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INTELLIGENT CONTROL SYSTEMS FOR MECHANICAL ENGINEERING TECHNOLOGY TASKS

Abstract. The article is devoted to solving the main tasks set in the work with the aim of analyzing and substantiating the implementation of intelligent control systems in technological processes of mechanical engineering, with an emphasis on increasing efficiency, accuracy, and reliability of production. The use of multi-agent systems and decentralized control systems, which significantly enhance the flexibility and adaptability of production, is analyzed. Special attention is paid to the role of physics-informed neural networks in fault diagnosis, which ensures increased reliability and reduced maintenance costs for equipment. The effectiveness of applying machine learning algorithms to optimize production processes, particularly in material processing and equipment maintenance, is evaluated. The impact of integrating intelligent control systems on production performance and quality, especially in the processes of milling and bonding large parts, is considered. Practical recommendations have been developed for the implementation of an adaptive intelligent production management system (AIPMS), which combines multi-agent systems, neural networks, digital twins, and innovative materials. The implementation of the artificial intelligence concept in production processes will contribute to the further development of mechanical engineering from a technological perspective, enabling enterprises to adopt innovations more rapidly, increase automation, and enhance the adaptability of technological processes, which in turn will lead to significant improvements in product quality and competitiveness. The use of such systems allows optimizing technological processes, reducing the number of defects, lowering energy consumption, and improving environmental efficiency.

Keywords: intelligent control systems, machine learning, neural networks, maintenance, digital twins, decentralized control, optimization of production processes.

Introduction

In recent years, intelligent control systems have become the foundation of modern manufacturing processes, particularly in the field of mechanical engineering. The development of artificial intelligence technologies and cyber-physical production systems (CPPS) has opened new opportunities for optimizing technological processes, including production, maintenance, and equipment monitoring [1,2,3,4]. Modern decentralized approaches to production management enable the integration of multi-agent systems, providing greater flexibility and adaptability in managing robotic systems, especially when performing complex technological tasks such as milling and welding [1,2,3]. An essential component of intelligent systems is their ability to integrate with physically based models for more precise control of production processes and fault detection. In particular, the use of probabilistic neural networks enhances the reliability of diagnosing mechanical components, including bearings, which is crucial for minimizing equipment downtime and increasing production efficiency [5]. The implementation of such systems significantly improves quality control, especially under dynamic changes in production processes. Moreover, intelligent control systems are used to optimize technological processes through deep learning and Bayesian optimization, allowing real-time adjustment of process parameters to achieve optimal results. The application of these approaches in milling and bonding large parts confirms their effectiveness in ensuring zero defects in production [6,7].

Analysis of the issues addressed in the article

In modern mechanical engineering, intelligent control systems are becoming an integral part of the automation process and increasing production efficiency. The main issues addressed in this article include the optimization of material processing processes, the integration of physically-based models into control systems, and the application of artificial intelligence to improve prediction and control. The importance of these issues is confirmed by numerous studies emphasizing the development of adaptive and self-learning systems for complex manufacturing tasks.

First and foremost, the issue of integrating intelligent systems into manufacturing processes is gaining particular relevance due to the development of cyber-physical production systems (CPPS) and multi-agent control systems [3,4,8,9,10,11]. This approach allows the creation of decentralized control networks where each production unit makes autonomous decisions based on data, significantly improving operational efficiency. This is evidenced by the implementation of robotic systems for operations such as milling, which can automatically adapt to material processing conditions and improve precision [12]. Another important aspect is the use of physics-informed neural networks for fault diagnosis in mechanical systems. For instance, physics-based probabilistic models are used to predict failures in bearings and other components, allowing not only to detect potential malfunctions but also to reduce the risk of accidents [5]. The use of such systems is key to ensuring the uninterrupted operation of complex production lines and minimizing maintenance costs.

Moreover, intelligent systems play an essential role in optimizing production processes through machine learning algorithms. For example, the use of deep reinforcement learning allows the adaptation of disassembly processes under uncertain conditions, which increases efficiency and reduces inventory accumulation [6]. Similarly, Bayesian optimization can be employed for precise milling parameter adjustments, reducing defects and improving processing quality [6].

