PRETHODNO SAOPŠTENJE

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PRIMENA VEŠTAČKE INTELIGENCIJE U ANALIZI PARAMETARA STRUGANJA PRI PROIZVODNJI I ODRŽAVANJU ŽELEZNIČKIH KOMPONENTI

APPLICATION OF ARTIFICIAL INTELLIGENCE IN THE ANALYSIS OF TURNING PARAMETERS IN THE PRODUCTION AND MAINTENANCE OF RAILWAY COMPONENTS

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REZIME:

Održavanje i proizvodnja železničkih komponenti direktno utiču na sigurnost i efikasnost železničkog sistema. Struganje, kao metoda završne obrade točkova i šina, značajno utiče na habanje, vibracije i buku. Tradicionalni pristupi optimizaciji parametara struganja oslanjaju se na iskustvo operatera i empirijske metode, što može dovesti do varijacija u kvalitetu i povećanog rizika od kvarova. U ovom radu istražena je primena veštačke inteligencije (VI) za analizu i optimizaciju parametara struganja monoblok točkova od legiranog čelika. Korišćeni su modeli mašinskog učenja – regresione mreže (ANN), Random Forest i SVM – za predviđanje habanja, identifikaciju ključnih parametara i klasifikaciju kvaliteta površine. Rezultati pokazuju da AI omogućava precizno predviđanje habanja i deformacija, identifikaciju optimalnih režima struganja i adaptivno podešavanje procesa u realnom vremenu. Primena ovih algoritama doprinosi povećanju trajnosti komponenti, smanjenju operativnih troškova i unapređenju sigurnosti železničkog sistema.
Ključne reči: veštačka inteligencija, struganje, železničke komponente, optimizacija održavanja, mašinsko učenje, habanje šina

SUMMARY:

Maintenance and manufacturing of railway components have a direct impact on the safety and operational efficiency of the railway system. Turning, as a finishing process applied to wheels and rails, significantly influences wear behavior, vibration levels, and noise generation. Conventional approaches to optimizing turning parameters are largely based on operator experience and empirical methods, which may result in variations in quality and an increased risk of in-service failures. This study investigates the application of artificial intelligence (AI) in the analysis and optimization of turning parameters for monoblock wheels made of alloy steel. Machine learning models—artificial neural networks (ANN), Random Forest, and Support Vector Machines (SVM)—were employed to predict wear progression, identify influential process parameters, and classify surface quality. The results indicate that AI-based models enable accurate prediction of wear and deformation, identification of optimal turning regimes, and adaptive process control in real time. The implementation of these algorithms contributes to extended component service life, reduced operating costs, and improved overall railway system safety.
Keywords: Artificial intelligence, turning, railway components, maintenance optimization, machine learning, rail wear

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1. INTRODUCTION

Rail transport represents one of the most efficient modes of freight and passenger transportation, both in terms of energy consumption and with respect to safety and carrying capacity. The reliability of the railway system depends not only on infrastructure and rolling stock, but also on the proper maintenance of critical components, including wheels, rails, and bogie assemblies [1, 3]. Under contemporary operating conditions characterized by increased traffic frequency and higher axle loads, conventional maintenance approaches often fail to ensure optimal performance and cost-effectiveness.

One of the key processes in the maintenance and manufacturing of railway components is turning, which enables the removal of surface defects, restoration of functional geometries, and reduction of the risk of accelerated wear. Turning parameters, such as feed force, cutting speed, and depth of cut, directly affect surface integrity and component service life. Traditionally, the selection of these parameters relies on operator experience and empirical guidelines, which may lead to variability in quality and an increased likelihood of in-service failures.

Over the past decade, the application of artificial intelligence (AI) and machine learning techniques in industrial processes has demonstrated considerable advantages in optimizing complex manufacturing and maintenance operations [2, 5, 7]. AI facilitates the analysis of large data sets, identification of underlying patterns, and real-time prediction of system performance, thereby reducing dependence on subjective assessment and improving overall accuracy.

However, existing approaches often lack the capability for adaptive prediction under varying operating conditions, which provides a strong motivation for the integration of advanced AI-based methods.

