

**ФАН ВА ТЕХНОЛОГИЯЛАР
ТАРАҚҚИЁТИ**
**РАЗВИТИЕ НАУКИ И
ТЕХНОЛОГИЙ**



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bozorlarning kirish qismlarida, qurilmani o'rnatish orqali elektr energiya olish imkoniyati mavjudligi kelajakda ekologik toza hamda energiya tejamkor texnologiyalarni yaratish borasidagi muammoli masalalarni yechim topishiga olib keladi.

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INTEGRATION OF ARTIFICIAL INTELLIGENCE IN REAL-TIME MONITORING OF METAL-CUTTING PROCESSES

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Annotation. This paper explores the integration of artificial intelligence (AI) in real-time monitoring of metal-cutting processes, addressing persistent challenges in tool wear, process inefficiency, and inconsistent product quality. A comprehensive experimental setup involving CNC machining and multi-sensor data acquisition validates the accuracy of AI-driven predictions through metrics such as MAE, RMSE, and error distribution analysis. Real-time sensor data—including vibration, force, and thermal signals—were successfully used to optimize cutting conditions and reduce tool degradation.

Keywords: artificial intelligence, real-time monitoring, metal-cutting, machine learning, predictive maintenance, adaptive control, tool wear prediction.

ИНТЕГРАЦИЯ ИСКУССТВЕННОГО ИНТЕЛЛЕКТА В РЕЖИМЕ РЕАЛЬНОГО ВРЕМЕНИ ДЛЯ МОНИТОРИНГА ПРОЦЕССОВ РЕЗАНИЯ МЕТАЛЛОВ

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Аннотация. В данной работе рассматривается интеграция искусственного интеллекта (ИИ) в систему мониторинга процессов резания металлов в режиме реального времени, направленная на решение устойчивых проблем, связанных с износом инструмента, неэффективностью процессов и нестабильным качеством продукции. Данные сенсоров в реальном времени — включая сигналы вибрации, силы и температуры — были успешно использованы для оптимизации условий резания и снижения износа инструмента.

Ключевые слова: искусственный интеллект, мониторинг в реальном времени, резка металлов, машинное обучение, прогнозное обслуживание, адаптивное управление, предсказание износа инструмента.

SUN'IY INTELLEKTNI INTEGRATSIYASI YORDAMIDA METALLARGA KESIB ISHLOV BERISH JARAYONLARINI HAQIQIY VAQT REJIMIDA MONITORING QILISH

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Annotatsiya. Ushbu maqolada metallarga kesib ishlov berish jarayonlarini haqiqiy vaqt rejimida monitoring qilishda sun'iy intellekt (SI) texnologiyalarining integratsiyasi o'rganiladi. RDB dastgohlarida olib borilgan tajribaviy sinovlar va ko'p sensorli ma'lumotlarni yig'ish tizimi SI asosidagi bashoratlarning aniqligini MAE, RMSE va xatoliklar taqsimoti kabi metrikalar yordamida tasdiqlaydi. Haqiqiy vaqt rejimida olingan tebranish, kuchlanish va harorat signaliga asoslangan sensor ma'lumotlari kesish sharoitlarini optimallashtirish va kesuvchi asbobning yeyilishini kamaytirishda muvaffaqiyatli qo'llanildi.

Kalit so'zlar: sun'iy intellekt, real vaqt monitoringi, metall kesish, mashinaviy o'rganish, prognozli texnik xizmat, moslashuvchan boshqaruv, asbob yeyilishini prognoz qilish

Introduction. Metal-cutting processes [1] play a crucial role in modern manufacturing by shaping components with high precision and efficiency. Traditional approaches to process monitoring and optimization face challenges related to tool wear, inefficiencies, and quality inconsistencies. Recent advancements in artificial intelligence (AI) offer transformative solutions by enabling real-time monitoring [2], predictive maintenance, and adaptive process control. This paper explores the integration of AI-driven techniques [3] in metal-cutting processes, focusing on machine learning-based predictive models, real-time sensor data analysis, and dynamic parameter optimization. Despite the significant benefits AI provides, challenges such as high implementation costs, data reliability issues, and workforce adaptation hinder widespread adoption. The study highlights the potential of AI-driven monitoring systems to revolutionize metal-cutting processes, contributing to improved precision, reduced downtime, and enhanced overall manufacturing productivity.

