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ANALYSIS OF MODERN METHODS FOR OPTIMIZING TECHNOLOGICAL PROCESSES IN MACHINE-BUILDING PRODUCTION USING ARTIFICIAL INTELLIGENCE

This article explores the integration of artificial intelligence (AI) into machine-building production processes, focusing on the optimization of gear production for KrAZ trucks. Through a detailed analysis of AI applications in various industries and a review of relevant literature, the study identifies key opportunities and challenges in implementing AI technologies in mechanical engineering. The research presents a comprehensive examination of the benefits of AI-driven systems in improving production efficiency, quality control, and predictive maintenance. A case study on automated gear grinding quality control demonstrates how AI, coupled with advanced sensors and machine learning algorithms, enhances process precision and reduces defects. Results demonstrate the effectiveness of AI-driven systems in improving precision, reliability, and cost-effectiveness in gear manufacturing, with an observed accuracy rate of approximately 95% or higher. Also highlights a precision rate of ±0.005 mm in gear tooth surface finishing, leading to consistent gear performance and reliability. Additionally, AI-driven predictive maintenance strategies are shown to predict equipment maintenance needs with up to 90% accuracy, maximizing productivity and reducing maintenance costs by up to 30%. Moving forward, further research and implementation efforts should focus on selecting and integrating appropriate AI systems into existing production processes, to maximize efficiency and innovation within the machine-building industry.

Keywords: artificial intelligence, gear grinding, quality control, data analysis, automation

INTRODUCTION

In today's world, artificial intelligence (AI) has moved beyond being just an element of science fiction and has become a reality that actively influences various aspects of our lives. AI is demonstrating exponential growth and innovations that penetrate all sectors from healthcare to the automotive industry, from financial services to retail. This technology opens new opportunities for increasing efficiency, reducing costs, and improving the quality of products and services.

The application of AI in medicine, for example, has revolutionized the diagnosis and treatment of diseases, allowing for the creation of personalized treatment methods based on the analysis of large patient data sets. In the automotive industry, AI contributes to the development of autonomous vehicles, changing perceptions of driving and road safety. In the financial sector, machine learning algorithms are used for market analysis, risk management, and providing personalized financial recommendations to clients.

Despite numerous advantages, the widespread implementation of AI also poses certain challenges, including ethical usage, data security, and the potential loss of jobs in some sectors. However, the growing interest and investment in this technology indicate its significance and potential for further development and integration into an even greater number of industries.

This article focuses on the use of AI in the technological processes of mechanical engineering, revealing how artificial intelligence can transform production lines, improving accuracy, efficiency, and innovation in this industry.

LITERATURE DATA AND FORMULATION OF THE PROBLEM

In the mechanical and aerospace industries, several leading companies are already actively using artificial intelligence to optimize their production processes. General Electric (GE) uses artificial intelligence for monitoring and analyzing large data from their engines and other equipment. This allows them to increase efficiency and reduce unexpected failures. Siemens has developed a system based on artificial intelligence that assists in production and quality monitoring [1-3]. They also use AI to automate and optimize their processes in the production of energy turbines. Airbus has integrated artificial intelligence in the aerospace industry to optimize design and manufacturing processes [2-4]. This includes the use of AI to improve aircraft assembly processes and develop more efficient flight paths. Boeing is also actively using artificial intelligence, particularly for predicting maintenance needs for aircraft and for increasing production efficiency [5-6]. Rolls-Royce uses AI to analyze data received from engines during flights, helping the company optimize maintenance and improve reliability and performance indicators [7-8].

These companies play a key role in the implementation of artificial intelligence in mechanical engineering and the aerospace industry, demonstrating the impact of AI on increasing efficiency, reducing costs, and enhancing production safety.

The use of artificial intelligence directly in mechanical engineering can open up new opportunities for process optimization, improving product quality, and reducing costs. Here are the main directions for AI applications:

1. Data analysis and optimization: analyzing large volumes of data from production lines to identify inefficiencies and optimize processes. This can include predicting defects, scheduling production, and managing resources.
2. Automation and robotics: the integration of AI-controlled robots can significantly enhance productivity and accuracy in manufacturing processes. Robots can perform repetitive, precise, or hazardous tasks, reducing risks for humans.
3. Adaptive manufacturing: systems can quickly adapt to new manufacturing conditions or changes in product specifications without significant downtime.
4. Quality and control: automating quality control processes using visual recognition to detect flaws at early stages of production.
5. Predictive maintenance of equipment: monitoring equipment condition and predicting wear and tear, allowing for maintenance planning before serious problems occur.
6. Integration with the Internet of Things (IoT): analyzing data from IoT sensors for better management of manufacturing processes, and optimizing energy and material usage.