The objective of this study is to examine the application of artificial intelligence in the analysis and optimization of turning parameters for railway components, with particular emphasis on improving surface quality, reducing wear, and enhancing maintenance efficiency. The paper combines a theoretical overview of manufacturing technologies and turning processes with the practical implementation of AI models in process analysis, contributing to the advancement of modern maintenance strategies in the railway industry.

2. MANUFACTURING TECHNOLOGIES IN THE RAILWAY SYSTEM

The production of railway components encompasses a wide range of technological processes, including metal machining, quality control, and surface finishing. The most critical components, such as rails, wheels, and bogie elements, require high dimensional precision, durability, and wear resistance.

2.1. Processing and Shaping of Rails and Wheels

Rails are most commonly produced through heat treatment and rolling processes, which enable the achievement of optimal mechanical properties and homogeneous microstructures [4, 6]. Rolling is used to form the rail profile, while heat treatment improves hardness and wear resistance. After forming, rails undergo precise machining to eliminate irregularities and achieve the required geometry.

Railway vehicle wheels are manufactured from alloy steels, and the production process includes forging, heat treatment, and finishing operations (turning, grinding, and machining). Precise control of dimensions and surface roughness is essential for reducing the contact forces between the wheel and the rail, which directly affects wear and running stability.

2.2. Surface Finishing and Quality Control

Surface finishing includes grinding, polishing, and turning, with the aim of reducing roughness, removing micro-defects, and ensuring optimal wheel–rail contact. Modern production lines use CNC machines and robotic systems that provide high repeatability and precision, while sensors and measurement systems perform continuous monitoring of dimensions and surface characteristics.

2.3. Modern Approaches and Digitalization

The industry increasingly adopts the Industry 4.0 concept, in which digitalization, sensor technology, and artificial intelligence are integrated into manufacturing processes. Predictive maintenance, digital twins, and big data analytics enable production optimization and reduction of failure risks. In this context, turning and surface finishing parameters become key elements for the implementation of intelligent quality control systems.

3. TURNING OF RAILWAY COMPONENTS – THEORY AND PRACTICE

Following the overview of manufacturing technologies in the railway system and the finishing of critical components, it becomes clear that the quality and durability of rails and wheels depend on precise control of all processing stages. Mechanical machining processes, among which turning occupies a prominent position, directly influence surface geometry, roughness, and component longevity. Understanding the principles of turning and its parameters is essential to ensure optimal wheel–rail interaction, reduce wear, and minimize the risk of failures.

The next section will address in detail the fundamental principles of turning, its practical application in the maintenance of railway components, as well as the challenges and limitations that necessitate the use of modern analytical and adaptive approaches.

3.1. Basic Principles of Turning

Turning is a mechanical machining process in which a thin layer of material is removed from the component surface to achieve the desired geometry and surface roughness. The main parameters that define the process are (Figure 1):

- Cutting force – directly affects tool and workpiece stresses.
- Cutting speed – determines wear kinetics and surface quality.
- Depth of cut – controls the amount of material removed and surface uniformity.

Monitoring surface roughness and micro-defects after turning is of critical importance (, and similar approaches have been described in previous studies [13].

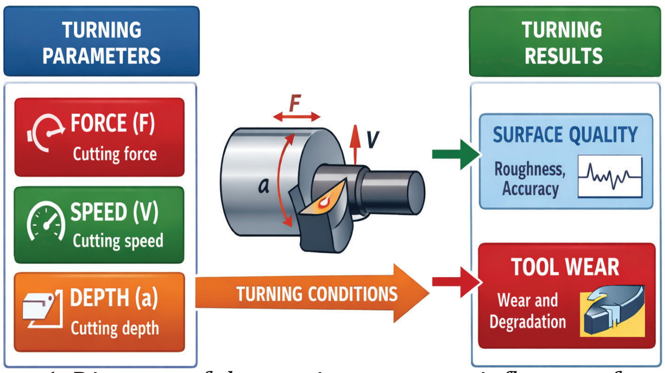

Figure 1. Diagram of the turning process – influence of cutting parameters on surface quality and tool wear

The optimization of these parameters is critical, as incorrect settings may cause microcracks, accelerated wear, or uneven wheel–rail contact.