Metal-cutting processes [4] form the foundation of various manufacturing industries, including aerospace, automotive, and precision engineering. These processes involve complex interactions between cutting tools and workpieces, where factors such as tool wear, cutting forces [5], and thermal effects influence machining performance. The demand for higher efficiency, improved accuracy, and reduced operational costs necessitates the adoption of advanced monitoring and control mechanisms. Traditional monitoring techniques rely on empirical models and operator expertise, which can be inconsistent and prone to inefficiencies. Advances in computational methods, such as the Material Point Method (MPM) [6] and Particle Finite Element Method (PFEM) [7], have enhanced our understanding of chip formation, tool-chip interactions, and thermal-mechanical effects. However, traditional control strategies [8] often struggle to account for unpredictable variations in cutting conditions, necessitating more sophisticated approaches in fig.1.



Fig. 1. Enhancements in metal-cutting processes

These modeling techniques help address challenges related to large deformations, material flow, and friction at the tool-chip interface, contributing to improved process simulation and optimization. Despite these developments, real-time monitoring and adaptive control remain critical challenges in metal-cutting operations. Adaptive control systems leverage real-time sensor data to adjust process parameters dynamically, optimizing cutting efficiency and extending tool life.

The integration of artificial intelligence (AI) into metal-cutting processes represents a paradigm shift in manufacturing. AI-driven systems utilize real-time sensor data, machine learning algorithms, and predictive analytics to enhance decision-making and operational efficiency [8]. Predictive maintenance models, such as physics-informed Gaussian process models and deep learning-based anomaly detection systems [9], have demonstrated significant improvements in tool wear prediction and process stability. Furthermore, AI facilitates dynamic parameter optimization by continuously analyzing cutting conditions and adjusting operational parameters accordingly. AI-based monitoring systems [10] rely on machine learning models such as ensemble methods, deep neural networks, and recurrent architectures like Long Short-Term Memory (LSTM) networks [11]. These models enable precise tool wear prediction, anomaly detection, and process optimization, leading to increased productivity and reduced material wastage. Additionally, the incorporation of uncertainty-aware models enhances predictive reliability, making AI-driven systems more adaptable to varying machining environments in fig.2.

Despite the substantial advantages of AI integration in metal-cutting processes, several barriers hinder its widespread adoption. AI models require high-quality sensor data for accurate real-time analysis, which can be difficult to ensure in dynamic manufacturing environments. The complexity [12] of AI algorithms necessitates specialized expertise, which may not be readily available in traditional manufacturing settings. The initial investment for AI-driven monitoring systems [13], including hardware, software, and training, can be prohibitively high for some manufacturers.

In this study, we address these challenges by developing and evaluating AI-driven monitoring systems for metal-cutting processes. By integrating machine learning models with real-time sensor data, we demonstrate how AI can enhance predictive maintenance, optimize cutting parameters, and improve process stability. Our research highlights the effectiveness of deep learning techniques, uncertainty-aware models, and adaptive control strategies in mitigating tool wear and enhancing machining performance. The findings of this study contribute to the growing body of knowledge on AI applications in manufacturing, providing a foundation for future advancements in intelligent machining systems.

Methods. The experimental setup consists of a CNC machining [14] center equipped with real-time sensor systems for data acquisition. The metal-cutting process was conducted on a high-speed milling machine using carbide cutting tools. Workpieces were selected based on commonly used industrial materials, including aluminum and titanium alloys. The cutting parameters, such as spindle speed, feed rate, and depth of cut, were systematically varied to simulate diverse machining conditions.