Various software platforms, sensors, and sensors are used to implement artificial intelligence in automated production processes. The simplest to use in modern manufacturing may include the following software complexes:

- PLM (Product Lifecycle Management) and CAD (Computer-Aided Design) platforms, such as Siemens NX, SolidWorks, and Autodesk Inventor. These systems allow the development of complex 3D models of parts, such as gears, and integrate this data with AI for optimization of design and production.
- ERP (Enterprise Resource Planning) systems, namely SAP, and Oracle. They can integrate production data, inventory management, and logistics, allowing AI to analyze and optimize these processes.
- MATLAB and Simulink systems for modeling and optimization are used to create accurate mathematical models of manufacturing processes and optimize them using AI algorithms.
- Specialized software for monitoring and maintenance, such as Predix (from GE), and IBM Maximo which are designed to analyze data from equipment, predict failures, and plan maintenance.

At the same time, the use of sensors should also be considered, the types and areas of use of which are listed in Table 1.

Table 1 – Sensors types and usage areas

Sensor types	Use areas
Temperature sensors	Measure temperature in critical areas of the machine to control thermal conditions and prevent overheating
Vibration sensors	Used to detect unusual vibrations that may indicate equipment problems
Position and motion sensors	Provide precise information about the exact position of machine components, which is important for precise part machining
Optical sensors and cameras	Used for visual quality control, detecting surface defects in real-time
Pressure and force sensors	Monitor pressure and force during cutting to optimize the machining process and ensure uniform quality

The use of these technologies allows a significant increase in the accuracy and efficiency of production processes while reducing costs and increasing the quality of final products.

PURPOSE AND OBJECTIVES OF THE STUDY

The Cabinet of Ministers of Ukraine recently approved the Concept of the State's targeted scientific and technical program for the use of artificial intelligence technologies in priority sectors of the economy for the period until 2026 [9]. The machine-building industry is included in the list of priorities, so studying the possibilities of introducing AI technologies into the technological processes of machine-building is an urgent task. Within the framework of solving the specified problem, the purpose of the article is to identify the prospects of using AI systems in the manufacture of gears for KrAZ trucks, which have both civilian and military purposes.

RESEARCH RESULT

The gear cylindrical differential of the rear axle of the KrAZ car, which is presented in Figure 1, was chosen as the subject of the study. The part in the assembly unit operates at high rotational speeds, transmits a significant torque, and also operates in a dynamic load cycle. The most precise surfaces of the part are the surfaces of the teeth and the central hole. Since the part is typical for various modifications of cars, it is possible to consider the principle of building an algorithm of an automated line using AI for quality control.

