

# Modelling and artificial intelligence technologies in modern approaches to automation of metallurgical industries

Vladislav Gerashchenko<sup>1\*</sup>, Nafisa Kulmurodova<sup>2</sup>, and Zarifjon Kulmurodov<sup>3</sup>

<sup>1</sup>Department of Materials Science and Metalworking Technology, Siberian Federal University, Krasnoyarsk, Russian Federation

<sup>2</sup>Navoi State University of Mining and Technologies, Navoi, Uzbekistan

<sup>3</sup>Navoi Mining Metallurgical Combinate, Navoi, Uzbekistan

**Abstract.** The article examines modern approaches to the automation of metallurgical production, focusing on increasing productivity, improving product quality, and minimizing costs. The main methodologies and implemented technologies are described, with particular emphasis on modeling and simulation techniques. The study highlights the application of industrial control systems, big data analytics, and artificial intelligence technologies in metallurgical processes. A key aspect of the research is the use of advanced modeling tools, such as digital twins and process simulation software, to optimize various stages of metallurgical production. The paper presents a detailed analysis of casting process modeling using ESI Group ProCast software, demonstrating how virtual experiments can predict temperature distribution, metal flow vectors, and potential defect formation in castings. The research also explores the integration of machine learning models for process control and quality assurance in real-world metallurgical operations. An analysis of the practical application of these technologies is conducted, discussing both the advantages and challenges of implementing such advanced systems in the metallurgical industry. The study concludes by emphasizing the transformative potential of modeling and AI technologies in modernizing traditional metallurgical processes and improving overall operational efficiency.

## 1 Introduction

The metallurgical industry plays a crucial role in the global economy, providing the raw material base for various industrial sectors such as mechanical engineering, construction, aircraft manufacturing, and others. Modern trends in increasing competitiveness, the need to meet environmental standards, and optimize production processes require the implementation of automation technologies. Automation of metallurgical processes significantly reduces production costs, improves product quality, minimizes human error, and increases the level of production safety [1].

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\* Corresponding author: [mr.vlad08@mail.ru](mailto:mr.vlad08@mail.ru)

Technological advancements in the field of ACS (Automated Control Systems) and IT have led to the creation of new opportunities for full integration of production processes and their continuous monitoring. The rapid development of artificial intelligence (AI) and machine learning (ML) technologies has opened up new horizons for predictive maintenance, quality control, and process optimization in metallurgical industries.

The integration of Internet of Things (IoT) devices and sensors throughout the metallurgical production chain has enabled real-time data collection and analysis, providing unprecedented insights into process efficiency and equipment performance. This wealth of data, combined with advanced analytics and AI algorithms, allows for more accurate predictions of maintenance needs, optimization of energy consumption, and fine-tuning of production parameters to achieve optimal quality and yield.

Furthermore, the adoption of digital twin technology in metallurgical industries has revolutionized the way processes are designed, simulated, and optimized. Digital twins provide a virtual representation of physical assets and processes, allowing engineers to test various scenarios and optimizations in a risk-free virtual environment before implementing changes in the actual production line. This approach significantly reduces the time and cost associated with process improvements and helps in identifying potential issues before they occur in real-world operations [2].

This study is dedicated to analyzing current trends and technologies being implemented in metallurgical production to improve efficiency. Special attention is given to the application of AI and ML in various aspects of metallurgical processes, from raw material processing to final product quality control.

The aim of this work is to investigate modern approaches and automation systems used in the metallurgical industry, identify their features, capabilities, and limitations, as well as analyze ways of their further implementation to increase production efficiency. Additionally, this paper explores the potential of Industry 4.0 concepts and their application in the context of metallurgical production, considering the unique challenges and opportunities presented by this sector.

## **2 Materials and methods**

This study employed a comprehensive approach to investigate modern automation techniques in the metallurgical industry. The research began with an extensive analysis of literature and scientific publications focused on automation in metallurgical processes. This review encompassed a wide range of sources, including academic journals, industry reports, and technical documentation, to provide a thorough understanding of the current state of automation in the field.

To gain practical insights, the study compared the experiences of leading metallurgical enterprises that have implemented advanced automation systems. This comparative analysis allowed for the identification of best practices, challenges encountered during implementation, and the overall impact of automation on production efficiency and product quality [3].