The purpose of this article is to analyze and justify the implementation of intelligent control systems in manufacturing processes with a focus on improving the efficiency, accuracy, and reliability of production. The article explores modern methods of integrating multi-agent systems, artificial intelligence, and physics-informed models into the control of material processing operations, and also proposes new approaches to fault diagnosis and the optimization of manufacturing processes.

The tasks set in this work and addressed within its content include:

1. Analyze modern approaches to the use of intelligent control systems in manufacturing processes of mechanical engineering, particularly multi-agent systems and decentralized control systems [3,11].
2. Consider the role of physics-informed neural networks for fault diagnostics in mechanical engineering and justify the necessity of their implementation to improve system reliability [5].
3. Evaluate the effectiveness of applying machine learning algorithms to optimize manufacturing processes, including material processing and equipment maintenance [6,13].
4. Investigate the impact of integrating intelligent control systems on overall productivity and product quality in mechanical engineering, particularly in milling and bonding of large parts [7,12].
5. Develop recommendations for the implementation of intelligent control systems in real manufacturing environments to improve the efficiency and accuracy of mechanical engineering processes.

1.Analysis of modern approaches to the use of intelligent control systems in manufacturing processes of mechanical engineering

One of the key areas for the development of manufacturing processes in mechanical engineering is the integration of intelligent control systems, which ensure automation, adaptability, and flexibility in production. The most promising approaches include multi-agent systems (MAS) and decentralized control systems, which enhance productivity and reliability under complex and dynamically changing production conditions.

Multi-agent systems are considered one of the most flexible approaches to managing manufacturing processes. In MAS, each agent is an independent intelligent module that can interact with other agents and make decisions based on its local information [4,8,9,10]. These agents can perform various functions, from production planning to quality control and equipment condition monitoring. MAS are particularly effective in addressing planning and logistics tasks in production processes, optimizing material flows and route selection for automated transport vehicles [11]. By utilizing agents for task distribution and monitoring production lines, MAS enables optimal resource utilization and reduces the likelihood of errors. Agents make decisions based on real-time environmental data, significantly enhancing system flexibility and adaptability. Another notable example is the use of MAS in managing robotic milling lines, where each agent is responsible for controlling specific segments of the production process, allowing the system to quickly adapt to changing conditions [12]. This illustrates MAS's ability to rapidly adapt to dynamic production environments.

Decentralized control systems avoid the limitations of centralized management, such as dependence on a single decision-making center and reduced adaptability to changes. In decentralized systems, each production unit independently makes decisions based on local data and information received from other units. These systems can integrate intelligent devices into production processes, allowing the creation of autonomous control systems at the level of individual milling stations or logistics cells [3]. This approach enhances flexibility and resilience to changes in the production environment, enabling rapid adaptation to new requirements or unforeseen situations. Decentralization also improves system reliability, as the absence of a single control center reduces the likelihood of global failures in case one component malfunctions. This is confirmed by studies in the field of automated control of welding robots, where decentralized systems provide greater precision and adaptability to various types of welding processes [14].

Modern decentralized and multi-agent systems cannot function effectively without integration with cyber-physical production systems (CPPS), which provide continuous data exchange between the physical components of the production process and their digital twins. This allows real-time control of production processes and adaptation to changing conditions. CPPS facilitate the integration of advanced maintenance and production management methods based on data, reducing downtime and improving the efficiency of production lines [15]. Digital twins used in CPPS provide a high level of automation and prediction, particularly for early detection of potential equipment failures. Intelligent control systems based on multi-agent and decentralized approaches are a crucial component of modern mechanical engineering. They provide increased flexibility, adaptability, and reliability in manufacturing processes, which is critical for companies seeking to remain competitive in rapidly changing market conditions. The integration of intelligent systems with cyber-physical systems adds new opportunities for production control and optimization, making these approaches key to the future development of mechanical engineering. This is supported by numerous studies proving the effectiveness of multi-agent systems and decentralized control across various manufacturing sectors [3,4,8,9,10,11,12,15].