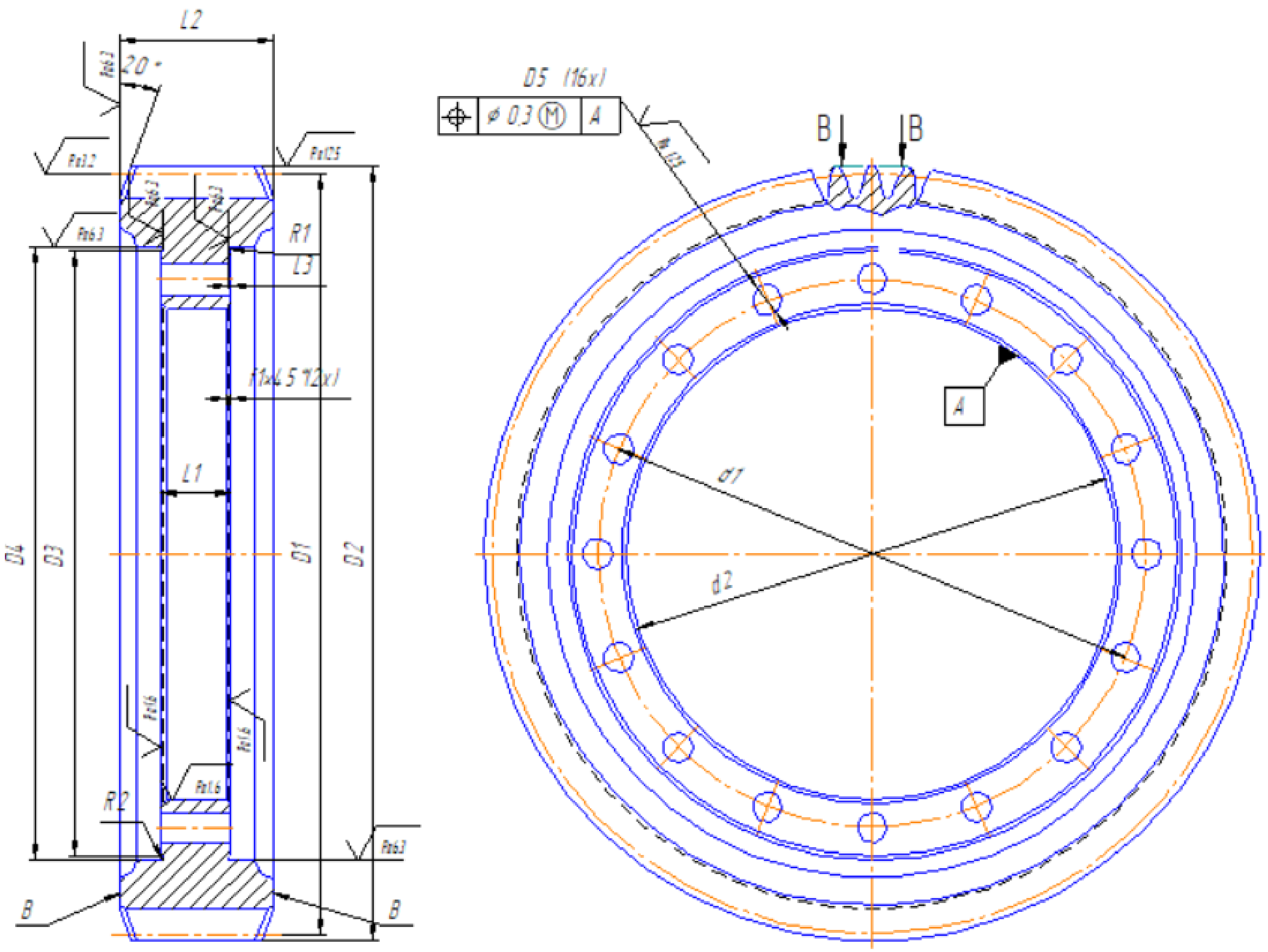

Figure 1 – Drawing of a cylindrical gear

The quality of the gear tooth surface is a critical factor in the performance and reliability of gear systems. One of the key challenges in gear grinding is the occurrence of grinding burns, which can significantly impact the surface integrity and functionality of the gear teeth.

Grinding burns can lead to various forms of thermal damage to the gear tooth surface, including oxidation burn, rehardening burn, thermal softening, and cracking [10]. These types of thermal damage can compromise the gear's performance, reducing its load-carrying capacity, surface fatigue resistance, and overall service life

Given the critical importance of the gear tooth surface quality, the monitoring and control of the grinding process to mitigate grinding burns is a crucial aspect of gear wheel production. For experimental purposes, we consider a detailed example of a gear grinding operation on an automated production line, where various sensors and software are used to collect data, transfer, and analyze information, and further process it using AI.

The process stages are shown in Fig. 2 as a flowchart.

