

KPI-BASED EFFICIENCY EVALUATION IN ALUMINIUM PRODUCTION WITH VARYING LEVELS OF AUTOMATION AND DIGITIZATION

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Abstract

The aim of the study was to analyze the use of Key Performance Indicators (KPIs) in assessing the efficiency of companies with varying levels of automation, as well as to indicate how the selection of appropriate KPIs supports the implementation of smart manufacturing solutions in the foundry industry. The study compared traditional and automated production systems in terms of performance, quality, process stability and machine availability metrics. The empirical research was conducted as a comparative case study of two manufacturing plants within a Polish aluminum processing company, representing different stages of modernization and Industry 4.0 implementation. The research indicates that appropriately selected KPIs are the foundation of effective performance evaluation in the digital transformation process. The results reveal that fully exploiting the potential of automation requires not only technology, but also the integration of processes, data and organizational culture. The study may be useful for production managers, process engineers and decision-makers responsible for planning and implementing digital transformation objectives in the foundry industry.

Keywords: Smart manufacturing, Key Performance Indicators (KPIs), digital transformation, aluminum foundry, manufacturing systems

1. INTRODUCTION

Contemporary industrial units are increasingly facing challenges related to growing market expectations, the need to optimize costs, and increase production flexibility [1]. This phenomenon is particularly significant in the aluminum industry, which has been growing rapidly in recent years, driven by increased demand for lightweight, durable and highly recyclable products [2]. The complex nature of technological processes in the aluminum industry (smelting, refining, forming, die casting, CNC machining, quality control using non-destructive techniques) requires constant monitoring of parameters and rapid response to any deviations [3, 4]. At the same time, market requirements related to increasing repeatability, improving quality indicators and shortening cycle times are forcing the implementation of increasingly advanced technological solutions [5]. In this respect, automation, digitalization and the Industry 4.0 concept play an important role, enabling companies to improve the quality, efficiency and stability of their processes while reducing the risk of operational errors [6, 7]. In the aluminum industry, where processes are heavily dependent on precise control of cycle time, temperature, casting machine parameters and tool condition, the implementation of intelligent production systems can significantly affect the level of efficiency of companies with varying degrees of automation [8, 9].

In environments where production processes are increasingly digitized, efficient business management requires the use of tools that enable the analysis and interpretation of data to support decision-making. Key

Performance Indicators (KPIs) play a key role among these tools [10]. These indicators allow for the monitoring and evaluation of the efficiency of processes, machines and production systems in companies with varying levels of automation. They allow for the identification of operational barriers and the assessment of operational stability and resource utilization. KPIs support the evaluation of production results and the level of an organization's readiness for digital transformation [11]. In the reality of smart manufacturing, KPIs also monitor aspects of data quality, IT system integration and organizational culture, making them not only a measurement tool, but also an important element of the development and digital transformation strategy of enterprises [12].

Despite numerous studies on the use of KPIs in monitoring industrial processes, the literature refers only to a limited extent to the issue of assessing the efficiency of plants operating at different levels of automation [13]. The available studies mainly concern analyses using KPIs in individual companies, in highly automated conditions [14, 15], or in the implementation of selected Industry 4.0 technologies [16]. There are relatively few studies comparing KPI sets and their informative usefulness in enterprises with varying degrees of digitalization and automation in the aluminum industry. sets and their informational usefulness in companies with different levels of digitization and automation in the aluminum industry. The gaps are particularly noticeable in the foundry sector, where processes are highly technologically diverse. The gap also relates to the assessment of their ability to identify differences in operational efficiency between traditional and automated production systems.

The digital transformation of the foundry industry also involves the transfer of advanced analytical methods from other fields, such as medicine [17], bioengineering [18] and materials science [19-21], where data processing standards are exceptionally high. The use of 3D image analysis [17] and machine learning [22] algorithms, originally developed for the precise assessment of complex structures, is a benchmark for detecting and classifying internal defects in aluminum castings. Implementing such high-fidelity diagnostic methods, supported by machine learning, is crucial for improving key performance indicators (KPIs) related to quality (QR) and process stability, especially in automated environments where nondestructive testing (NDT) generates large amounts of tomographic data.