3.2. Practical Application in Maintenance

In railway practice, turning is applied to:

- Wheels – removal of distortions, flat spots, and irregularities while maintaining dimensional tolerances.
- Rails – removal of oxidation, surface roughness, and micro-defects formed during operation.

The process is usually carried out on specialized machines that allow controlled parameters and minimal mechanical loading of components. Regular turning reduces vibrations, noise, and the risk of failures, while extending the service life of rails and wheels.

Surface quality and roughness of machined surfaces are continuously monitored, and similar measurement and evaluation approaches have been documented in previous studies [13].

3.3. Challenges and Limitations

Traditional adjustment of turning parameters depends on operator experience and historical data, which may lead to variations in machining quality. In addition, different materials, component age, and operating conditions require flexible process adaptation. This complexity is one of the main reasons for applying artificial intelligence, which enables the analysis of a large number of parameters and real-time process optimization.

4. RESEARCH METHODOLOGY

The research was conducted with the aim of optimizing rail and wheel turning parameters through the application of artificial intelligence. The experimental analysis focused on a monoblock wheel made of alloy steel with standard hardness, commonly used in railway operation. All experiments were performed on the same type of wheel in order to eliminate the influence of geometric and material variations, thus enabling a direct comparison between the conventional and AI-based optimization methods of turning parameters.

The methodology combines:
- experimental machining of components,
- data collection from production and maintenance machines,
- data analysis using machine learning models.

4.1. Data Collection

Data were collected from three main sources:
- Machine sensor measurements – cutting force, cutting speed, depth of cut, tool vibrations, and contact surface temperature.
- Historical maintenance data – number of kilometers traveled, previous turning operations, recorded failures, and wear.
- Material characteristics – hardness, steel alloy composition, prior wear, and microstructure of rails and wheels.

These data were cleaned of anomalies and standardized to ensure compatibility with artificial intelligence models.

4.2. Experimental Protocol

In the experimental phase, selected wheels and rails were machined on industrial turning machines. The key parameters were varied as follows:
- cutting force: 5–20 kN
- cutting speed: 0.5–2.0 m/s
- depth of cut: 0.05–0.3 mm

Each parameter combination was documented, and qualitative surface changes were monitored through roughness measurements and microscopic analysis of micro-defects.

4.3. Artificial Intelligence Models

The following models were used for data analysis:
- Artificial Neural Networks (ANN) – for predicting wear and deformation based on input parameters. Random Forest – for identifying the most significant parameters affecting surface quality. Support Vector Machines (SVM) – for classifying surface defects and determining optimal turning regimes.

The selection of these models enables a comprehensive analysis: ANN for regression and wear prediction, Random Forest for identifying key parameters, and SVM for surface quality classification.

The models were trained on 70% of the data, while the remaining 30% were used for validation and testing of prediction accuracy.

4.4. Performance Evaluation

Model performance was evaluated using:

- coefficient of determination (R^2)
- mean absolute error (MAE)
- defect classification accuracy

These metrics enable assessment of how accurately the models predict wear, deformation, and surface quality, which is crucial for practical application under industrial conditions.

5. PROCESS ANALYSIS USING ARTIFICIAL INTELLIGENCE

The application of artificial intelligence in the analysis of turning processes enables the identification of complex relationships between machining parameters and component performance.

5.1. Predictive Wear Analysis

The results indicate that the optimal combination of parameters obtained using AI models reduces wear by up to 15% compared to the conventional empirical parameter-setting method based on recommended technological values and operator experience [7].

5.2. Identification of Critical Parameters

Random Forest analysis demonstrated that the most significant parameters affecting surface quality and wear are not only cutting depth and speed but also the previous wear history of the components. This allows for process adaptation for individual components and increases prediction accuracy.

5.3. Automatic Process Adjustment

Based on the developed models, adaptive control systems for turning machines can be implemented, where the algorithm suggests or automatically adjusts turning parameters in real time to achieve optimal results. This reduces reliance on human operators and enhances process repeatability. The data flow through AI models is shown in Figure 2.