The research also involved a synthesis of developments in the digitalization of production processes, big data analytics, and AI applications specific to the metallurgical industry. This aspect of the study aimed to understand how these cutting-edge technologies are being integrated into traditional metallurgical processes and their potential for future advancements.

Furthermore, the study included an in-depth analysis of contemporary technical solutions and developments in the field of APCS. This analysis focused on the latest hardware and software solutions designed to optimize various stages of metallurgical production, from raw material processing to final product quality control.

By combining these methodological approaches, the study aimed to provide a comprehensive overview of the current state of automation in the metallurgical industry and to identify promising directions for future development and implementation of advanced automation technologies in this sector [4].

### 3 Results and discussion

APCS play a pivotal role in the metallurgical industry, as they significantly influence production efficiency, product quality, energy conservation, and safety. In metallurgy, technological processes are inherently complex, characterized by high temperatures, substantial energy consumption, and stringent requirements for precision and quality in metal and alloy smelting.

The primary objectives of APCS implementation in metallurgy include:

1. Enhancement of metallurgical product quality through improved precision in process parameter control and reduction of human error.
2. Optimization of energy and material resource consumption, facilitated by efficient raw material utilization and reduced electricity consumption through improved feedback and automatic control mechanisms.
3. Increased productivity, achieved through accelerated raw material processing due to precise control and management of processes.
4. Improvement of environmental safety, focusing on the optimization of pollutant emissions (CO<sub>2</sub>, slag, dust) and automated accounting and monitoring of emissions.
5. Ensuring occupational safety by automating hazardous production stages, monitoring equipment condition, and preventing emergency situations.

The architecture of APCS for metallurgical enterprises encompasses a wide integration of sensor systems, computer technologies, and cloud solutions. These systems enable the control and management of complex processes such as steel smelting, metal rolling, and heat treatment.

Studies by authors [5] elucidate the fundamentals of automatic control theory, principles of constructing control systems for technological objects, methods of analysis and tuning of automatic regulators, and basics of logical control. They also provide information on technical automation tools and principles of designing and constructing APCS for technological processes in metallurgical production [6].

According to review articles and research conducted over the past two decades, the automation of metallurgical processes is being implemented in several key directions:

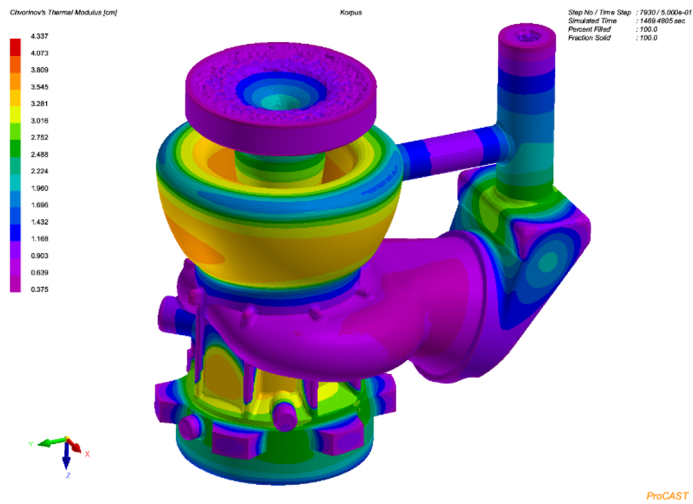
1. Equipment modernization which involves the introduction of automated production lines, the use of robotic manipulators, and the implementation of Computer Numerical Control (CNC) systems.
2. Development of digital twins with many contemporary studies dedicated to creating digital models of metallurgical enterprises, enabling real-time process control and testing of optimization scenarios.

These advancements in APCS and related technologies are driving significant improvements in the efficiency, quality, and sustainability of metallurgical operations, paving the way for the industry's future development.

