The 56th International October Conference on Mining and Metallurgy
22-25 October 2025, Bor Lake, Bor, Serbia
www.ioc.tfbor.bg.ac.rs

DOI: 10.5937/IOC25721P *Review paper*

APPLICATION OF METAHEURISTIC ALGORITHMS IN METALLURGICAL INDUSTRY: A REVIEW OF METHODS AND APPLICATIONS

Marijana Pavlov-Kagadejev[1a], Aleksandra Milosavljevic[1b]

[1] Mining and Metallurgy Institute Bor, Alberta Ajnštajna 1, 19210 Bor, Serbia
[1a] marijana.pavlov@irmbor.co.rs, 0000-0003-1090-6351
[1b] aleksandra.milosavljevic@irmbor.co.rs, 0000-0003-3841-7357

Abstract
Optimization is important in metallurgy due to the complexity of processes, the large number of parameters, and the challenge of finding a balance between cost and quality. Problems associated with the traditional experimental approach are common due to nonlinearity, multi-objective goals, the high cost of experiments, as well as the time required for their execution. The application of metaheuristic algorithms has proven to be effective in solving complex problems. This paper aims to provide an overview of metaheuristic algorithms and their application in the metallurgical industry.

***Keywords**: metaheuristics, metallurgical industry, optimization*

1. INTRODUCTION

The complexity of industrial processes, the large number of process parameters, and the diverse objectives that must be met have made optimization a critical component in the metallurgical industry. Furthermore, the presence of nonlinear relationships, multi-objective requirements, and the need to reduce experimental costs has highlighted the importance of optimization not only in metallurgy but across various industrial sectors. By applying optimization techniques, the duration and cost of experimental procedures can be significantly reduced, making the overall process more economical and efficient. This paper examines the use of metaheuristic algorithms in the optimization of metallurgical processes. These algorithms have shown strong potential in improving key areas such as casting and melting operations, alloy design, and production scheduling, thereby enhancing efficiency and overall performance in manufacturing systems [1, 2].

2. METAHEURISTICS

Optimization is a process used to improve performance in both decision sciences and physical system analysis. To utilize optimization correctly, it is first necessary to identify a goal - a quantitative measure of the performance of the system being studied. This objective can be profit, time, potential energy, or any quantity that can be represented by a single number. It depends on certain characteristics of the system, called variables or unknowns, and it is necessary to find the values of the variables that optimize the goal [3].

The classification of optimization algorithms can be done in several ways. One way is to divide them into deterministic and stochastic algorithms. Conventional and classical algorithms mostly belong to the group of deterministic algorithms, while heuristics and metaheuristics can be classified as stochastic algorithms. Heuristics algorithms belong to approximate algorithms and can be divided into two categories: specific heuristics and metaheuristics.

Metaheuristic algorithms represent improved heuristics. There is no agreed-upon definition of heuristics and metaheuristics in the literature. The two main components of every metaheuristic algorithm are intensification (exploitation) and diversification (exploration). A good combination of these components can ensure reaching global optimality [4, 5].

Metaheuristic algorithms are often inspired by natural systems. Among the most well-known are swarm intelligence techniques and genetic algorithms, which mimic collective animal behavior and evolutionary processes. Others are based on physical phenomena such as gravity or electromagnetism, or abstract models including human cognition and mathematical patterns like trigonometric oscillations. These approaches provide flexible strategies for solving complex optimization problems by balancing exploration and exploitation [6].

Some of the most frequently used metaheuristic algorithms in metallurgical industry are:

- **Genetic Algorithms (GA) -** represent simulations of natural selection that can solve optimization problems. These algorithms are ideally suited for solving problems with discrete variables and, in most cases, find the global optimal solution [7].
- **Particle Swarm Optimization (PSO) -** imitates the collective behavior of birds and fish to efficiently search for food-rich areas [8].
- **Ant Colony Optimization (ACO) -** the basic idea of these optimization algorithms is to simulate the cooperative behavior of real ants in order to solve optimization problems [9].
- **Simulated Annealing (SA)** - simplest and most well-known metaheuristic methods for solving difficult global optimization problems, inspired by the annealing process used in metallurgy [10, 11].
- **Hybrid Metaheuristic Algorithms** - combination of the different methods for improved performance in complex problems.

The No Free Lunch (NFL) theorem [12] highlights that there is no algorithm that is the best for all problems, implying that an individualized approach is preferable. In recent times, the number of metaheuristics, especially those inspired by nature, is increasing daily.

Metaheuristic algorithms in the metallurgical industry are most commonly applied to optimize the following processes:

- **Casting and melting**, where parameters such as temperature, time, and alloy composition are optimized to minimize defects and improve product quality.
- **Alloy design**, in which algorithms search for an optimal alloy composition to achieve target properties like mechanical strength, material conductivity, and cost.
- **Production scheduling**, where metaheuristics optimize resource utilization-such as furnaces, materials, and personnel to improve scheduling efficiency and reduce delays.