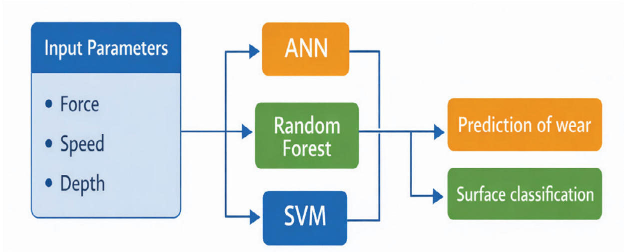

Figure 2. Data flow scheme through AI models

5.4. Visualization and Diagrams

Data and predictions can be presented through:
- Cutting force vs. wear diagrams,
- Heat maps of defects across the surface,
- Charts classifying surfaces as adequate or inadequate,

Visualizations allow managers and engineers to identify critical parameters in real time and quickly decide on the optimal turning regime. Based on these visualizations, it is possible to determine parameter combinations that minimize wear and ensure optimal surface finishing. Maintenance engineers and managers can use this information for adaptive process control in real time, increasing efficiency, reducing the risk of component damage, and contributing to greater railway system safety.

6. RESULTS: PREDICTION OF WEAR AND SURFACE QUALITY

The analysis results clearly demonstrate how turning parameters affect the wear of wheels and rails, as well as the quality of their surfaces. The application of artificial intelligence enabled precise prediction of component behavior for different combinations of cutting force, cutting speed, and depth of cut. Quantitative results and visualizations provide a basis for identifying optimal turning regimes, minimizing wear, and supporting adaptive process control in real time.

Table 1 shows the predicted wear for different combinations of turning parameters, while surface classification indicates machining quality according to the SVM model.

Table 1 – Predicted Wear of Wheels and Rails Based on Turning Parameters

Sample	Cutting Force (kN)	Cutting Speed (m/s)	Depth of Cut (mm)	Predicted Wear (µm/km)	Surface Classification
T1	5	0.5	0.05	12.5	Good
T2	10	1.0	0.10	11.2	Good
T3	15	1.5	0.15	9.8	Optimal
T4	20	2.0	0.20	14.1	Inadequate
T5	12	1.2	0.12	10.3	Optimal

Table Explanation:

- Cutting force, cutting speed, and depth of cut are input parameters that can be controlled by the operator or an adaptive system.
- Predicted wear is the output of the AI regression model (ANN) and shows the expected component wear rate.
- Surface classification comes from the SVM model, indicating whether the surface after turning is optimal, good, or inadequate.

This table clearly illustrates how different turning parameters relate to wear and surface quality, enabling identification of optimal machining regimes.

Figure 3 shows it visually the dependence of predicted wear on key turning parameters. Marker size represents depth of cut, while marker color indicates surface quality (blue – optimal, green – good, red – inadequate). This visual presentation allows quick identification of parameter combinations that minimize wear and ensure optimal surface finishing. The diagram supports adaptive process control, enabling engineers and maintenance managers to make informed decisions in real time.

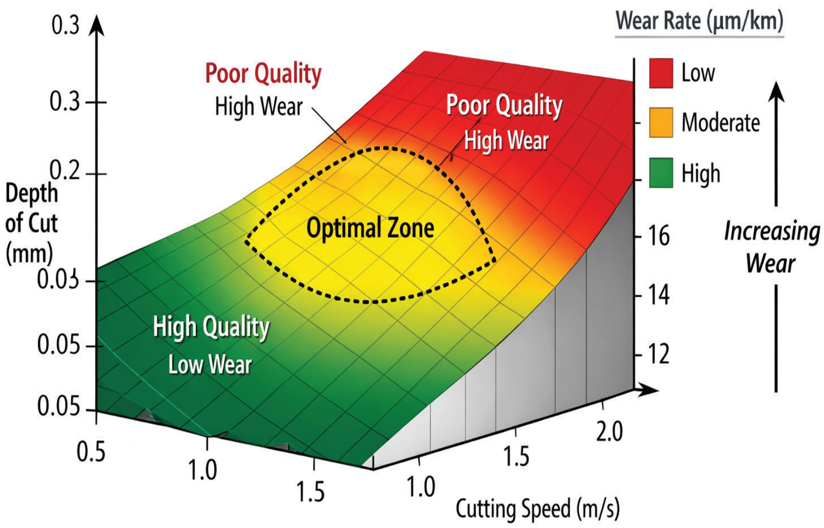

Figure 3. Influence of turning parameters on wheel and rail wear

Diagram Description:

