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МОДЕЛЮВАННЯ ПРОЦЕСІВ В МЕТАЛУРГІЇ ТА МАШИНОБУДУВАННІ

MODELING OF PROCESSES IN METALLURGY AND MECHANICAL ENGINEERING

UDC 621.941:004.85

APPLICATION OF MACHINE LEARNING METHODS FOR MODELING THE QUALITY AND STABILITY OF THE TURNING PROCESS

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Purpose. *Development and validation of a predictive modeling methodology that enables multi-objective analysis of the turning process by simultaneously predicting two key parameters: average surface quality and process stability (variability).*

Research methods. *A comparative analysis of models based on Multiple Linear Regression (empirical formula) and the Random Forest algorithm was conducted. The models were trained on an open experimental dataset for $42CrMo_4$+QT steel. Accuracy was evaluated using R^2 and MAE metrics on a test set. Validation was performed on an independent dataset.*

Results. *The Random Forest model demonstrated slightly higher predictive capability for average roughness (R^2=0.59 vs. 0.53) and significantly higher capability for process stability (R^2=0.139 vs. negative values for the formula). The dominant influence of feed rate and tool nose radius on quality was established, as well as the key role of cutting speed and tool geometry on stability.*

Scientific movelty. *An approach for the simultaneous modeling of the quality and stability of the turning process is proposed. The substantial advantage of flexible ML models over classical regression for analyzing stochastic aspects of the process, such as process variability, has been quantitatively proven.*

Practical *Value. The developed methodology serves as a tool for the multi-objective optimization of cutting parameters. Recommendations for improving process reliability have been formulated: increasing the depth of cut to enhance productivity, avoiding low-speed regimes (v<95m/min), and using a tool with a nose radius of r=0.8mm, which reduces the maximum expected process variability by more than 16%.*

Key words*: machine learning, Random Forest algorithms, surface roughness, process stability, optimization, turning, multi-objective analysis.*

Introduction

Ensuring high surface quality and stable operation of turning processes is a key task in modern mechanical engineering. This issue is of particular importance in the production of critical components – aircraft engine elements, high-load shafts, axles, and hydraulic system parts – where even minor deviations in surface layer parameters can lead to a significant reduction in reliability, fatigue strength, or operational failure. Surface roughness parameters and process repeatability depend on a complex set of operational and structural factors, the interaction of which exhibits a pronounced non-linear character.

Classical approaches to selecting cutting parameters rely on empirical power laws and tabular recommendations. While these often provide an acceptable quality level, they fail to account for the complex non-linear interconnections and stochastic effects inherent in real-world cutting processes. Furthermore, such approaches are primarily focused on predicting the mean value of the roughness parameter and practically do not consider process variability, which is critically important in the context of increasing production stability.

The development of machine learning (ML) methods opens the possibility of transitioning from simplified analytical relationships to flexible models capable of reflecting the complex behavior of technological systems in a multidimensional parameter space. However, the challenge of applying them in metal machining remains open due to the limited amount of high-quality experimental data and the insufficiently studied ability of ML approaches to model not only the mean values of quality parameters but also their stability.

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Therefore, there is a scientific and practical need to create a comprehensive predictive model capable of simultaneously predicting average surface quality and the stability of the turning process, taking into account non-linear interactions between technological parameters.

Analysis of Research and Publications

Modern research in surface roughness prediction for turning is characterized by a gradual transition from traditional empirical methods to the application of machine learning algorithms. Early works were largely based on constructing analytical dependencies of the mean value $\overline{R_a}$ on cutting parameters and tool geometry, primarily using power equations and response surface models. Although such approaches provided basic engineering interpretation, they demonstrated limited capability in describing the non-linear and interdependent effects inherent to the cutting process [1, 2].

Further progress in this field was driven by the implementation of machine learning methods capable of modeling multidimensional non-linear dependencies. Recent publications have employed Support Vector Machines (SVM), Random Forest, Gradient Boosting (XGBoost), Gaussian Process Regression (GPR), as well as deep neural networks and neuro-fuzzy systems. Most researchers indicate a significant advantage of ensemble and deep models over classical regression methods regarding $\overline{R_a}$ prediction accuracy, especially under conditions of limited and noisy experimental data [3–5]. Certain works demonstrate the potential of using GPR for tasks requiring not only point forecasts but also probabilistic uncertainty assessment, which is critical in production environments [1, 6].

An important research vector has been the integration into predictive models of informative features derived not only from process parameters but also from sensor signals – vibrations, acoustic emission, and drive current signals. The use of temporal and spectral characteristics allows for the effective identification of dynamic effects and process instability, particularly the onset of self-excited vibrations (chatter), which have a significant impact on surface microgeometry. Studies [7–9] have proven that the addition of vibration and acoustic features significantly improves the accuracy of both machining regime classification and roughness regression analysis.

Despite the intensive development of this topic, a critical review of the literature highlights a number of unresolved problems. Firstly, the vast majority of works focus on predicting the mean value $\overline{R_a}$, while variability indicators, specifically the standard deviation S_{Ra}, are practically not considered as independent modeling objects [10, 11]. This limits the possibilities for quantitative analysis of process stability and risk assessment of production fluctuations, although the consistency of quality indicators is often a decisive factor in industry. Secondly, many publications use relatively small experimental datasets on which models show high accuracy on test samples, but external validation of results is often absent [4, 12]. Consequently, the question of model generalization and scalability in real production conditions remains relevant. Thirdly, the degree of integration of such models into online monitoring systems remains insufficient to ensure automatic adjustment of parameters or early detection of deviations.