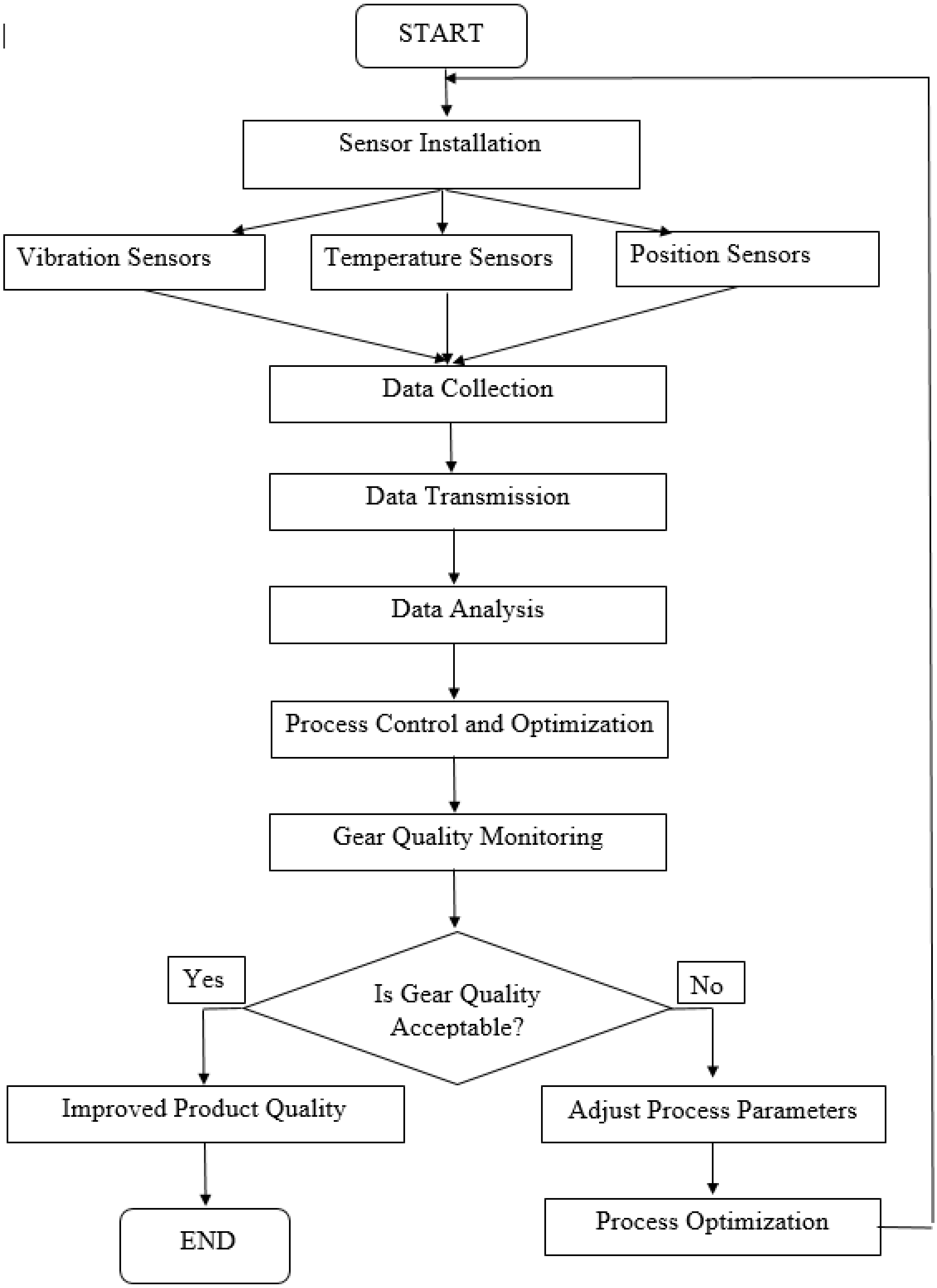

Figure 2 – The flowchart of the grinding process monitoring and control

The process of automated quality control of tooth grinding using sensors and machine learning has the following stages:

1. Installation of sensors and data collection. In an automated gear grinding production line, various sensors are employed to closely monitor the grinding process and detect any potential issues:

1.1 Acoustic Emission (AE) Sensors [11]:

- One AE sensor (AE-S) is mounted at the tool spindle center and rotates with the grinding wheel to capture signals from the grinding zone.

- Another AE sensor (AE-T) is placed on the tailstock to capture waves originating from the workpiece.
- The AE signals are preprocessed with amplification, filtering, and digitization to extract relevant features.

1.2Spindle Current Sensors:

- Current clamps are installed on the electrical wires to measure the 3-phase spindle current components (Iv, Iw).
- The RMS transformation is applied to convert the current components into an equivalent direct current (Irms).

1.3Spindle Power Measurement:

- A true power meter is used to measure the electrical tool spindle power (Pel) with a high sampling rate

2. Data Acquisition and Analysis. The sensor data is collected and organized using a data acquisition system

2.1 Data Preprocessing:

- The AE signals are preprocessed with amplification, filtering, and digitization to extract relevant features.
- The spindle current and power data are also preprocessed and synchronized with the AE signals.

2.2Controlled Grinding Burn Generation [12]:

- A touch dressing procedure is applied to the grinding wheel to generate controlled grinding burn on the workpiece.
- This allows the system to collect data under both normal and faulty grinding conditions.

