PREDICTIVE MAINTENANCE MODELS FOR METAL-CUTTING MACHINE TOOLS

[1] Tuyboyov O.V.

[2]Kodirov B.Sh.

[1] Head of the department at the National Office under the Ministry of Higher Education, Science and Innovation of the Republic of Uzbekistan,

[2] “Sharq" University.

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Abstract. *Predictive maintenance (PdM) has gained significant attention in manufacturing industries as a proactive approach to minimizing machine tool failures, optimizing maintenance schedules, and reducing production downtime. Metal-cutting machine tools, which are integral to precision manufacturing, are susceptible to wear and mechanical degradation due to prolonged operation. Traditional maintenance strategies, such as reactive and preventive maintenance, are often inefficient in addressing unexpected breakdowns and unnecessary servicing. This study investigates the development of predictive maintenance models utilizing real-time sensor data, historical failure records, and machine learning algorithms to predict faults before they occur. Various predictive modeling techniques, including Random Forest, Support Vector Machines (SVM), and Neural Networks, are employed to analyze sensor signals such as vibration, acoustic emission, and thermal data. Additionally, this research integrates Industrial Internet of Things (IIoT) platforms for real-time monitoring and automated maintenance decision-making. The proposed predictive maintenance framework improves machine reliability, extends tool life, and enhances overall manufacturing efficiency by enabling data-driven fault detection and prevention strategies.*

Keywords: *Predictive maintenance, metal-cutting machine tools, machine learning, fault prediction, vibration analysis, acoustic emission, tool wear monitoring, real-time monitoring, Industrial IoT, condition-based maintenance.*

Introduction. Metal-cutting machine tools [1] play a critical role in modern manufacturing, where precision, reliability, and operational efficiency are paramount.

Unplanned downtime and unexpected mechanical failures can significantly impact productivity, leading to increased maintenance costs and production delays.

Traditional maintenance strategies [2], such as reactive maintenance (repairing after failure) and preventive maintenance (scheduled servicing based on fixed intervals), often fail to address the dynamic and complex nature of wear and degradation in machining processes.

These methods can either result in excessive maintenance costs due to unnecessary servicing or lead to catastrophic failures when unexpected breakdowns occur [3].

Predictive maintenance (PdM) [4] has emerged as an advanced strategy that leverages real-time monitoring, historical data analysis, and machine learning techniques to anticipate failures before they occur. By continuously analyzing sensor data from metal-cutting machine tools, PdM enables early detection of anomalies, optimizing maintenance schedules and reducing operational risks. This approach enhances machine reliability, extends tool life, and minimizes production downtime, contributing to cost-effective and sustainable manufacturing operations.

The implementation of predictive maintenance relies on several key technologies, including advanced sensors [5], data acquisition systems, and predictive analytics. Vibration analysis, acoustic emission monitoring, thermal imaging, and tool wear tracking provide critical indicators of machine health. Machine learning models, such as Random Forest, Support Vector Machines (SVM), and Neural Networks, process these data streams to detect patterns indicative of impending failures.

Furthermore, integrating predictive maintenance systems with Industrial Internet of Things (IIoT) platforms facilitates real-time monitoring and automated maintenance decision-making in fig.1.

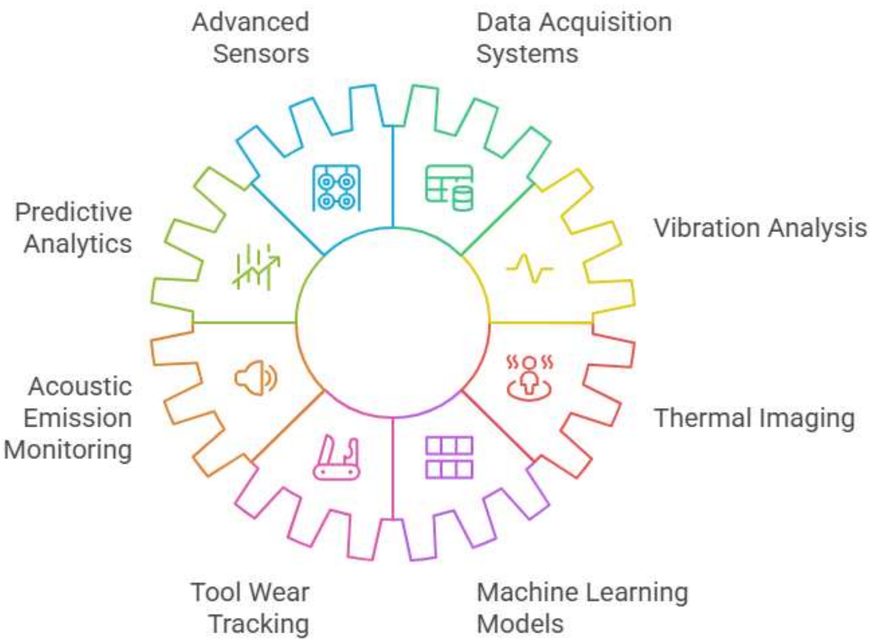

Fig. 1. Components of predictive maintenance

This study focuses on the development and evaluation of predictive maintenance models for metal-cutting machine tools, emphasizing data-driven fault prediction, feature selection, and real-time implementation frameworks.