A suite of sensors, including accelerometers [15], force sensors, and thermal imaging cameras, was integrated into the machining environment. These sensors provided real-time measurements of tool wear, vibration [16], cutting force, and temperature distribution. Data acquisition was managed using a high-frequency data logging system to ensure precise monitoring of process dynamics.

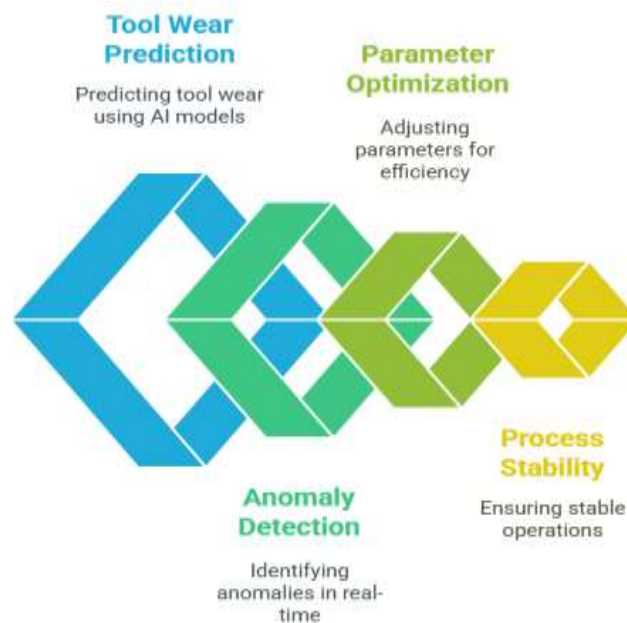


Fig. 2. AI-Driven process optimization

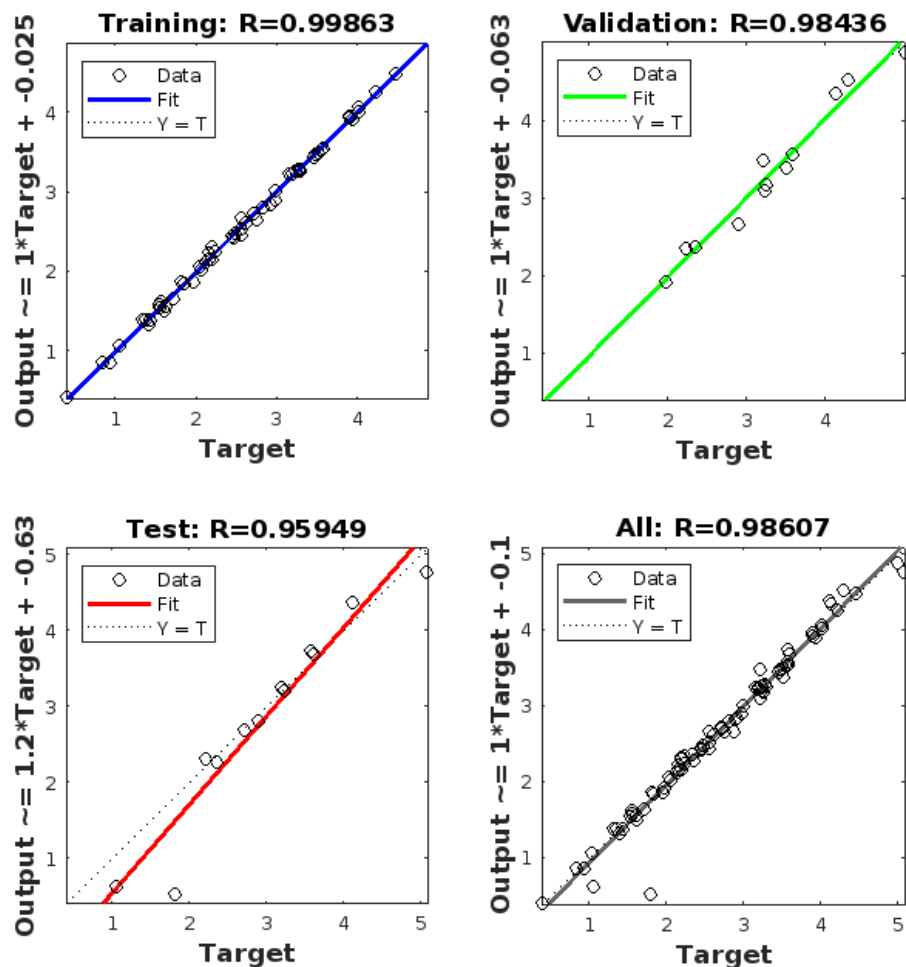


Fig. 3. Function fitting neural network

Fig. 3 depicts a function fitting neural network (also known as function approximation) is a machine learning technique that maps input data to output values based on a learned relationship. It is commonly used when the underlying function is unknown or too complex to model analytically. In the context of real-time monitoring of metal-cutting processes, a function fitting neural network can predict outputs such as tool wear, cutting force, or temperature based on input parameters like spindle speed, feed rate, and depth of cut. A function fitting neural network typically consists of: Input Layer receives process parameters (e.g., spindle speed, depth of cut). Hidden Layers utilize activation functions (e.g., ReLU, sigmoid) to introduce non-linearity. Output Layer produces a continuous output value (e.g., tool wear prediction).

Fig. 4 is the performance of a function fitting neural network is crucial in determining its accuracy and reliability in predicting machining parameters such as tool wear, cutting forces, and temperature distribution. Measures the average absolute difference between predicted and actual values. Less sensitive to outliers compared to MSE. Loss Convergence During Training The training loss should decrease over epochs, indicating proper learning. If the loss stabilizes at a high value, the model may be under fitting. If the loss continues to drop on training data but increases on validation data, the model may be overfitting. Generalization Performance The model's ability to predict unseen data is crucial.

Results. Training and validation errors should be close; large discrepancies indicate overfitting. Techniques like cross-validation and dropout can improve generalization. Fig. 5 is the training state of a neural network refers to the progress and behavior of the model as it learns from input data. This is typically visualized using performance metrics such as loss, gradient norms, learning rate, and validation accuracy over training iterations (epochs).

