INTELLIGENT PRODUCT LIFECYCLE MONITORING BASED ON ARTIFICIAL INTELLIGENCE

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ANNOTATION

With the rapid development of digital technologies and the transition to Industry 4.0, the development of integrated product lifecycle monitoring systems at industrial enterprises is becoming increasingly important. This article examines the theoretical and practical aspects of developing such systems, integrating artificial intelligence methods to create an intelligent decision-making system. A systematic approach is proposed, incorporating the use of Internet of Things technologies, cloud computing, and big data analytics, enabling continuous monitoring of product parameters and technological processes. Machine learning, neural networks, and fuzzy logic methods used for data analysis and product condition prediction are discussed.

Introduction

Modern industrial enterprises operate in a globalized economy and increasingly competitive environment, requiring innovative approaches to production process management. One of the key factors for enhancing competitiveness is effective product lifecycle management, encompassing all stages – from development to disposal.

Traditional production control and management methods often fail to provide the necessary speed and accuracy for decision-making, especially when processing large volumes of data. Consequently, the role of digital technologies, including artificial intelligence, the Internet of Things, and big data analytics systems, is growing [1-3].

The integration of these technologies enables the creation of intelligent monitoring systems capable of not only recording the current state of products, but also predicting their behavior, identifying potential defects, and automatically generating management decisions.

Thus, the development of an integrated system for monitoring the life cycle of products using artificial intelligence methods is a pressing scientific and technical task that is of great importance for improving the efficiency of industrial production [4].

Product life cycle monitoring system

The product life cycle monitoring system is a multi-level information and analytical system that ensures continuous collection, processing and analysis of data on the state of products at all stages of their existence [5,6].

During the design phase, information is collected on the product's design parameters, materials used, and process limitations. This data forms the basis for further analysis and optimization of product performance.

During the production stage, process parameters such as temperature, pressure, processing speed, and other indicators are monitored. The use of sensors and integrated measurement systems allows for real-time data acquisition, significantly improving control accuracy.

During the operational phase, monitoring the product's condition under real-world conditions is particularly important. This allows for the detection of deviations from normal operating conditions and the prevention of emergency situations.

The final stage – disposal or recycling – also requires consideration of product parameters, which is important for environmental safety and the rational use of resources.

Fig.1. Architecture of the industrial IoT monitoring system.

The implementation of such systems ensures transparency of all processes, improves manageability and reduces the likelihood of defects.

Artificial intelligence in decision-making systems

Artificial intelligence plays a key role in the creation of intelligent decision-making systems, enabling the automation of data analysis and the generation of optimal management actions.

Modern machine learning methods enable the construction of models capable of adapting to changing production conditions. For example, classification algorithms are used to identify defective products, and regression methods are used to predict process parameters [7].

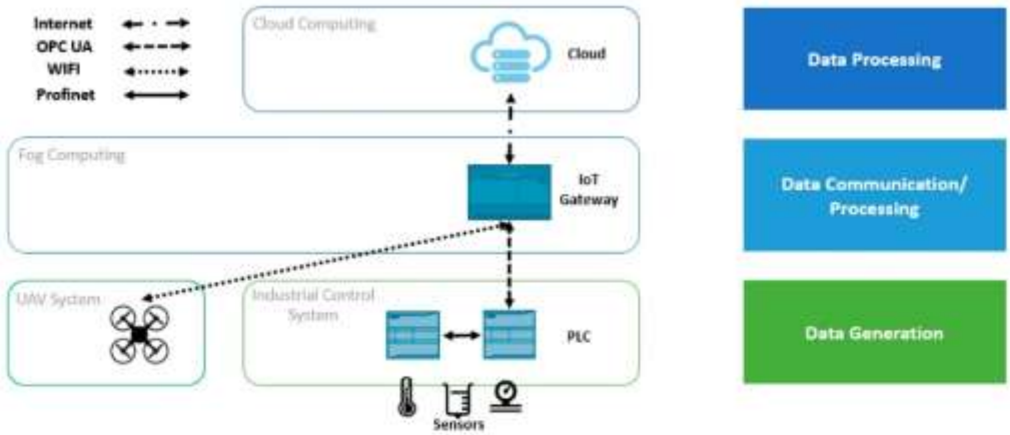

Fig.2. Data flow and analytics based on artificial intelligence.

Deep learning based on multilayer neural networks enables the efficient processing of complex and unstructured data, such as images, signals, and time series. This is particularly relevant for equipment diagnostics and product quality control.

Expert systems formalize specialist knowledge and enable its use in automated decision-making. Fuzzy logic, in turn, is used in conditions of uncertainty and allows for the consideration of imprecise or incomplete data.

