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INTELLIGENT PRODUCTION LINE CONTROL SYSTEMS IN THE FOOD INDUSTRY BASED ON MACHINE LEARNING

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The possibilities of introducing intelligent production process control systems in the food industry, taking into account modern challenges and automation needs, are investigated. The relevance of the study is due to the need to increase the efficiency of production lines, reduce costs, improve quality control and compliance with international food safety standards, in particular ISO 22000, HACCP, BRC Global Standard, FSSC 22000 and IFS. It has been established that traditional approaches to automation do not provide sufficient flexibility and adaptability to changes in technological parameters and market conditions, which necessitates the implementation of systems based on machine learning, predictive analytics, and IoT.

The purpose of the study is to develop approaches to automation of production lines in the food industry by integrating machine learning, robotics, and IoT to improve the efficiency of production processes. The methodological basis is based on analytical and comparative research methods that allowed us to evaluate the effectiveness of existing automation approaches, as well as modeling an adaptive control system.

The results of the study confirm that the integration of IoT sensors, machine learning algorithms, and predictive analysis can significantly improve the accuracy of monitoring and control of production processes. The main problems of implementing such systems are identified, including the high cost of modernization, the complexity of integration with existing infrastructure, the need for qualified personnel and compliance with regulatory requirements. It is proved that the gradual introduction of intelligent systems using predictive analytics to monitor the technical condition of equipment and prevent failures can reduce risks, minimize production losses and improve product quality.

Prospects for further research include the development of deep learning algorithms to improve the accuracy of the analysis of production parameters, as well as the study of the economic aspects of implementing such technologies in various segments of the food industry.

Key words: *production automation, predictive analytics, cyber-physical systems, quality control, digital transformation.*

Нікулін А. С. Інтелектуальні системи управління виробничими лініями у харчовій промисловості на основі машинного навчання

Досліджено можливості впровадження інтелектуальних систем управління виробничими процесами в харчовій промисловості, з урахуванням сучасних викликів та потреб автоматизації. Актуальність дослідження зумовлена необхідністю підвищення ефективності виробничих ліній, зменшення витрат, покращення контролю якості та відповідності міжнародним стандартам безпеки харчових продуктів, зокрема ISO 22000, HACCP, BRC Global Standard, FSSC 22000 та IFS. Встановлено, що традиційні підходи до автоматизації не забезпечують достатньої гнучкості та адаптивності до змін технологічних параметрів і ринкових умов, що обумовлює потребу у впровадженні систем на основі машинного навчання, предиктивної аналітики та IoT.

Метою дослідження є розробка підходів до автоматизації виробничих ліній у харчовій промисловості шляхом інтеграції машинного навчання, робототехніки та IoT для підвищення ефективності виробничих процесів. Методологічну основу становлять аналітичні та компаративні методи дослідження, що дозволили оцінити ефективність існуючих підходів до автоматизації, а також моделювання адаптивної системи управління.

Результати дослідження підтверджують, що інтеграція IoT-сенсорів, алгоритмів машинного навчання та предиктивного аналізу дозволяє значно підвищити точність моніторингу та контролю виробничих процесів. Виявлено основні проблеми впровадження таких систем, серед яких висока вартість модернізації, складність інтеграції з існуючою

інфраструктурою, потреба у кваліфікованому персоналі та дотриманні регуляторних вимог. Доведено, що поступове впровадження інтелектуальних систем із використанням предиктивної аналітики для контролю технічного стану обладнання та запобігання збоям дозволяє знизити ризики, мінімізувати виробничі втрати та підвищити якість продукції.

Перспективи подальших досліджень полягають у розробці алгоритмів глибокого навчання для підвищення точності аналізу параметрів виробництва, а також у дослідженні економічних аспектів впровадження таких технологій у різних сегментах харчової промисловості.

Ключові слова: *автоматизація виробництва, предиктивна аналітика, кіберфізичні системи, контроль якості, цифрова трансформація.*

Problem statement. Intelligent production line control systems in the food industry based on machine learning are a key research area, as traditional approaches do not provide sufficient adaptability to changing conditions, which leads to resource overruns and reduced productivity. The introduction of machine learning allows automating data analysis, predicting deviations, and optimizing production processes in real time, which increases efficiency and product quality. The growing demands on the food industry require the development of systems that are adaptable, energy efficient, and integrated into digital platforms. The use of artificial intelligence in combination with sensor technologies and cloud computing contributes to the implementation of the concept of smart factories, where automated control ensures continuous process improvement. The scientific significance of the problem lies in the development of methods to improve the reliability and efficiency of such systems, while the practical value lies in the creation of technological solutions for automation and increasing the competitiveness of food enterprises.