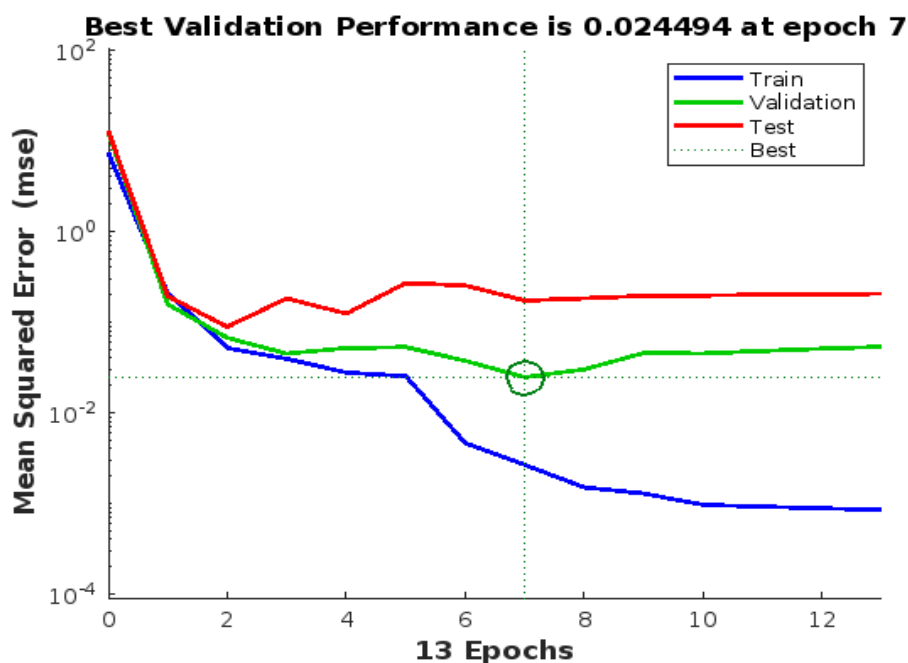


Fig. 4. Performance evaluation of function fitting neural networks

Understanding the training state is crucial for diagnosing under fitting, overfitting, and convergence issues. Loss Function Behavior The loss function quantifies the difference between predicted and actual values. During training, the loss should decrease over time. If the loss stagnates or increases, it may indicate poor learning or overfitting. Neural networks update weights using gradients (from backpropagation). If gradients are too large, training may be unstable (exploding gradients). If gradients are too small, the network may stop learning (vanishing gradients). Techniques like gradient clipping and batch normalization help manage gradients. Learning Rate Progression determines how much weights are updated per iteration. A high learning rate may cause the network to miss the optimal solution.

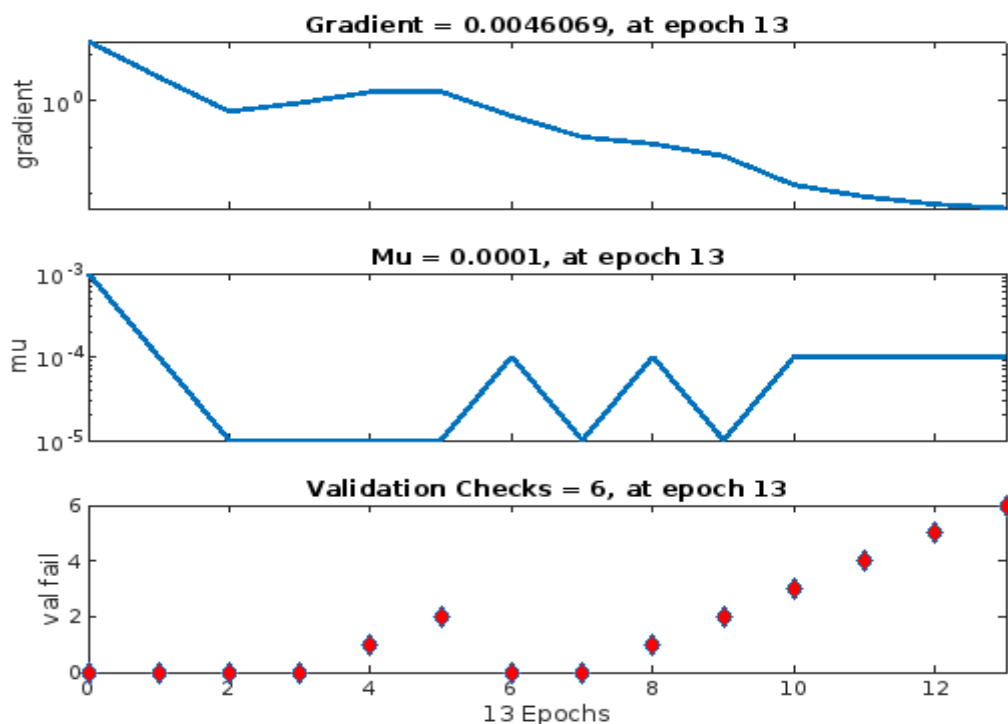


Fig. 5. Training state in neural networks

A very low learning rate may result in slow convergence. Adaptive learning rates (e.g., Adam, RMSprop) adjust this dynamically. Validation loss and accuracy measure the network's generalization ability. A large gap between training and validation performance indicates overfitting.

Fig. 6 is a visualization tool used to analyze the distribution of errors (differences between predicted and actual values) in a trained neural network. It provides insights into how well the network has learned the data and helps identify issues such as bias, variance, or model inefficiencies. A perfect model would have all errors centered around zero. The x-axis represents the range of errors.