The use of artificial intelligence can significantly improve forecast accuracy, reduce decision-making time, and reduce the influence of human factors.

Integration of monitoring and intelligent systems

Integrating a product lifecycle monitoring system with an intelligent decision-making system requires the creation of a unified digital platform that unites all levels of production management.

The data collection layer utilizes sensors and IoT devices to provide information about the status of equipment and products. This data is transmitted via communication networks to the storage layer, which utilizes databases and cloud technologies [8].

Next, the data is analyzed using artificial intelligence algorithms, which allows for the identification of patterns and forecasting of process developments. Based on the results obtained, a decision support system is developed, capable of automatically generating recommendations or management commands.

An important element of the system is the user interface, which provides data visualization and convenient operator interaction with the system.

Integrating all components into a single system ensures a continuous management cycle, increases production efficiency, and minimizes risks.

Methods for developing an intelligent system

The development of an intelligent monitoring and decision-making system is a complex multi-stage process that requires an integrated approach [9].

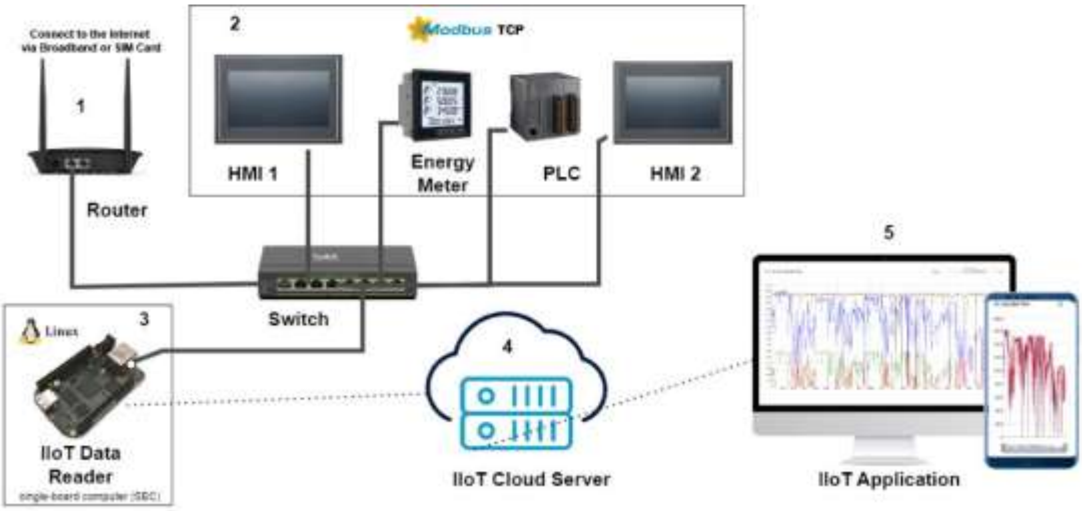

Fig.3. Structure of the real-time monitoring system.

At the initial stage, the system's goals and objectives are defined, key performance indicators and functional requirements are determined. This allows us to set the direction for further development.

The next stage involves collecting and preparing data, which is critical for successfully training AI models. The data must be cleaned of noise, structured, and standardized.

Algorithms are selected based on the specifics of the tasks being solved. For example, regression methods and neural networks are used for forecasting, while clustering methods are used for anomaly detection.

Models are trained using historical data, followed by testing and validation. This allows us to assess the system's accuracy and reliability.

During the implementation phase, the system is integrated into the existing enterprise infrastructure, which requires consideration of compatibility with the technologies used.

The final stage involves assessing the effectiveness of the system and its subsequent optimization.

The implementation of a product life cycle monitoring system and an intelligent decision-making system provides significant benefits for industrial enterprises.

First and foremost, product quality is improved through continuous monitoring and timely detection of defects. This reduces the rate of defects and increases customer satisfaction.

Cost reduction is achieved through optimised resource use, reduced equipment downtime and reduced repair costs.

In addition, the system helps improve production safety by enabling the timely identification of potentially hazardous situations.

Conclusion

This article examines modern approaches to developing a product lifecycle monitoring system for industrial enterprises using artificial intelligence methods. An analysis of the system architecture, data processing methods, and intelligent analysis algorithms is provided. The proposed integration model allows for the unification of monitoring and decision-making processes into a single system, ensuring highly efficient production management.

The study's findings confirm that the use of artificial intelligence in combination with Internet of Things technologies and big data analytics opens up new opportunities for improving the competitiveness of enterprises.

In the future, further research may be aimed at developing autonomous control systems, increasing the level of intellectualization of production processes, and expanding the scope of application of digital technologies in industry.

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