The analysis of scientific research confirms that intelligent production line management systems in the food industry based on machine learning are aimed at improving the efficiency of production processes, optimizing resources, and ensuring the stability of food supply.

Research on the automation of production processes considers the potential of artificial intelligence to increase productivity, reduce costs, and minimize the impact of the human factor. I. Kollia, J. Stevenson, S. Kollias [1] investigate how AI-oriented systems contribute to the efficiency and safety of food supply, emphasizing the importance of optimizing logistics operations and demand forecasting. E. Drijver, R. Pérez-Dattari, J. Kober, C. D. Santina, Z. Ajanović [2] analyze the use of reinforcement learning algorithms to optimize packaging processes in the food industry, which reduces costs and increases productivity. G. Bai [3] explores real-time technologies for optimizing production lines in the food industry, demonstrating the role of intelligent systems in improving operational efficiency. Further research should be aimed at assessing the long-term impact of automation on the costs and productivity of food production, as well as at analyzing the effectiveness of adaptive production lines.

In the field of production planning and management, research focuses on the use of machine learning to improve the accuracy of forecasting and optimization of production processes. J. P. Usuga Cadavid, S. Lamouri, B. Grabot [4] analyze the role of artificial intelligence in the management of production processes, emphasizing its importance in optimizing planning and control. O.E. Oluyisola, S. Bhalla, F. Sgarbossa [5] investigate the development of smart production management systems in the context of Industry 4.0, which allows to improve forecasting accuracy and reduce raw material losses. J. Wang, Y. Ma, L. Zhang, R. X. Gao, D. Wu [6] describe the application of deep learning for smart manufacturing, in particular in predicting production parameters and process optimization. It is advisable to complement this area by analyzing specific cases of AI implementation in production management and assessing its economic efficiency.

In the context of digitalization of quality control and energy management, research is aimed at improving safety standards and efficient use of resources. J. A. García-Esteban, B. Curto, V. Moreno, I. González-Martín, I. Revilla, A. Vivar-Quintana [7] investigate strategies for digitalizing quality control based on artificial intelligence algorithms, emphasizing their role in improving food monitoring. I. Kumar, J. Rawat, N. Mohd, S. Husain [8] analyze the possibilities of AI and machine learning in improving food technology, focusing on improving product quality and safety. L. Zhu, P. Spachos, E. Pensini, K. N. Plataniotis [9] investigate the use of machine vision for automated product quality control, including defect recognition and sorting. Additionally, S. Baliuta, L. Kopylova, V. Kuevda, I. Kuievda, I. Lytvyn [10] propose the development of an intelligent energy management system based on forecasting electricity consumption in food production, which helps to reduce energy costs and optimize resource use. Further research should consider the integration of such technologies into large-scale production and their ability to improve food safety standards.

A separate set of studies concerns the use of AI to ensure food safety. R. Khan [11] analyzes the possibilities of artificial intelligence in the food industry, emphasizing its role in preventing food threats and improving supply chain traceability. J. He, H. Huang, Y. Wang [12] investigate the latest food detection technologies using machine learning to detect fakes and contaminants. M. R. Mahmood, M. A. Matin, S. K. Goudos, G. Karagiannidis [13] conduct a comprehensive analysis of the use of machine learning in agriculture, which affects the food industry through the optimization of growing and storage of products. An important area for further research is to evaluate the effectiveness of such systems in real production conditions and to develop integrated platforms for food safety monitoring.

The general analysis shows that intelligent production line management systems in the food industry based on machine learning are a key factor in increasing efficiency, reducing costs, and ensuring product quality. Despite significant progress in the development of intelligent production line management systems, issues related to the integration of machine learning, IoT, and predictive analytics into a single adaptive system remain unresolved. The absence of unified standards makes it difficult to be compatible with different production platforms, and most solutions focus on controlling individual parameters without providing autonomous process adjustments in real time. Cybersecurity issues have also been insufficiently explored, as IoT integration increases the risk of unauthorized access to production data, which can threaten the continuity of production processes.