The aim of the study was to analyze the use of KPIs in assessing the performance of companies with varying levels of automation and to indicate how these indicators can support the digital transformation process in the foundry industry. The research was conducted in two plants of the same company, differing in the degree of automation. The difference in the level of automation resulted from the different stages of modernization of production lines and the scale of implementation of Industry 4.0-based solutions. The results may be useful for production managers, process engineers and employees responsible for monitoring and improving digitalization strategies in industrial enterprises.

2. METHOD

Identifying KPIs is a key element in the process of assessing the effectiveness of companies with varying levels of automation. A systematic approach to their selection allows for the strategic goals and specific characteristics of the enterprise to be taken into account. **Figure 1** presents the stages of the process that enable the comprehensive development and verification of KPIs, ensuring their adequacy, operational usefulness and consistency with stakeholder expectations.

Figure 1 shows the stages of KPI identification, ensuring a systematic approach to assessing the performance of companies with varying levels of automation. The process begins with an analysis of the company's context and level of automation, which allows KPIs to be aligned with strategic objectives. Next, key stakeholders are identified, existing indicators are analyzed, and the availability of operational data is assessed. This ensures a more complete understanding of the organization's information needs. The next stage involves the selection and verification of KPIs, including an assessment of their relevance and alignment with strategic objectives, followed by testing of selected indicators in real production conditions. Finally, the KPIs are optimized and

verified, and monitoring and reporting procedures are developed to ensure a reliable and comparable assessment of the company's performance.

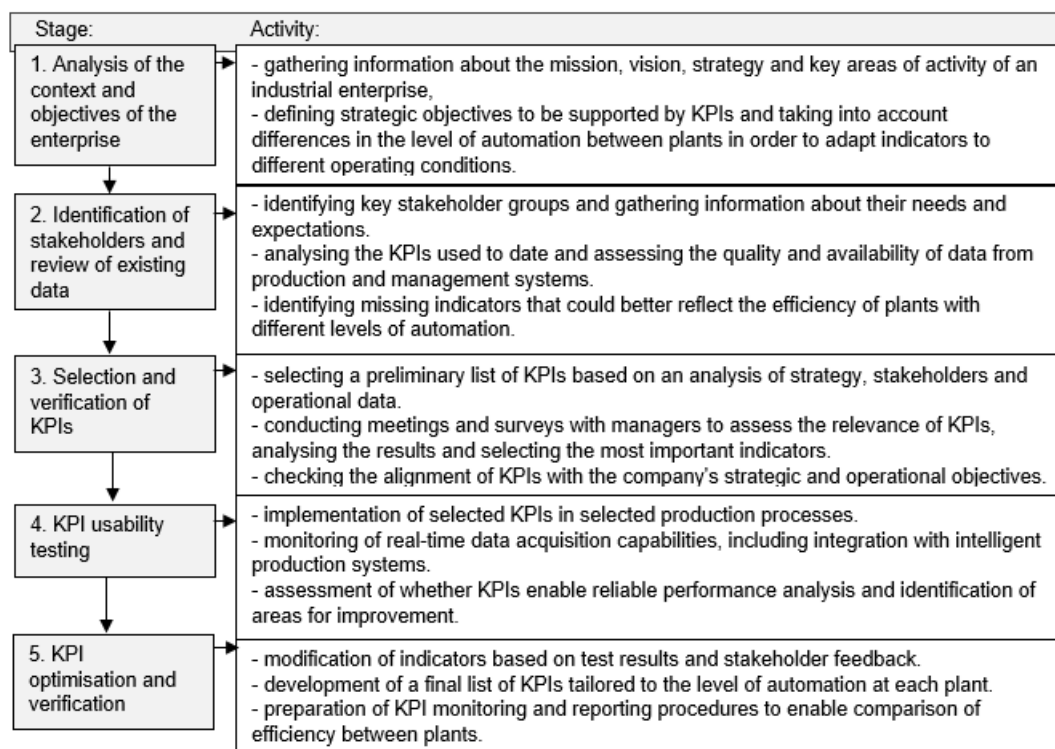


Figure 1 Generalized model for KPI selection and management in an automated environment