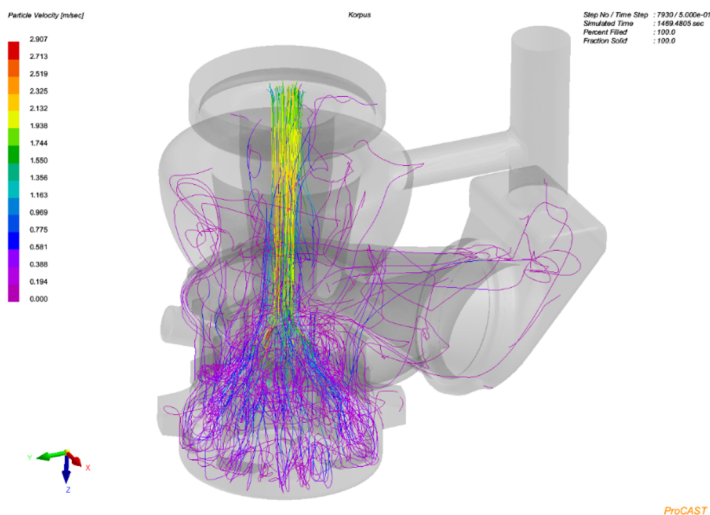
AI technologies are being increasingly applied to optimize technological processes, determine product quality parameters, and minimize production defects in the metallurgical industry. For instance, machine learning systems are utilized to analyze large volumes of data collected from video surveillance cameras and sensors. The modeling of production equipment and technological processes in the form of digital twins provides the opportunity to test and optimize processes without external impact on actual production [7].

Let us consider the modeling of casting processes using ESI Group ProCAST software [8]. This module enables the execution of virtual experiments, the results of which are presented in Figures 1-3. The obtained models, based on specified initial and boundary conditions, allow for the calculation of metal shrinkage and crystallization (Figure 1), analysis of metal flow vectors (Figure 2), and investigation of pore and shrinkage cavity formation in the casting (Figure 3).

Figure 1 shows the temperature distribution of the casting for a "Turbine housing" part. This visualization likely depicts how heat is distributed throughout the casting during the solidification process. The temperature gradient would be represented by different colors, with hotter areas typically shown in red or orange and cooler areas in blue or green. This temperature distribution is crucial for understanding how the part solidifies and where potential defects might occur due to uneven cooling.



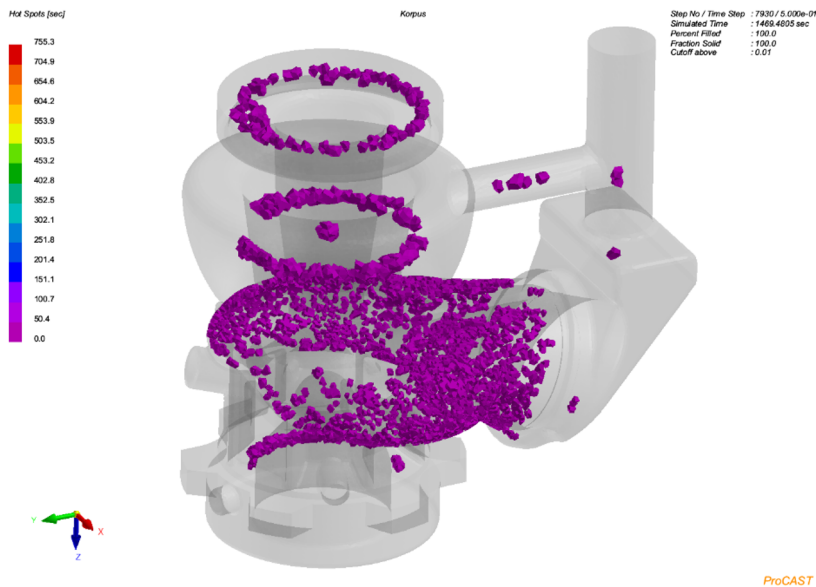
**Fig. 1.** Temperature distribution of the casting of the "Turbine housing" part.



**Fig. 2** Metal flow vectors in a casting.

Figure 2 presents the metal flow vectors in the casting. This visualization would show the direction and magnitude of molten metal movement within the mold cavity during the filling process. Arrows or streamlines would likely be used to indicate the flow direction, with their size or color potentially representing the flow velocity. This information is valuable for identifying areas of turbulence, potential entrapment of gases, or regions where the metal might not fill properly.