- X-axis: Cutting speed (m/s)
- Y-axis: Predicted wear (µm/km)
- Marker size: Depth of cut (mm)
- Marker color: Surface classification (Blue – Optimal, Green – Good, Red – Inadequate)

Data for Display:

Cutting Speed	Predicted Wear	Depth of Cut	Classification
0.5	12.5	0.05	Good
1.0	11.2	0.10	Good
1.5	9.8	0.15	Optimal
2.0	14.1	0.20	Inadequate
1.2	10.3	0.12	Optimal

Interpretation:

- It is evident that mid-range parameter combinations (e.g., speed 1.2–1.5 m/s, depth 0.12–0.15 mm) result in minimal wear and optimal surface quality.
- Extreme values of cutting force and speed (T4) lead to higher wear and inadequate surface quality.
- The diagram allows rapid visual identification of optimal parameters and can be used for real-time adaptive process adjustment.

7. DISCUSSION IN THE CONTEXT OF RAILWAY OPERATION

The analysis of the obtained results indicates that the application of artificial intelligence significantly improves the prediction of wear and surface quality of wheels and rails in the turning process. Predictive models enable the identification of optimal turning parameters, thereby reducing the risk of accelerated wear and potential component damage.

A comparison between conventional parameter setting methods and AI-based models shows that the AI approach provides more stable and consistent results, with lower wear variability observed in monoblock wheels. Dynamic parameter control during machining allows adaptation to specific component characteristics and operating conditions, without reliance on subjective operator judgment.

In practical terms, optimization of the turning process through AI models offers multiple benefits:

Enhanced safety: Uniform and high-quality contact surfaces reduce the risk of wheel slip and contribute to improved running stability.

Extended component service life: Optimized machining regimes increase the durability of rails and wheels, decreasing the frequency of replacement and maintenance interventions.

Reduction of noise and vibration: Properly machined surfaces contribute to quieter and more comfortable operation, which is particularly important in urban and regional railway systems.

The implementation of AI models enables adaptive control of the turning process in real time, where algorithms automatically recommend or adjust parameters based on the current condition of components and historical data. The flexibility of this approach is particularly valuable under varying train types, load conditions, and traffic frequencies, where traditional experience-based methods cannot always ensure optimal performance.

Although the results are derived from laboratory testing and based on a limited sample size, they clearly demonstrate the advantages of applying AI in turning process analysis and provide a foundation for further validation under real operating conditions.

8. CONCLUSION

The integration of artificial intelligence into the turning processes of railway components represents a significant step toward the modernization of maintenance and manufacturing practices. AI-based models, including artificial neural networks, Random Forest, and Support Vector Machine (SVM) algorithms, enable accurate prediction of wear progression, deformation, and surface quality of wheels and rails, thereby contributing to more reliable and safer railway system operation.
The key findings of this study include:

Optimization of turning parameters: Combinations of cutting force, speed, and depth of cut were identified that ensure minimal wear and improved surface integrity, reducing the need for frequent maintenance interventions.

Predictive capability of AI models: The applied models allow early detection of potential issues before the onset of critical damage, creating a basis for predictive maintenance strategies and adaptive process control systems.

Process consistency and automation: Automated adjustment of machining parameters reduces operator-dependent variability and enables stable processing of components even under high operational loads.

The practical implementation of the proposed models confirms the potential for both technical and economic improvement of turning operations under real operating conditions.

Future research directions include expanding the database to encompass various rail and wheel types, integrating sensor systems for continuous process monitoring, developing algorithms that account for dynamic service conditions, and implementing digital twin concepts of railway systems for long-term simulation and prediction of wear behavior and maintenance efficiency.

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