3. METHOD TEST AND RESULTS

The model was tested and the assumptions verified at a company operating in the aluminium processing sector in south-eastern Poland. The company specializes in the manufacture of light metal alloy components for the automotive, energy, robotics and aviation industries, as well as for mechanical engineering and engine technology. The research was conducted in the first half of 2025 at two of the company's plants, which differ in their degree of automation. Both plants manufacture similar products, and the difference in the level of automation results from the different stages of modernization of the production lines and the scale of implementation of Industry 4.0-based solutions. The first plant operates on the basis of more conventional technologies, while the second has undergone advanced automation, including robotic workstations, real-time process monitoring systems and intelligent solutions to support production management.

The research process began with a preliminary diagnosis of the company and identification of its operational practices. During meetings with the management, the technologies used were reviewed and the company's readiness to implement Industry 4.0 solutions was assessed. At the same time, key stakeholders were identified, their expectations were determined, and the indicators used to date and available information resources be analyzed.

The KPI selection process was expanded to include a survey. The selection of survey participants was carried out in cooperation with the HR manager, which ensured the participation of people with the appropriate competences. The respondents were exclusively representatives of the management staff, who assessed individual indicators on a five-point scale of importance (1 - least important, 5 - most important indicator). The assessment was carried out in terms of adequacy, operational value and compliance with the company's strategic objectives, and then the results were organized and key indicators were selected. All 53 questionnaires collected were completed in full, which indicates a high level of interest in the subject of the

research and a professional approach to completing the questionnaires on the part of the management staff. **Table 1** presents the results of the KPI selection – a set of indicators that form the basis for analysing and comparing the results achieved in different production environments.

Table 1 Selected KPIs for assessing the efficiency of plants with varying levels of automation

Indicator name	Pattern	Expected value	Purpose/interpretation
OEE - Overall Equipment Effectiveness	$OEE = \text{availability} \times \text{efficiency} \times \text{quality}$	75 -85% (good level)	OEE allows you to assess the efficiency of your machine park, taking into account downtime, productivity and production quality, which makes it easier to identify areas for optimization and compare results between plants.
A - Availability of machinery	$A = \text{working time/planned time}$	>90%	The indicator measures the readiness of machines for operation. Low availability indicates breakdowns, maintenance issues or downtime.
PR - Performance Rate	$PR = \text{actual speed/nominal speed}$	85-95%	The performance indicator shows how machines perform in relation to their maximum speed, helping to detect drops in efficiency resulting from delays or process problems, among other things.
QR - Quality Rate	$QR = \text{compliant products / all manufactured products}$	>98%	The quality index measures product compliance with standards and process stability, assessing the effectiveness of controls and the impact of automation on reducing non-compliance.
FPY – First Pass Yield	$FPY = \text{products compliant without corrections / all manufactured}$	90-98%	FPY measures 'first-time' production efficiency, indicating process stability and control, which is important when comparing plants with varying degrees of automation.

The summary of the presented KPIs (see **Table 1**) covers key areas of assessing the efficiency of production processes in foundry industry enterprises. The analysis of these indicators enables a comprehensive assessment of both the technical and operational aspects of a plant's operation, allowing the identification of potential areas for optimization. **Figure 2** shows a summary of KPIs in an automated and semi-automated plant. In **Figure 2**, each bar corresponds to one monthly time interval, allowing for six months of observation for each indicator in both automated and semi-automated plants.