The proposed study fills these gaps by developing a conceptual model of an intelligent system that combines automated control of technological parameters with the ability to autonomously control production. The analysis of the use of machine learning and IoT allows to improve the accuracy of deviation prediction, and the development of approaches to strengthening cybersecurity contributes to the protection of data in the digital production environment. The implementation of such solutions ensures not only flexibility and adaptability of automated systems, but also increases their cost-effectiveness and compliance with modern international standards.

The purpose of the study is to analyze effective approaches to automating production lines in the food industry based on machine learning, robotics, and IoT.

To achieve this goal, the following *tasks* have been identified:

1. To analyze modern methods of automation of production lines in the food industry and machine learning, artificial neural networks and IoT tools used for quality control and optimization of technological parameters.

2. Develop a conceptual model of an intelligent production process management system and identify the main problems of its implementation in the food industry.

3. Provide recommendations on the practical use of intelligent control systems to improve production efficiency, taking into account technological and organizational challenges.

Summary of the keynote material. Automation of production lines in the food industry is a key area of development in the industry aimed at increasing productivity, reducing costs and ensuring consistent product quality. Modern automation methods cover a wide range of technologies, including robotic systems, intelligent sensors, machine learning, the Internet of Things (IoT), and cyber-physical systems. The use of these solutions can significantly increase the level of control over production processes, minimize the human factor and ensure continuous monitoring of process parameters. Automated control systems are integrated with production lines to optimize logistics, regulate the supply of raw materials, control temperature conditions, identify deviations from quality standards, and predict technical failures (Table 1).

Table 1

Modern methods of automation of production lines in the food industry and their characteristics

Automation method	Main features	Areas of application
Robotic manipulators	Automated packaging, packing, and slicing operations	Packaging lines, product sorting, machining
Intelligent sensors and IoT	Real-time monitoring of temperature, humidity, equipment status	Control of storage conditions, automated parameter adjustment
Machine learning and predictive analytics	Data analysis, fault prediction, parameter optimization	Detecting deviations in product quality, preventing production stoppages a
Automated conveyor systems	Adjustable transport mechanisms with electronic control	Optimization of logistics, reduction of manual labor
Cyber-physical systems	Integration of physical devices with digital models	Modeling and optimization of production processes in real time

Source: compiled by the author based on [1; 2, p. 3; 7, p. 223; 8; 12]

Modern methods of automating production lines in the food industry are aimed at increasing productivity, process stability and product compliance with international standards. Robotic manipulators are used for machining, packaging, and packing, which reduces dependence on the human factor and increases the accuracy of production operations. Intelligent sensors and IoT provide continuous monitoring of production conditions, controlling parameters such as temperature, humidity, and contamination levels. Automated conveyor systems help to optimize logistics and synchronize technological stages, which reduces delays in production cycles. The use of machine learning allows analyzing data flows in real time, optimizing production parameters and predicting possible deviations [4, p. 1547]. Cyber-physical systems integrate physical production processes with digital models, which allows virtual testing and improvement of technological schemes without risk to real production. The use of these methods contributes to the flexibility of production systems, cost reduction and increased automation of food enterprises.

Machine learning, artificial neural networks, and IoT technologies form the basis of modern intelligent control systems in the food industry, automating quality control and optimizing process parameters. The use of these tools allows companies not only to analyze large amounts of data in real time but also to predict possible deviations, which significantly increases production efficiency. Artificial neural networks are widely used for product defect detection, spectral analysis, and compliance assessment. IoT technologies provide continuous monitoring of process parameters, allowing timely response to changes in production conditions. Predictive analytics plays an important role in predicting equipment malfunctions and optimizing costly processes (Table 2).