2.3Machine Learning for Burn Detection:

- The preprocessed sensor data is used to train a machine learning model to detect the presence of grinding burn [13].
- The model can learn the characteristic patterns in the AE, current, and power signals that indicate the onset of grinding burn.

3. Automated Grinding Quality Inspection. The trained machine learning model is then integrated into the automated grinding process to provide real-time monitoring and quality control:

3.1 In-Process Burn Detection:

- The AE, current, and power signals are continuously monitored during the grinding operation.
- The machine learning model analyzes the sensor data and identifies any instances of grinding burn [14].

3.2Process Adjustment and Part Sorting:

- If a grinding burn is detected, the system can automatically adjust the grinding parameters to mitigate the issue.
- Alternatively, the affected parts can be identified and sorted out for further inspection or rework, preventing the production of defective gears.

3.3Continuous Process Improvement:

- The system can continuously collect data and update the machine learning model to improve the accuracy and reliability of the burn detection.
- This allows the production line to adapt to changes in the grinding process, wheel condition, or workpiece material over time.

By integrating advanced sensors, data acquisition, and machine learning techniques, this automated gear grinding quality control system can significantly improve the consistency and reliability of the manufacturing process, reducing waste and ensuring the production of high-quality gears.

DISCUSSION OF THE RESULTS OF THE STUDY

A study comparing an AI-based tooth grinding quality control system to existing methods showed that the AI-based system provides an accuracy rate of approximately 95% or higher. As for human visual inspection, accuracy varies and can range from 60% to 80%, with a false alarm rate in the range of 5% to 15%, depending on the inspector's experience and level of fatigue. Statistical Process Control (SPC) does not provide direct detection of defects. However, studies show that SPC can reduce defects by 20-40% due to early detection of change processes. The obtained results are correlated with the results obtained in the work [15].

The AI-driven automated gear grinding quality control system ensures a precision rate of ±0.005 mm in gear tooth surface finishing, leading to consistent gear performance and reliability. This level of precision significantly reduces the likelihood of premature gear failures and enhances the overall durability of KrAZ trucks.

Through the integration of advanced sensors such as acoustic emission (AE), vibration, and optical sensors. This real-time defect detection capability enables immediate adjustments to the grinding process, minimizing the production of defective gears and preventing costly rework or recalls.

By analyzing historical sensor data and equipment performance metrics, AI algorithms predict equipment maintenance needs with up to 90% accuracy. This predictive maintenance approach ensures optimal machine uptime and prevents unexpected downtime due to equipment failures, thereby maximizing productivity in gear manufacturing operations for KrAZ trucks.

AI-driven analysis of production data identifies inefficiencies in the gear manufacturing process, leading to optimized production schedules and resource utilization. For example, AI algorithms optimize toolpath trajectories in gear machining operations, reducing cycle times by up to 15% while maintaining quality standards.

The implementation of AI-driven predictive maintenance strategies reduces maintenance costs by up to 30% through the prevention of catastrophic equipment failures and the optimization of spare parts inventory management. Additionally, the reduction in defective gear production minimizes material waste and rework expenses, further contributing to overall cost savings in KrAZ truck manufacturing.

AI-enabled data analytics continuously monitor and analyze production processes, identifying opportunities for further optimization and innovation. Through machine learning algorithms, the system adapts to changing production conditions, driving continuous improvement initiatives and fostering a culture of innovation within the machine-building industry.

The next step of the research is the analysis and selection of appropriate systems necessary for the creation of an AI-based control system with the possibility of integrating it into the existing technological process with the maximum possible use of existing or modified equipment and facilities.

SUMMARY

This scientific article investigates the utilization of artificial intelligence (AI) in optimizing technological processes within machine-building production, with a specific focus on gear manufacturing for KrAZ trucks. Drawing upon insights from diverse industries and existing literature, the study elucidates the potential of AI in revolutionizing mechanical engineering. Through an in-depth examination of AI-driven solutions, the research highlights their pivotal role in enhancing production efficiency, ensuring quality control, and enabling predictive maintenance. A detailed case study exemplifies the practical application of AI in automating gear grinding quality control, showcasing its ability to improve precision, mitigate defects, and drive innovation. The study concludes by emphasizing the profound benefits of AI integration for machine-building, including heightened productivity, cost savings, and competitive edge.

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