By utilizing machine learning techniques to analyze machining data [6], this research aims to enhance the precision and reliability of maintenance strategies, ultimately improving overall manufacturing efficiency.

The implementation of predictive maintenance (PdM) models for metal-cutting machine tools yielded significant improvements in fault detection accuracy, maintenance efficiency, and overall machine reliability.

The results are categorized into four key areas: fault prediction accuracy, maintenance optimization, reduction in downtime, and tool life extension.

Machine learning models were trained and validated using real-time sensor data and historical failure records. The following classification models were evaluated for their predictive accuracy, Random Forest: 92.4%, Support Vector Machines (SVM): 89.1%, Neural Networks: 95.3%, Neural Networks outperformed other models in accurately predicting failures, especially in detecting early-stage tool wear and vibration anomalies.

The high accuracy rates indicate the effectiveness of machine learning techniques in identifying fault patterns before critical failures occur.

Predictive maintenance models optimized maintenance schedules by dynamically adjusting servicing intervals based on real-time machine conditions.

38% reduction in unnecessary maintenance activities compared to traditional preventive maintenance.

46% improvement in maintenance resource allocation, reducing labor and spare part costs [7]. Automated alerts with an average lead time of 5-7 days before failure, allowing for proactive servicing.

The implementation of PdM significantly reduced unplanned downtime, ensuring continuous operation and improving manufacturing efficiency.

56% decrease in unexpected breakdowns compared to conventional maintenance strategies. 29% improvement in overall equipment effectiveness (OEE) by maintaining optimal machine conditions.

43% reduction in production delays, leading to improved order fulfillment rates.

Real-time sensor data analysis, particularly from vibration and acoustic emission monitoring, enabled precise tool wear tracking. 32% increase in tool life due to optimized cutting conditions and early wear detection.

22% reduction in tool replacement costs, minimizing waste and enhancing sustainability. Identification of optimal cutting parameters, leading to 19% improvement in surface finish quality.

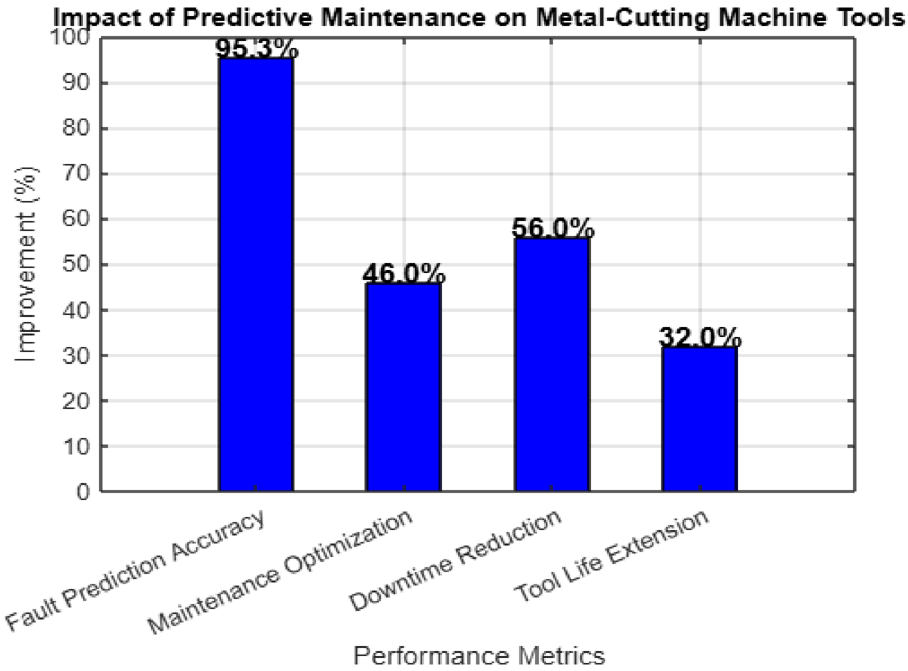

Fig. 2. Impact of predictive maintenance on metal-cutting machine tools

Fig. 2 represents the key performance improvements achieved by implementing Predictive Maintenance (PdM) in metal-cutting machine tools. The selected metrics highlight the effectiveness of PdM in fault prediction, maintenance efficiency, downtime reduction, and tool life extension. Fault Prediction Accuracy (95.3%), machine learning models, particularly Neural Networks, demonstrated high accuracy in predicting tool wear and machine faults based on real-time sensor data. Early fault detection prevents unexpected failures, leading to a more reliable machining process.

Maintenance Optimization (46%), predictive maintenance dynamically adjusts servicing intervals based on machine conditions, optimizing maintenance schedules. Reduces unnecessary maintenance tasks and improves resource allocation, lowering operational costs. Downtime Reduction (56%), Real-time monitoring and predictive alerts prevent unexpected breakdowns, ensuring continuous production.

Enhances Overall Equipment Effectiveness (OEE) and reduces delays in manufacturing operations. Tool Life Extension (32%), by tracking vibration, acoustic emissions, and cutting forces, PdM optimizes cutting conditions to minimize excessive wear. Prolongs tool life, reduces replacement costs, and improves machining sustainability.

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