3. PRACTICAL EXAMPLES

There are numerous examples of the metaheuristic algorithms application for process optimization in the metallurgical industry, as presented in published scientific papers. One example for each of the mentioned forms of optimization will be presented in this paper. The used algorithms will be briefly described, along with the optimized parameters.

According to [13], various metaheuristic techniques, including Genetic Algorithm (GA), Ant Colony Optimization (ACO), Simulated Annealing (SA), and Particle Swarm Optimization (PSO), were applied to optimize the feeder geometry in the casting process. The proposed methodology was applied in the design of the feeder for casting the Pelton turbine bucket, and the optimization results consist of the dimensional characteristics of the feeder. The best result from all the implemented optimization processes was selected for the final design. The validity of the proposed optimization approach was verified through numerical simulation of the casting process.

This study [14] focuses on enhancing the mechanical and electrical properties of the $CuNi_2Si_1$ alloy by combining experimental methods with metaheuristic optimization algorithms. Aging temperature and time were varied between 450-600°C and 1-420 minutes, respectively, to optimize hardness and electrical conductivity. Among the metaheuristic approaches tested-Student Psychology-Based Optimization (SPBO), Genetic Algorithm (GA), and Particle Swarm Optimization (PSO), SPBO demonstrated the highest prediction accuracy. It predicted an optimal aging temperature of 450°C for approximately 61.75 minutes, which was confirmed experimentally. These findings emphasize the potential of metaheuristic algorithms, particularly SPBO, as effective tools for optimizing alloy design parameters and tailoring material properties for industrial applications such as aerospace and electrical engineering.

This paper [15] presents a hybrid simulation-based optimization method for production planning and scheduling in metal casting, with a focus on multi-criteria optimization, including energy efficiency. A combination of deterministic exchange-based heuristics and a customized Genetic Algorithm (GA) is applied to optimize batch assignments and furnace scheduling in the heat treatment process. The method demonstrates that smaller population sizes in the GA lead to more efficient optimization for the given problem complexity, as they maximize the limited number of iterations available for finding high-quality solutions. The approach significantly outperforms manual planning, reducing planning time and offering around a 10% global optimization potential, including a 6% improvement in energy efficiency. Figure 1 represents overview of the production layout showing five heat treatment furnaces, cooling stations, FIFO buffers, and a crane for material handling.