2.The role of Physics-Informed Neural Networks for fault diagnosis in mechanical engineering

One of the key challenges in mechanical engineering is ensuring reliable and timely fault diagnostics in complex mechanical systems. This is especially important for equipment operating under intense loads and high precision requirements. Traditional diagnostic methods do not always provide the necessary level of accuracy and speed in detecting potential failures, which can lead to unexpected production line stoppages and significant financial losses. In this context, Physics-Informed Neural Networks (PINNs) have become an important tool for improving system reliability by combining mathematical models and machine learning methods.

Physics-Informed Neural Networks combine the advantages of traditional physical models with the flexibility of neural networks. Instead of simply learning from data, PINNs incorporate physical laws, such as Newton's equations or thermodynamics, to guide the training process. This allows for more accurate predictions, especially in cases where the data is incomplete or inaccurate. PINNs significantly improve the accuracy of mechanical fault diagnostics, such as bearing damage, by using physical models that describe the dynamic behavior of components. This not only enhances failure prediction but also reduces false alarms, thereby increasing the reliability of the entire system.

PINNs allow for modeling the degradation processes of mechanical components while accounting for real operating conditions. They can effectively predict bearing failures based on the analysis of vibration signals, temperature, and loads. This helps identify potential issues at early stages before they lead to production shutdowns. Additionally, integrating physical models into the neural network's learning process makes it possible to account for external factors such as temperature or humidity, which is crucial for equipment operating in harsh environments. For instance, in manufacturing processes involving high temperatures, such as welding or heat treatment of materials, PINNs provide accurate predictions of material degradation and other system components.

Another significant advantage of using Physics-Informed Neural Networks is the optimization of equipment maintenance. While Physics-Informed Neural Networks focus on enhancing fault diagnostics and improving equipment reliability, another crucial dimension of intelligent systems is the broader application of machine learning algorithms. These algorithms play a vital role not only in equipment maintenance but also in optimizing various manufacturing processes in real time. By accurately predicting failures, maintenance work can be planned in advance, reducing unforeseen downtime and increasing production line efficiency. This is especially important for complex production systems, where a failure in one component can affect the entire line. Integrating intelligent diagnostic systems based on neural networks can greatly reduce maintenance costs by forecasting failures and minimizing equipment downtime, thereby improving overall production efficiency and reducing operational costs.

PINNs can also be integrated into the concept of digital twins, enabling real-time monitoring of equipment condition and diagnostics based on collected data. A digital twin is an accurate virtual copy of a physical object that synchronizes with real equipment and allows for predicting its behavior under various conditions. Digital twins with integrated neural networks provide efficient prediction and control of equipment conditions at all stages of its lifecycle. This not only enhances diagnostic accuracy but also simplifies maintenance and repair processes.

Thus, Physics-Informed Neural Networks are a powerful tool for enhancing the reliability of mechanical engineering systems, providing accurate fault diagnostics and predicting potential failures. Their implementation reduces maintenance costs, minimizes downtime, and increases overall production efficiency. The integration of PINNs with digital twins creates new opportunities for real-time monitoring and management of complex mechanical systems, which is critical for modern manufacturing processes.

3.Evaluation of the effectiveness of machine learning algorithms for optimizing manufacturing processes

Modern mechanical engineering heavily relies on automation and the integration of artificial intelligence (AI) to enhance production efficiency. Machine learning algorithms, including deep learning methods, reinforcement learning, and Bayesian optimization, have become powerful tools for optimizing various stages of production processes, such as material processing and equipment maintenance.

Machine learning algorithms are used to improve the parameters of production processes in real-time. For example, in material milling processes, where precision and cutting dynamics are crucial, machine learning allows the adaptation of processing modes depending on changing material characteristics. The application of Bayesian optimization for parameterizing the milling force model significantly improves cutting accuracy and reduces the number of defects. This is achieved by integrating external sensor data and controller data, allowing real-time adjustments for optimal cutting performance [6]. Such technologies are especially important for the production of high-precision parts, such as components in the aviation or automotive industries, where any deviation can lead to defects and productivity losses. Additionally, deep learning algorithms are successfully applied to optimize complex processes like welding. AI enables the system to analyze process parameters (welding speed, temperature, laser power) and automatically adjust them to achieve the best results [14]. This helps improve the quality of welds and avoid defects, which is critical in manufacturing essential metal structures.

