254288	20.94	23.22
	20	1002.256042	1002.254021	28.79	32.46
3% noise	5	1000.994271	1002.705612	9.80	8.36
	10	1002.816469	1002.698680	17.66	16.96
	14	1002.483198	1002.696122	24.10	23.06
	20	1002.687248	1002.698546	34.60	32.21
6% noise	5	1001.500523	1001.151315	14.99	8.30
	10	1001.146872	1001.124914	24.26	16.29
	14	1001.087116	1001.115510	53.37	22.38
	20	1001.162915	1001.115541	64.47	31.68

TABLE II

The reconstructed coefficient κ value for 40 individuals using ABC and ACO algorithms.

40 bees/ants	No. of iter.	κ ABC	κ ACO	Time [min] ABC	Time [min] ACO
0% noise	5	999.846297	1000.000508	26.31	16.72
	10	999.952574	1000.000000	45.28	32.74
	14	999.934775	1000.000001	69.06	47.75
	20	999.996857	1000.000000	66.07	31.14
1% noise	5	1002.909695	1002.254873	24.43	16.29
	10	1002.335904	1002.254915	44.34	32.08
	14	1002.269312	1002.254286	78.86	44.59
	20	1002.267205	1002.254277	72.77	31.18
3% noise	5	1003.139062	1002.688222	23.15	16.39
	10	1002.712797	1002.696122	45.41	32.52
	14	1002.736922	1002.699048	59.15	44.55
	20	1002.674292	1002.696110	69.32	31.21
6% noise	5	999.809036	1001.120704	18.99	16.48
	10	1001.050950	1001.115526	45.84	31.92
	14	1001.098064	1001.115613	49.42	44.79
	20	1001.143278	1001.115613	63.40	68.80

It was assumed that the cast and the mold are separated by an interface subject to fourth-kind boundary conditions with κ ranging from 900 to 1500 W/(m^2 K). Reference temperatures of $\kappa = 1000$ W/(m^2 K) were obtained.

TABLE III

The reconstructed coefficient κ value for 60 individuals using ABC and ACO algorithms.

60 bees/ants	No. of iter.	κ ABC	κ ACO	Time [min] ABC	Time [min] ACO
0% noise	5	999.948838	999.999928	38.27	24.36
	10	999.986286	1000.000001	85.03	47.72
	14	1000.002601	1000.000001	105.39	7.06
	20	999.996033	1000.000001	124.31	46.40
1% noise	5	1001.887531	1002.255234	27.81	24.18
	10	1002.287868	1002.254035	46.74	47.90
	14	1002.262173	1002.254035	61.58	65.19
	20	1002.264247	1002.254036	96.19	103.14
3% noise	5	1003.290217	1002.696553	28.32	24.19
	10	1002.628311	1002.696089	49.31	47.83
	14	1002.655466	1002.696104	108.54	65.19
	20	1002.700633	1002.696108	86.35	103.21
6% noise	5	1000.400667	1001.118684	28.74	23.54
	10	1001.179342	1001.115590	55.92	46.92
	14	1001.193951	1001.115613	72.86	65.19
	20	1001.114989	1001.115613	109.23	103.15

Computational efficiency refers to a measure of algorithm performance and computational methods in the context of resources consumed, such as computation time or operating memory. Analysis of the data presented in Tables I–III shows differences in computation time between the ACO and ABC algorithms. Increasing the number of iterations increases the computation time for both algorithms; however, ACO still shows a smaller increase.

For example, for 60 individuals with 0% disturbance, for 5 iterations, the difference between ABC and ACO is 13.91 min, which indicates that ACO is the more efficient algorithm. On the other hand, for 20 iterations, ACO is 77.91 min more computationally efficient than ABC. Also affecting computation time is the degree of disturbance. ACO shows less time fluctuation, which suggests that the algorithm is more predictable and stable under varying computational conditions, highlighting its advantages in terms of computational efficiency.

The stability and predictability of the κ value in ACO, combined with its shorter computation time, suggest that ACO has better time efficiency. An increasing iteration number leads to a better representation of the reference κ value in both algorithms, but ABC shows greater variation in results. In addition, calculations for the ABC algorithm run slower than the ACO algorithm when the number of iterations increases. However, these differences are not large and are within the error range.

The increase in κ coefficient is influenced by the increase in the degree of disturbance, however, ACO is better at maintaining stable κ values at different levels of disturbance. There is a noticeable relationship between the number of individuals and computation time, i.e., a higher number of individuals increases the computation time for both algorithms. The ACO algorithm remains more time-efficient in any configuration. Therefore, ACO is the more optimal choice for cases requiring fast results.

4. Conclusions

AI is emerging as a promising tool for reproducing parameter values in thermomechanics. The presented research provides valuable insights to engineers and researchers in the foundry industry, supporting improved process design and management, and thus improving quality and production efficiency in the metallurgical sector.

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