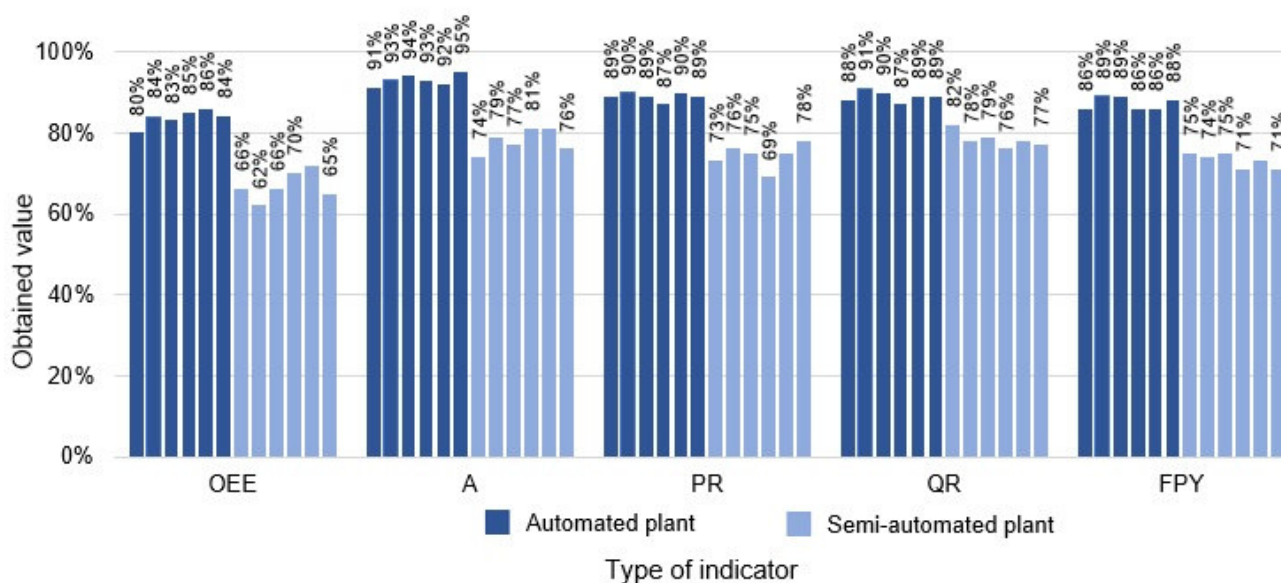


Figure 2 Indicator values achieved by automated and semi-automated plants

The results of the indicator measurements (see **Figure 2**) for two plants of the same company, differing in the level of automation, clearly show the impact of automation on the efficiency and quality of production processes. In the plant with a higher level of automation, the indicators: OEE, machine availability, production efficiency, quality index and FPY remain at a high and fairly stable level. This translates into efficient use of resources, fewer downtimes and product non-conformities, which is important in the production of precision aluminum components. Automation allows for precise control of casting and machining parameters, which reduces the risk of human error, increases process repeatability and enables a stable level of quality to be maintained across different production batches. In contrast, in a semi-automated plant, the analyzed indicators show greater fluctuations – downtime is more frequent, production efficiency is lower, and the need to repair manufactured products is more common. In semi-automated production, processes are more dependent on the experience of operators, which affects quality variability and extends order fulfilment times. A higher level of non-compliant products also results in greater material losses and increases production costs.

The comparison of two production environments with different levels of automation enabled the comparison of operational efficiency, the identification of key differences in work organization, and the assessment of the impact of automation on data quality, information availability, and decision-making processes. This made it possible to thoroughly test the developed model in contexts with different levels of technological maturity.

4. CONCLUSION

Assessing the effectiveness of production processes requires the use of an appropriate set of indicators that objectively reflect important aspects of a production plant's operation. The aim of the study was to analyze the use of Key Performance Indicators (KPIs) in assessing the efficiency of companies with varying levels of automation, as well as to indicate how the selection of appropriate KPIs supports the implementation of smart manufacturing solutions in the foundry industry.

In an industrial environment, KPIs that enable the monitoring of machine availability, performance, quality and process stability are important. Research conducted in two plants with varying degrees of automation confirmed the correctness of the research assumptions. Analysis using KPIs showed that a higher degree of automation in a production plant not only ensures more stable and predictable processes, but also enables more efficient adaptation to changes in orders and customer expectations. An additional benefit of automation in production is improved work safety and reduced risk of operational errors. At the same time, automation ensures lower production costs and higher quality of finished products, which increases competitiveness on the market.

Future research aims to develop an integrated method for assessing digital maturity, enabling the synchronization of KPIs with real-time information provided by intelligent manufacturing systems.

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