The application of machine learning algorithms for predicting the technical condition of equipment and planning its maintenance is a key component of the smart manufacturing concept. Data-driven failure prediction algorithms significantly reduce maintenance costs and prevent downtime caused by unexpected equipment failures. The integration of predictive and recommendation-based maintenance systems allows for considerable cost savings and reduces the number of unplanned equipment stoppages [15]. With machine learning, patterns that precede failures can be identified, and maintenance can be planned based on the actual condition of the equipment, rather than relying on pre-established service intervals. This ensures more rational use of resources and minimizes the risk of failures, which is important in complex production processes.

Reinforcement learning (RL) algorithms are widely applied to optimize production processes under uncertainty or non-standard situations. For example, reinforcement learning can be used to optimize product disassembly processes. These algorithms allow systems to learn from their own experience and adapt their behavior to changing production conditions, which significantly increases efficiency and reduces costs [13]. This approach is also effective in automated material transportation processes within manufacturing. Multi-agent systems that use RL enable transport robots to coordinate their actions, avoid collisions, and optimize movement on production lines [11]. This reduces the time required for material transportation and improves the overall productivity of production lines.

The application of machine learning is not limited to optimizing material processing and equipment maintenance. An important area is the optimization of energy consumption in production. By analyzing historical data and real-time equipment performance metrics, algorithms can predict energy needs and develop strategies for its efficient use. This is especially relevant for high-performance systems, such as metallurgical or chemical plants, where energy costs are a critical factor. The use of machine learning algorithms in optimizing production processes and equipment maintenance demonstrates high efficiency, especially in complex and dynamic conditions. Machine learning significantly increases the precision of material processing, reduces defects, and optimizes resource usage. Equipment condition prediction algorithms and reinforcement learning ensure timely maintenance and adaptation of production lines to changing conditions, reducing downtime and maintenance costs. The influence of machine learning on the optimization of production processes cannot be overstated. However, the real transformative potential of intelligent control systems becomes evident when these technologies are fully integrated into the manufacturing process. This integration has a profound impact on overall productivity, quality, and the adaptability of production lines to dynamic conditions.

4.The impact of the integration of intelligent control systems on overall productivity and production quality in the field of mechanical engineering

The integration of intelligent control systems into manufacturing processes in mechanical engineering has a significant impact on the productivity, quality, and reliability of production. These systems allow for the automation of production process management, reducing resource costs, minimizing human error, and enhancing the accuracy of material processing. Their impact is particularly notable in complex technological processes such as milling and bonding of large components. Milling is one of the most precise and critical technological processes in mechanical engineering, where the accuracy and quality of part processing are crucial. The use of intelligent control systems optimizes this process by automatically adjusting processing parameters in real-time and adapting to changes in materials or processing conditions. The application of intelligent systems for online parameterization of milling through Bayesian optimization not only reduces the number of product defects but also enhances processing accuracy by automatically correcting cutting modes based on external sensors and controller data [6]. Intelligent systems can adapt cutting speed, cutting depth, and other parameters according to the current material properties, ensuring high product quality without the need for stoppages for adjustments. The integration of intelligent systems into milling processes also reduces the processing time of complex parts, which directly impacts production productivity. By operating in real-time, these systems minimize equipment downtime, allowing for an increase in the number of parts produced per unit of time. As we have seen, the integration of intelligent control systems significantly enhances the efficiency and precision of manufacturing processes. To achieve these improvements in real-world settings, a systematic approach to the implementation of these systems is essential. The following section provides practical recommendations for enterprises aiming to adopt intelligent control systems effectively.

Another important aspect of the integration of intelligent control systems is their use in bonding processes for large components that require high precision and continuous quality control. Bonding processes are often used in the production of large components such as aircraft or car bodies, where errors in bond quality can lead to serious consequences. A multifunctional feedback system for bonding large components, aimed at detecting defects in real-time and automatically adjusting the process, allows for zero-defect production by automatically monitoring the quality of adhesive joints and correcting the positioning of components during bonding [7]. The systems also use digital twins to track and simulate processes, enabling rapid responses to changing production conditions and ensuring high bond quality. This contributes to the reliability of large structures, which is critical in industries such as aerospace, automotive, and energy.