Figure 3 illustrates the shrinkage pores and loose spaces after the metal crystallization process. This figure would highlight areas where shrinkage porosity and other solidification-related defects are likely to form. These defects would appear as voids or low-density regions within the solidified casting. The visualization helps in identifying critical areas prone to defects, allowing engineers to optimize the casting design, gating system, or process parameters to minimize these issues.



**Fig. 3.** Shrinkage pores and loose spaces after the metal crystallization process.

Thus, Figures 1-3 collectively provide a comprehensive view of the casting process, from the initial filling and heat distribution to the final solidification and potential defect formation. They demonstrate the power of simulation software in predicting and visualizing complex phenomena in metal casting, enabling engineers to optimize their designs and processes before physical production [9-10].

The Severstal metallurgical production facility presents a compelling case study in the successful implementation of advanced automated systems in the metallurgical industry. The facility has deployed a range of innovative solutions that leverage machine learning, artificial intelligence, and computer vision technologies to enhance various aspects of its operations.

A notable implementation is a software complex for managing rolling pace and slab extraction from furnaces, based on machine learning models. Deployed at the 2000 mill of the Cherepovets Metallurgical Plant, this system optimizes the pause before slab extraction, resulting in increased productivity. Complementing this, an artificial intelligence-based solution for the continuous pickling unit has been implemented, which has demonstrated a productivity increase exceeding 6.5%. This AI system dynamically calculates and adjusts the control speed of the unit's middle section in real-time.

From the point of view of quality control, Severstal has introduced a sophisticated system for metal defect recognition utilizing neural networks. This system processes images from cameras and employs high-performance graphics processors to detect, classify, and parameterize defects. Such an approach significantly enhances the accuracy and efficiency of quality assurance processes.

Safety in production processes has been markedly improved through the implementation of neural network-based solutions augmented with computer vision algorithms. These systems analyze video streams to monitor personnel presence in hazardous areas, verify the use of personal protective equipment, and oversee the safe movement of machinery. The efficacy of these safety measures is evidenced by a reduction in dangerous actions by more than threefold in most projects, with some instances reporting complete elimination of such actions.

Furthermore, Severstal has implemented an automated management system for normative technological data. This system creates a unified technological information base for the company's products and technologies, thereby streamlining the maintenance of technological data, automating technical expertise of orders, and expanding capabilities in planning, production, and product certification.

These implementations at Severstal exemplify the practical application of cutting-edge automation and AI technologies in the metallurgical industry. The resultant improvements in productivity, safety, and overall operational efficiency underscore the transformative potential of these technologies in modernizing traditional industrial processes.

## **4 Conclusion**

The implementation of advanced automation and artificial intelligence technologies in the metallurgical industry has demonstrated significant potential for enhancing productivity, quality, and safety across various production processes. This study has highlighted the crucial role of APCS in optimizing complex metallurgical operations, from raw material processing to final product quality control. The integration of IoT devices, big data analytics, and machine learning algorithms has enabled real-time monitoring and predictive maintenance, leading to improved resource utilization and reduced downtime.

The case study of Severstal's metallurgical production facility exemplifies the transformative impact of these technologies. Through the deployment of AI-driven systems for process control, quality assurance, and safety management, Severstal has achieved notable improvements in productivity and operational efficiency. The use of digital twin technology, as demonstrated by the ESI Group ProCast software simulations, further illustrates the power of virtual modeling in optimizing casting processes and predicting potential defects before physical production.

As the metallurgical industry continues to evolve, the adoption of Industry 4.0 concepts and advanced automation technologies will be crucial for maintaining competitiveness and meeting increasingly stringent environmental and quality standards. While challenges remain in terms of implementation costs and the need for specialized expertise, the benefits of these technologies in terms of improved product quality, reduced waste, and enhanced safety are clear. Future research should focus on further integration of AI and machine learning across the entire metallurgical value chain, as well as addressing the specific challenges of adapting these technologies to the unique requirements of different metallurgical processes.

In conclusion, the ongoing digital transformation of the metallurgical industry, driven by automation and AI technologies, represents a significant step towards more efficient, sustainable, and competitive metal production. As these technologies continue to mature and evolve, they will undoubtedly play a central role in shaping the future of metallurgical operations worldwide.

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