Table 2

Machine learning, neural networks and IoT tools in quality control and production optimization

Tool	Appointment	Example of application
Deep Learning	Defect detection, image recognition, spectral data analysis	Product quality control using computer vision
Artificial neural networks (ANN, CNN, RNN)	Classification, forecasting, parameter optimization	Automatic detection of non-compliance with standards (ISO 22000, HACCP, 16.BRCGS)
Predictive analytics	Predicting equipment failures, analyzing process efficiency	Minimize downtime through early detection of technical deviations
Internet of Things (IoT)	Equipment condition monitoring, temperature and humidity control	Optimization of storage and transportation of raw materials
Smart sensors and RFID technologies	Product tracking in the production cycle, logistics control	Automate the supply chain and reduce product losses

Source: compiled by the author on the basis of [1; 3, p. 1191; 4, p. 15-35; 6, p. 146; 7, p. 222; 8; 14-16]

The application of these technologies in practice contributes to an integrated approach to quality control and production management. Computer vision based on deep learning is used for automated defect detection, which can significantly increase the accuracy of inspection compared to visual inspection [6, p. 149]. Neural networks perform product classification and help manufacturing companies optimize their compliance processes. Predictive analytics allows not only to prevent equipment malfunctions but also to optimize costs by determining the most efficient technological modes. IoT systems provide continuous monitoring of critical parameters such as temperature, humidity, and contamination levels, which is especially important for the food industry [13, p. 2580]. The use of RFID tags and smart sensors contributes to the automation of logistics processes, allowing enterprises to control the movement of raw materials and finished products in real time. In modern conditions, such solutions ensure high efficiency of production processes, minimize the risks of non-compliance with standards and help reduce costs.

An intelligent production process control system in the food industry is a complex adaptive platform that combines machine learning algorithms, neural networks, IoT technologies, and predictive analytics to optimize production. Such a system is needed to improve the efficiency of production lines, reduce quality control costs, automate decision-making processes, and increase overall enterprise productivity. Unlike traditional automated solutions that operate according to strictly defined algorithms, the proposed model has the ability to self-learn, analyze large amounts of data in real time, and predict possible deviations in equipment operation.

The conceptual model is based on the integration of several key components: a sensor system for data collection, a central analytical module based on machine learning, predictive analytics for predicting possible failures, and adaptive management of production parameters. It involves the use of IoT devices that transmit information to a cloud or local analytical system, where the received data is processed. Neural network algorithms analyze production parameters, recognize anomalies, and make optimal decisions about equipment settings or the need for maintenance (Fig. 1).

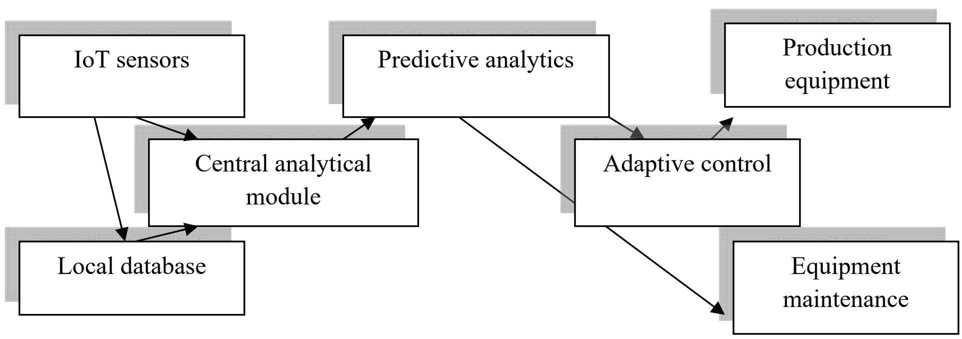

Fig. 1. Conceptual model of an intelligent control system for production processes in the food industry

Source: author's own development

The proposed conceptual model of an intelligent production process control system involves the integration of IoT sensors, an analytical module based on machine learning, predictive analytics, and adaptive production control. IoT sensors collect data on key parameters of the production process, including temperature, humidity, product flow rate, and equipment condition. This data is transmitted to a central analytical module that processes it using machine learning algorithms and detects anomalies.

A local database is used to store historical data and generate trends, which improves forecasting accuracy. Based on the analysis, predictive analytics calculates the probability of equipment failures or product quality deviations, after which the adaptive control module makes the necessary adjustments to the production process. This may include changing process parameters, activating additional checks, or initiating preventive maintenance of equipment.

Thanks to this approach, the system reduces downtime, reduces repair costs, improves product quality, and optimizes resource utilization. The use of feedback between production equipment and IoT sensors allows the system to learn from the data received, which increases its efficiency in the long run. The implementation of this model contributes to the transition of food companies to smart production, where processes are controlled automatically with minimal human intervention.