Intelligent control systems integrated into manufacturing processes significantly improve overall production productivity due to several key factors:

– adaptability and automation, when the systems allow manufacturing processes to adapt to changing conditions in real-time, minimizing delays and disruptions. This is important in mass production or when processing unique parts where each process may require individual adjustments [6,7];

– reduced maintenance and repair costs, when, by using intelligent systems, equipment breakdowns can be predicted, and maintenance can be performed at precisely defined times, minimizing downtime and repair costs [9];

– optimization of resource usage, when intelligent systems enable more efficient use of materials and energy resources by optimizing technological processes and reducing waste and defects [16].

Thus, the integration of intelligent control systems becomes a critical factor in improving the competitiveness of enterprises in mechanical engineering and ensuring stable product quality [6,7,15].

5.Recommendations for the implementation of intelligent control systems in real manufacturing environments to improve the efficiency and accuracy of technological processes in mechanical engineering

Based on the analysis of global experience, the phased implementation of intelligent control systems at machine-building enterprises is advisable, as it will significantly improve the efficiency, accuracy, and reliability of production processes. The introduction of ICS should begin with a comprehensive analysis of current production processes to identify potential bottlenecks that limit productivity and cause equipment failures. Such an analysis will help identify key processes where automation can provide the greatest benefit. Attention should be focused on the analysis of part processing time, defect rates, equipment reliability, and its usage intensity. Particular emphasis should be placed on welding, milling, thermal treatment, and other key manufacturing operations, where ICS automation will not only increase efficiency but also reduce defect rates. Upon completion of the analysis, it is recommended to identify priority areas for ICS implementation, which will ensure rapid economic returns from investments and rational allocation of enterprise resources.

To integrate intelligent control systems with existing production facilities, a modular approach should be applied, allowing for the gradual integration of new system components without halting the production cycle. An important part of this process is the seamless integration with existing production control systems, such as SCADA (Supervisory Control and Data Acquisition) or MES (Manufacturing Execution Systems). This will enable real-time data collection and analysis, allowing for quick responses to process changes and preventing potential defects or equipment malfunctions. Special attention should be given to upgrading equipment to support digital twins and sensors for data collection. This step will provide transparency across all production processes and enhance production management capabilities based on real data, forming the foundation for further automation.

Based on global experience, the implementation of machine learning algorithms for optimizing technological parameters of production processes is advisable. Machine learning algorithms, particularly reinforcement learning, can automate the process of adjusting technological parameters in real time, adapting the system to changing production conditions. This will minimize defects and improve overall production efficiency. In addition, Bayesian optimization will provide adaptive adjustment of parameters such as cutting speed or depth, improving material processing quality. Predictive algorithms should also be implemented for planning equipment maintenance based on actual data about its condition, reducing unforeseen repair costs and preventing production downtime.

An important component of implementing intelligent control systems is ensuring continuous monitoring of production processes and analyzing collected data for quick responses to changes in production conditions. This can be achieved by introducing digital twins that create virtual copies of physical systems and allow real-time monitoring of equipment and technological processes. These technologies will facilitate production quality control and create opportunities for modeling various scenarios, enabling process optimization without interrupting their operation. It is also proposed to regularly collect and analyze data from sensors, which will help identify potential problems before they arise, ensuring continuous equipment operation and minimizing downtime.

Based on best practices, it is essential to provide staff training for working with new intelligent control systems. Engineers and line operators must be prepared to work with new technologies, not only mastering the tools but also understanding the principles of ICS operation for their effective use. It is recommended to organize regular training and skill enhancement courses to improve proficiency with digital tools and artificial intelligence technologies, ensuring adaptation to the new demands of modern production. This will also allow personnel to quickly respond to production changes and optimize processes based on real conditions.

Continuous development and the introduction of innovative technologies, such as 4D printing and metamaterials, are crucial for maintaining the competitiveness of enterprises. Investing in the research and development of new technologies that enable the automation of complex material processing tasks is advisable. The use of metamaterials that change their properties under external stimuli and advanced printing technologies will create new opportunities for flexibility in production processes. Furthermore, the implementation of modular solutions for ICS will allow for the easy adaptation of new technologies to existing production systems without significant changes to the production structure, enhancing flexibility and the ability of enterprises to quickly respond to new market challenges.