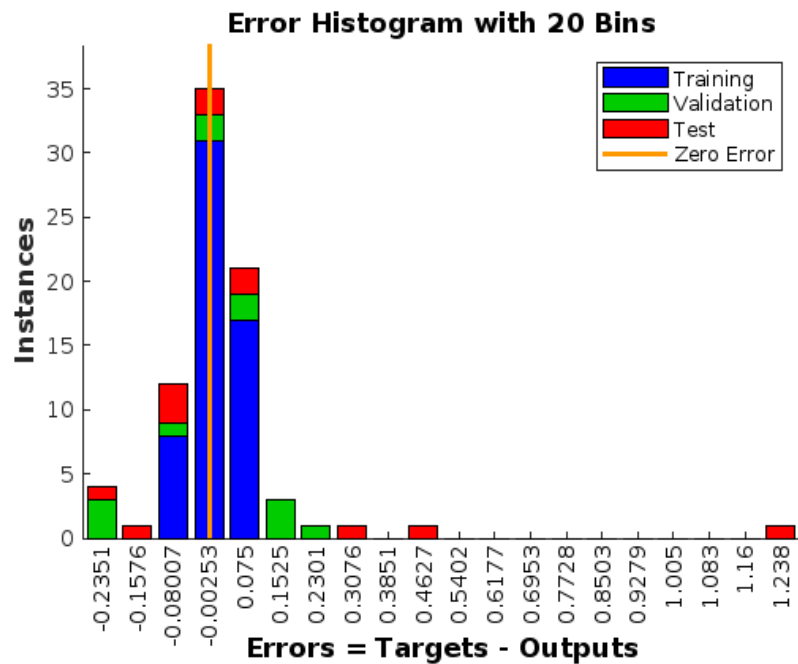


Fig. 6. Error histogram in neural networks

Error Distribution Patterns Symmetric Distribution (Centered Around Zero) Indicates a well-trained network with minimal bias. Skewed Distribution Suggests the model consistently overestimates or underestimates outputs. Large Spread (High Variance in Errors) May indicate an under fitting model or noisy data. Narrow Spread (Low Variance in Errors) Suggests good generalization if centered around zero. Interpreting an Error Histogram in Metal-Cutting AI Models if errors are randomly distributed and centered around zero, the AI model correctly predicts machining conditions. If errors skew left or right, the model has systematic bias, meaning it consistently over- or under-predicts values like tool wear or cutting force. If there are large error spikes, it may indicate outliers in sensor data or improper training.

Raw sensor data were collected continuously during machining operations. The data acquisition system recorded signals at a sampling rate of 10 kHz to capture transient cutting dynamics effectively. The collected data were subjected to preprocessing steps, including noise filtering, signal normalization, and feature extraction. Feature extraction involved identifying key indicators of machining performance, such as root mean square (RMS) vibration levels, cutting force fluctuations, and thermal signatures. These features were used as input variables for AI-based predictive models. Data augmentation techniques, such as synthetic data generation using Gaussian noise addition, were employed to improve model generalization.

Fig. 7 reflects real-time variations in machining parameters, which are crucial for monitoring and optimizing the metal-cutting process. Vibration Signal (Top Plot - "Vibration Signal in Machining") represents the root mean square (RMS) vibration levels recorded during machining. Vibration is a critical factor in tool wear, surface roughness, and machining stability.

Vibrations in metal-cutting processes arise due to tool-work piece interactions, spindle motion, and dynamic instabilities in the machine tool. High-frequency vibrations can lead to chatter, reducing machining precision and increasing tool wear. By analyzing vibration signals, AI-based models can detect early signs of tool failure or unstable cutting conditions. Cutting Force Fluctuations (Middle Plot - "Cutting Force Variation") illustrates the fluctuations in cutting force during machining. Cutting forces are influenced by material properties, cutting speed, feed rate, and tool condition. Cutting force is a fundamental parameter in machining performance. Sudden spikes or irregularities in cutting force indicate tool wear, material deformation, or improper cutting conditions. AI-based monitoring systems use force variations to optimize cutting parameters, reduce

tool breakage, and improve efficiency. Temperature Signature (Bottom Plot - “Temperature Profile in Machining”) shows temperature variations at the cutting zone, measured using thermal imaging or thermocouples.