The introduction of automated systems in the food industry is accompanied by a number of challenges that cover technical, economic, organizational and regulatory aspects [4, p. 1545]. One of the main problems is the high cost of modernizing production lines, which includes the purchase of robotic equipment, integration of IoT technologies and implementation of intelligent control systems. Many enterprises, especially small and medium-sized businesses, face financial constraints, which complicates the introduction of full automation and forces them to use mixed production models with partial involvement of manual labor [12].

Technical difficulties are associated with the compatibility of new automated solutions with old production lines, which requires significant costs for adaptation and modernization of infrastructure [2, p. 5]. The lack of common standards for hardware and software integration creates problems when implementing integrated control systems that combine IoT, machine learning, and predictive analytics. The quality of input data is also a significant challenge, as the effectiveness of analysis and forecasting algorithms depends on the accuracy, completeness, and speed of processing information received from sensors and other sources [13, p. 2571].

Organizational barriers include the need to retrain staff to work with new automated systems, which requires significant time and financial resources. Employee resistance to change can also slow down the modernization process, as automation is often perceived as a threat to traditional jobs [12]. Implementation of such systems requires a new approach to human resources management, expanding employees' competencies and creating professional adaptation programs.

Regulatory requirements in the food industry, including compliance with international safety standards such as ISO 22000 [14], HACCP [15], and BRC Global Standard [16], impose additional restrictions on the implementation of automated systems. Such standards require strict quality control, documentation of processes, and compliance with sanitary and hygienic standards. The use of intelligent control systems requires advanced cybersecurity mechanisms, as the integration of IoT solutions and cloud platforms increases the risks of unauthorized access, possible failures and cyber threats [6, p. 151].

Optimization of production processes in the food industry with the help of intelligent control systems requires not only technical implementation but also a strategic approach to their integration. Given the identified problems, the primary task is to gradually introduce automated systems, which will allow enterprises to minimize the risks associated with the high cost of modernization and the complexity of adapting the existing infrastructure. The choice of technologies should be based on a thorough analysis of production needs, assessment of economic feasibility and compliance with food safety standards, including ISO 22000 [14], HACCP [15], BRC Global Standard [16], FSSC 22000 [17] and IFS [18].

Successful integration of intelligent control systems is possible if solutions are gradually implemented that maximize the effect at minimal cost. For example, the initial stage may involve the installation of smart sensors and IoT devices to monitor critical parameters, which will allow the company to assess the real capabilities of the technology without significant interference with production processes. The next stage involves connecting analytical platforms that use machine learning algorithms to predict malfunctions and optimize equipment performance. This will help reduce maintenance costs and prevent unplanned production outages.

An important aspect is to train staff to work with new technologies, which requires the implementation of training programs and adaptation of the company's organizational structure. Employees should acquire the necessary skills to work with analytical systems, as well as an understanding of cybersecurity principles to minimize the risks of unauthorized access to production data. Additionally, the integration of quality management systems should be considered, which will automate the control of product compliance with established standards and reduce the risk of deviations.

The long-term effectiveness of automated systems depends on their ability to scale and adapt to changing market conditions. Investing in flexible platforms that support algorithm updates and integration with new technological solutions will allow businesses to remain competitive in the face of the dynamic development of the food industry. Creating a unified information ecosystem where all production elements are integrated into a single management network will significantly increase efficiency, reduce production costs and ensure the stability of technological processes.

It has been established that automation of production processes in the food industry is a key factor in increasing efficiency, reducing costs and ensuring compliance with international quality and safety standards. The proposed conceptual model of an intelligent control system is based on the integration of IoT sensors, machine learning, and predictive analytics, which allows automating the control of technological parameters and reducing the risk of deviations in production.

The main challenges of implementing such systems are the high cost of modernization, the complexity of integration with existing equipment, the lack of digital readiness of enterprises, the need for staff training and compliance with ISO 22000, HACCP, BRC Global Standard, FSSC 22000 and IFS standards.

A phased introduction of IoT technologies, machine learning for parameter analysis, and predictive maintenance to minimize downtime is recommended. Particular attention should be paid to staff training and the development of strategies for the gradual digitalization of enterprises.

Prospects for further research are focused on improving automated control models, increasing the accuracy of production data analysis algorithms, and assessing the economic efficiency of implementing intelligent systems at real enterprises.

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