Summarizing these recommendations, the creation of an adaptive intelligent production management system (AIPMS) is advisable, combining multi-agent systems, physics-informed neural networks, digital twins, innovative materials, and machine learning algorithms for optimizing quality, energy consumption, and productivity.

The given block diagram (Fig. 1) represents the general architecture of the adaptive intelligent production management system.

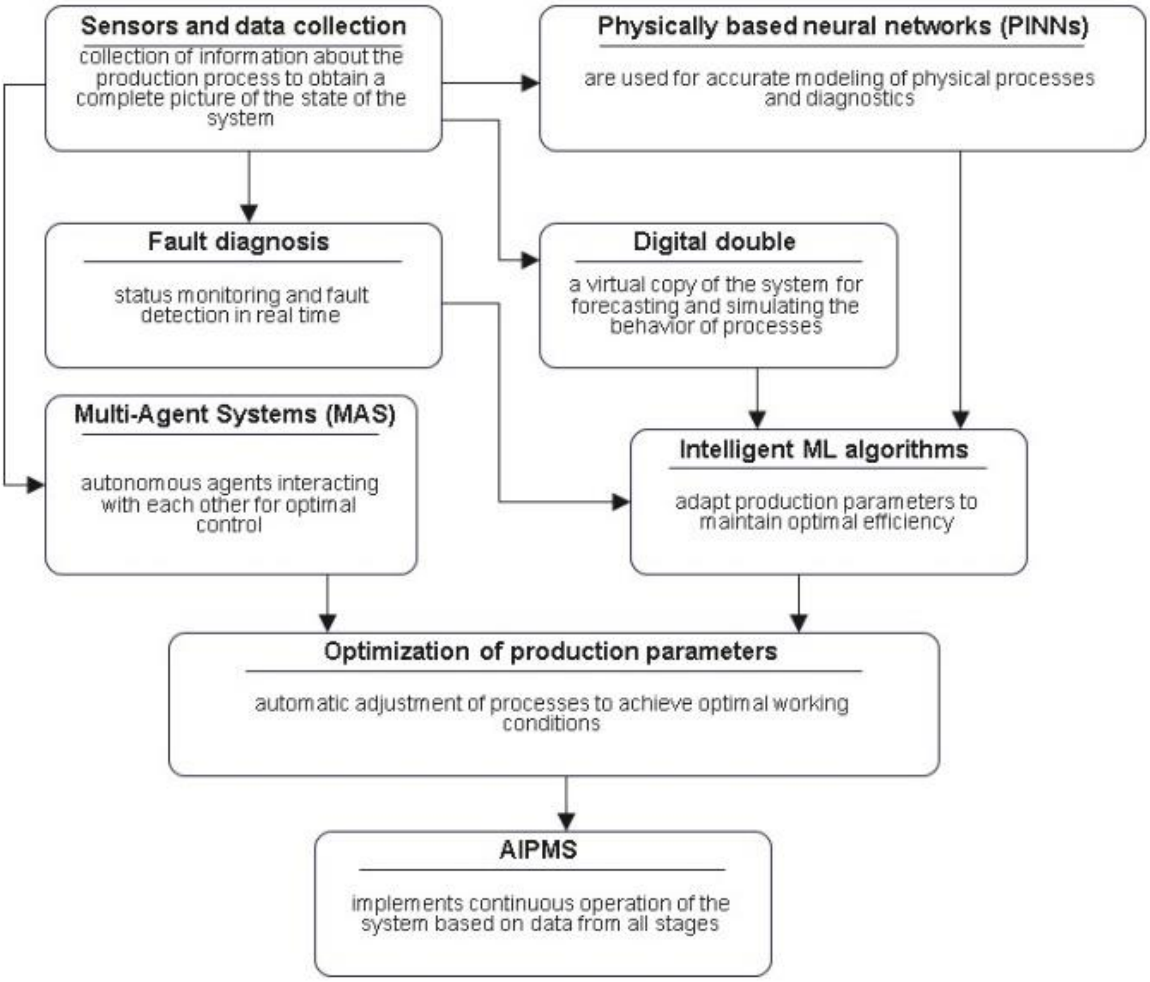

Fig. 1. Architecture of AIPMS

Mathematical model of setting the optimization problem.