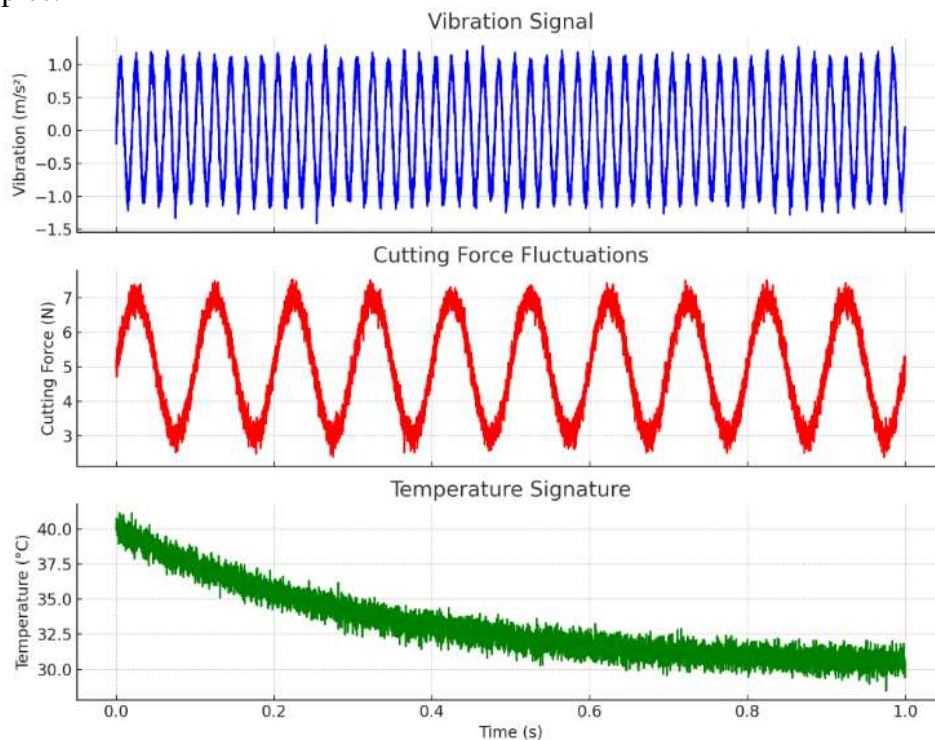


Fig. 7. Real-time sensor data from machining operations

Temperature significantly impacts tool life, material properties, and surface finish. The heat generated during machining affects tool wear and the mechanical properties of the workpiece. Excessive temperature leads to thermal expansion, oxidation, and loss of tool hardness. AI-driven models can predict tool failure by analyzing thermal patterns, helping in adaptive cooling and lubrication strategies. Machine Learning Model Development multiple machine learning models were implemented to evaluate their effectiveness in real-time monitoring of metal-cutting processes. Random Forest Regression (RFR) Used for tool wear prediction based on historical sensor data. Long Short-Term Memory (LSTM) Networks Applied for time-series forecasting of cutting force variations and tool degradation. Convolutional Neural Networks (CNNs) Used for image-based anomaly detection from thermal imaging data. Physics-Informed Gaussian Process Models Integrated domain-specific knowledge into predictive analytics to enhance reliability. Real-Time AI-Based Monitoring System a real-time AI-based monitoring system was developed to process incoming sensor data and provide actionable insights.