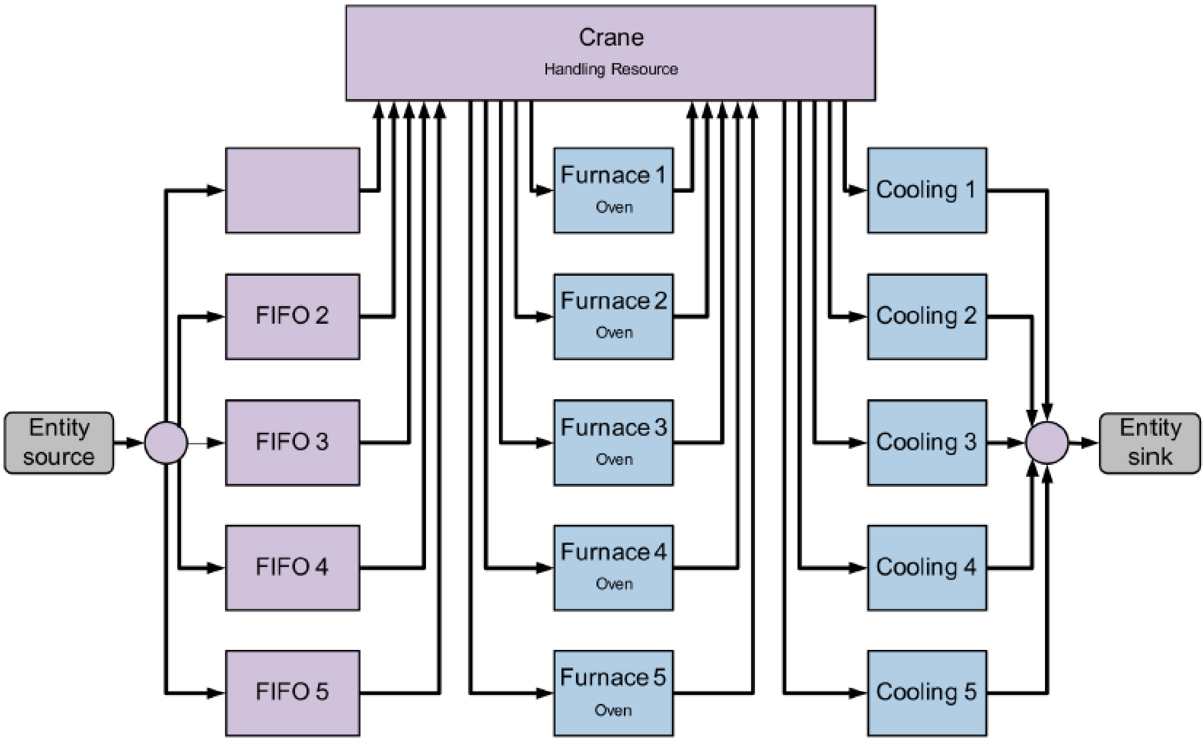

Figure 1. Schematic layout showing five heat treatment furnaces, cooling stations, FIFO buffers, and a crane for material handling [15] used under the terms of CC-BY

4. CONCLUSION

The application of metaheuristic algorithms to optimize various processes in the metallurgical industry contributes to improving product quality, reducing costs, and increasing production efficiency. Metaheuristic algorithms in the metallurgical industry are applied to optimize processes like casting and melting, alloy design, and production scheduling. Future development directions include the integration of metaheuristic algorithms with machine learning techniques and other artificial intelligence methods. Further research in this area, through the development of new algorithms and hybrid combinations of existing ones, can significantly improve the solution of complex problems faced in the metallurgical industry.

ACKNOWLEDGEMENTS

This work was financially supported by the Ministry of Science, Technological Development and Innovations of the Republic of Serbia, Contract on Realization and Financing the Scientific and Research Work of the Mining and Metallurgy Institute Bor in 2025, Registration No. 451-03-136/2025-03/200052.

REFERENCES

[1] A. Poonia, K. Modalavalasa, K.P.R. Ayyagari, Designing of high entropy alloys with high hardness: a metaheuristic approach, *Sci. Rep.*, 14 (1) (2024) 7692.
[2] P.A. Huegler, F.J. Vasko, Metaheuristics for meltshop scheduling in the steel industry, *J. Oper. Res. Soc.*, 58 (6) (2007) 791–796.
[3] J. Nocedal, S. J. Wright, *Numerical Optimization*, Springer, New York, NY, 2006. https://doi.org/10.1007/978-0-387-40065-5
[4] E.G. Talbi, *Metaheuristics: From Design to Implementation*, John Wiley & Sons, 2009.
[5] X.S. Yang, *Nature-Inspired Metaheuristic Algorithms*, Luniver Press, 2010.
[6] I. Fister Jr., X.-S. Yang, I. Fister, J. Brest, and D. Fister, "A brief review of nature-inspired algorithms for optimization," *arXiv preprint arXiv:1307.4186*, 2013. [Online]. Available: https://arxiv.org/abs/1307.4186
[7] S. Nayak, *Fundamentals of Optimization Techniques with Algorithms*, Academic Press, 2020.
[8] J. Yang, R. Kennedy, R. Eberhart, Particle swarm optimization, in: *Proc. ICNN'95 – Int. Conf. on Neural Networks*, vol. 4, IEEE, 1995, pp. 1942–1948.
[9] M. Dorigo, *Optimization, Learning and Natural Algorithms*, Ph.D. Thesis, Politecnico di Milano, 1992.
[10] D. Delahaye, S. Chaimatanan, M. Mongeau, Simulated Annealing: From Basics to Applications, in: M. Gendreau, J.Y. Potvin (Eds.), *Handbook of Metaheuristics*, Int. Ser. Oper. Res. Manag. Sci., vol. 272, Springer, Cham, 2019.
[11] J. Derrac, S. García, D. Molina, F. Herrera, A practical tutorial on the use of nonparametric statistical tests as a methodology for comparing evolutionary and swarm intelligence algorithms, Swarm Evol. Comput., 1 (1) (2011) 3–18.
[12] D.H. Wolpert, W.G. Macready, No free lunch theorems for optimization, IEEE Trans. Evol. Comput., 1 (1) (1997) 67–82.
[13] R. Radiša, N. Dučić, S. Manasijević, N. Marković, Ž. Ćojbašić, Casting improvement based on metaheuristic optimization and numerical simulation, *Facta Universitatis, Series: Mechanical Engineering*, 15 (3) (2017) 397–411.
[14] J. Konieczny, K. Labisz, S. Ürgün, H. Yiğit, S. Fidan, M. Ö. Bora, Ş. H. Atapek, Metaheuristics algorithm-based optimization for high conductivity and hardness CuNi2Si1 alloy, Materials, 18 (2025) 1060. https://doi.org/10.3390/ma18051060
[15] T. Sobottka, F. Kamhuber, B. Heinzl, Simulation-based multi-criteria optimization of parallel heat treatment furnaces at a casting manufacturer, J. Manuf. Mater. Process., 4 (3) (2020) 94.