1.Description of model components:

x — vector of control parameters to be optimized;

$S(t)$ — a set of data received from sensors at a point in time t;

$D(t)$ — the dynamic state of the digital double, which displays the current values of the system parameters;

$A(t)$ — a vector of agents of a multi-agent system, each of which performs specific management functions;

$M(t)$ — matrix of interactions between system agents and production components;

$P(t)$ — physical parameters of the system modeled by neural networks (PINNs);

$Q(t)$ — optimized production parameters, which are the result of the work of ML-algorithms;

$Diag(t)$ — diagnostic indicators reflecting the state of reliability and serviceability of the system.

2. The system of differential equations (1) describes the dynamics of the model component:

$$\begin{cases} \frac{dD_i}{dt} = f_i(S(t), D(t), x, t)\ ; \\ \frac{dA_j}{dt} = g_j(S(t), D(t), x, t)\ ; \\ \frac{dP}{dt} = h(S(t), D(t), x, t)\ ; \\ \frac{dM}{dt} = k(S(t), D(t), x, t)\ ; \\ \frac{d\mathrm{Diag}}{dt} = l(S(t), D(t), x, t)\ ; \\ \frac{dQ}{dt} = \arg\max_x J(x)\ ; \\ \text{limitation:} \\ \frac{dU}{dt} = \mathrm{m}(\mathrm{Q(t)}, \mathrm{Diag(t)}, \mathrm{x})\ . \end{cases}$$

where U is a vector of control actions or parameters used for adaptive control of the production process.

In the context of a system of differential equations U is the result of optimization algorithms taking into account the objective function $J(x)$ and constraints for choosing optimal values of control actions. It provides adaptation of all parameters and system components in real time, directing the system to optimal functioning.

3.Objective function: (2) the optimization goal of the model is to minimize costs and resources:

2)

$$J(x) = \int_0^T (\,a_1F_1(x) + a_2F_2(x) + \cdots + a_mF_m(x))dt,$$

where $F_i(x)$ — performance parameters to be optimized.

4. The system of restrictions ensures compliance of production parameters with conditions and requirements (3):

3)

$$\begin{cases} G_\mathrm{i}(\mathrm{x}) \le \mathrm{B_i}, & \mathrm{i} = 1, \dots, \mathrm{k} \\ \mathrm{H_j}(\mathrm{x}) = \mathrm{C_j}, & \mathrm{j} = 1, \dots, \mathrm{l} \\ \mathrm{K_s}(\mathrm{x}) \ge \mathrm{D_s}, & \mathrm{s} = 1, \dots, \mathrm{p} \\ \mathrm{R_t}(\mathrm{x}) \le \mathrm{E_t}, & \mathrm{t} = 1, \dots, \mathrm{q} \end{cases}$$

where $Gi(x), Hj(x), Ks(x), Rt(x)$ — constraint functions that describe the allowable limits of the parameters.

These recommendations serve as practical guidelines for enterprises seeking to improve the efficiency and accuracy of their technological processes through intelligent control systems. They can also form the basis for further research and development in the field of automation and machine learning in production.

Conclusions

As a result of the research, the main objectives set in the study have been achieved. Modern approaches to the implementation of intelligent control systems in manufacturing processes in the field of mechanical engineering, particularly multi-agent and decentralized control systems, were analyzed. It has been confirmed that these approaches significantly enhance the adaptability and flexibility of production. The necessity of implementing physics-informed neural networks for fault diagnosis has been substantiated, which ensures improved reliability and reduces maintenance costs of equipment.

The analysis of the impact of intelligent control systems on the manufacturing processes of large-scale products demonstrated a significant increase in production efficiency and quality. Based on the research results, recommendations have been developed for the implementation of an adaptive intelligent production management system (AIPMS), which combines multi-agent systems, neural networks, digital twins, and machine learning algorithms to improve the efficiency, accuracy, and environmental sustainability of manufacturing processes in mechanical engineering.

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