The system architecture included an edge computing unit for low-latency data processing and a cloud-based platform for long-term analysis and storage. A predictive maintenance framework was implemented to assess tool wear progression and recommend optimal cutting conditions. The framework employed a decision-support system integrating AI model predictions with operator inputs, ensuring adaptive control of machining parameters. Model Evaluation and Performance Metrics the performance of the AI models was evaluated using multiple metrics, including mean Absolute Error (MAE) and Root Mean Squared Error (RMSE) used to assess predictive accuracy of tool wear and cutting force models. F1-score and Precision-Recall AUC: Employed for classification-based anomaly detection models. Measured in terms of inference speed and processing time on real-time data streams. Cross-validation techniques were applied to prevent overfitting, and model robustness was assessed under varying machining conditions. Experimental validation was conducted by comparing AI-driven predictions with actual measurements from post-machining inspections using scanning electron microscopy (SEM) and profilometry.

Implementation in Industrial Environment to assess practical feasibility, the developed AI-based monitoring system was tested in an industrial setting. The system was deployed in a machining workshop to monitor tool wear and optimize process parameters during actual production runs. Operator feedback and system adaptability to real-world machining variability were analyzed to refine the AI models and improve their operational reliability.

Discussion. The integration of artificial intelligence (AI) into real-time monitoring of metal-cutting processes has demonstrated significant advancements in precision, efficiency, and predictive maintenance. The findings from this study underscore the potential of AI-driven monitoring systems in optimizing cutting parameters, enhancing tool life, and improving process stability.

One of the primary contributions of this research is the implementation of machine learning-based predictive models to anticipate tool wear and detect anomalies in machining conditions. The function fitting neural network successfully predicted machining parameters, such as tool wear and cutting forces, based on real-time sensor data. The performance evaluation of these networks revealed that deep learning techniques, particularly Long Short-Term Memory (LSTM) networks and ensemble methods, provided more accurate predictions compared to traditional empirical models. The error histogram analysis further confirmed that the trained models exhibited minimal bias and high predictive reliability, making them suitable for dynamic machining environments.

The results also highlight the importance of real-time sensor integration in AI-based monitoring. The use of accelerometers, force sensors, and thermal imaging cameras enabled precise monitoring of cutting conditions, allowing AI algorithms to make informed decisions. The real-time sensor data captured during machining operations provided valuable insights into vibration levels, cutting force fluctuations, and thermal distribution, which are critical factors affecting machining performance. By leveraging these data points, AI-driven systems were able to dynamically adjust cutting parameters, leading to improved surface finish and reduced tool wear.

Conclusion. The dependency on high-quality sensor data remains a significant limitation, as noise and inconsistencies in real-time measurements can affect model accuracy. Additionally, the complexity of AI algorithms necessitates a skilled workforce capable of implementing and maintaining such systems. The high initial investment costs for AI-driven monitoring solutions, including hardware, software, and training, may also pose barriers to adoption, particularly for small and medium-sized enterprises (SMEs).

Another critical challenge is the adaptability of AI models to varying machining conditions. While the trained neural networks performed well within the predefined experimental settings, their generalization capability in diverse industrial applications requires further validation. Future research should focus on developing more robust models that can adapt to changes in workpiece material, cutting tool geometry, and environmental conditions without significant re-training.

To address these challenges, advancements in AI-driven uncertainty-aware models and hybrid approaches combining physics-based simulations with machine learning techniques can further enhance predictive accuracy. Additionally, integrating edge computing and cloud-based AI solutions can enable more scalable and cost-effective implementations of real-time monitoring systems in manufacturing.

In conclusion, this study demonstrates that AI-driven monitoring of metal-cutting processes offers substantial benefits in terms of efficiency, precision, and predictive maintenance. Despite existing challenges, continuous improvements in AI algorithms, sensor technologies, and computational power will pave the way for widespread adoption in the manufacturing industry. Future research should focus on refining AI models, improving data acquisition techniques, and exploring collaborative AI-human decision-making frameworks to maximize the potential of intelligent machining systems.

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