In this context, the scientific novelty and aim of this study are as follows. First, the work is aimed at modeling not only the mean roughness value $\overline{R_a}$ but also its variability S_{Ra}, which allows for filling one of the key gaps in modern research. Second, the choice of the Random Forest ensemble method is justified, providing the necessary balance between prediction accuracy and model interpretability, allowing for an assessment of the contribution of each factor to the formation of both mean and variable roughness indicators. The clarity of the model structure is a critical requirement for engineering practice [3, 4]. Third, conducting external validation on an independent dataset increases the reliability of the obtained results and confirms the robustness of the proposed approach across a wider range of conditions, which distinguishes this work from many previous studies. Finally, the formulated practical recommendations facilitate the transition from theoretical modeling to the optimization of technological processes in real production [13].

Thus, the analysis of the current state of the problem confirms both the relevance and feasibility of the chosen research direction: comprehensive modeling of mean and variable roughness characteristics using ensemble machine learning methods and ensuring external validation allows for expanding existing methodological approaches and creating a foundation for developing reliable prediction systems for turning quality.

Aim of the Study

The aim of this work is to develop and validate a predictive modeling methodology that ensures the simultaneous forecasting of two key characteristics of the turning process for $42CrMo_4$+QT steel:

- mean surface roughness ($\overline{R_a}$);
- process stability, defined by the standard deviation of roughness (S_{Ra}).

To achieve this aim, the following objectives must be met:

- form a representative experimental dataset;
- construct two models: an empirical power law formula (linear regression) and a Random Forest model;
- perform a comparative accuracy assessment using R^2 and MAE metrics;
- conduct an engineering interpretation of the influence of cutting factors on the target variables;
- validate the approach on an independent dataset;
- formulate recommendations for optimizing cutting parameters.

Material and Research Methodology

The study utilizes the open experimental dataset MaRoReS [14] for the turning of $42CrMo_4$+QT steel. The dataset contains the results of 68 independent experiments,

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each accompanied by three parallel measurements of the roughness parameter R_a. The input data includes the main technological parameters of the turning process: v – cutting speed in the range of 76–200 m/min, f – feed rate (0.05–0.25 mm/rev), d – depth of cut (0.05–0.25 mm), and r – tool nose radius (0.4 or 0.8 mm). This structure ensures a representative factor space sufficient for building models to predict surface quality indicators and assess process stability based on machine learning methods.

Data preprocessing involved calculating integral characteristics for each experiment. The arithmetic mean of the roughness was defined as $\overline{R_a}$, and the standard deviation between the three measurements was defined as S_{Ra}, which was interpreted as a quantitative assessment of process stability (variability). Table 1 demonstrates the structure of the dataset using the first five rows as an example.

Table 1 – First 5 rows of the dataset

№	r	d	s	f	$\overline{R_a}$	S_{Ra}
0	0.4	0.05	138	0.15	0.857667	0.004726
1	0.4	0.05	138	0.15	1.078333	0.023629
2	0.4	0.10	107	0.10	0.408667	0.014012
3	0.4	0.10	107	0.10	0.558000	0.007810
4	0.4	0.10	107	0.20	1.133333	0.034819
5	0.4	0.10	107	0.20	1.185000	0.011358

In the first stage of modeling, an empirical power model was built based on multiple linear regression in logarithms. This approach yielded a formula of the form:

$$R_a = C \cdot r^a \cdot d^b \cdot v^c \cdot f^d, \quad (1)$$

which reproduces the traditional form of the dependence of roughness on cutting parameters.

For comparison, a Random Forest Regressor model was also built with hyperparameter tuning using the GridSearchCV method. The data was split into training and test sets in a 75/25 ratio. An analysis of the importance of input parameters on the target roughness variable was also conducted.

Subsequent analysis focused on modeling process stability, represented by the S_{Ra} value. For this purpose, a Random Forest model was also applied, trained on the same four technological factors. The influence of critical cutting parameters on process stability and a comparison of stability for tools with different nose radii were also investigated.

The final stage was the external validation of the models on an independent dataset [15], which contains 20 experimental data points regarding the dependence of surface roughness on cutting regimes.

Research Results

Based on the power model (1), the following empirical formula was obtained to determine the mean roughness value:

$$R_a = 24.824 \cdot r^{-0.456} \cdot d^{-0.1811} \cdot v^{-0.5643} \cdot f^{0.7435}. \quad (2)$$

Despite its simplicity and convenience, formula (2) demonstrated a somewhat limited capability in predicting the mean roughness value $\overline{R_a}$. On the test sample, the coefficient of determination was only $R^2 = 0.53$, indicating that the model explains only 53% of the data variability. The Mean Absolute Error (MAE) was 0.13µm. These results suggest a significant discrepancy between the linear model and the actual nature of parameter dependencies in cutting processes, as well as an inability to adequately reproduce interactions between them. This is consistent with the fact that the roughness formation process has a pronounced non-linear character, limiting the effectiveness of traditional regression formulas.

The application of the Random Forest model allowed for a slight improvement in prediction accuracy. On the test dataset, $R^2 = 0.59$ and MAE = 0.127µm were obtained. Figure 1 compares the predictions of both models with the actual experimental values on the test sample.

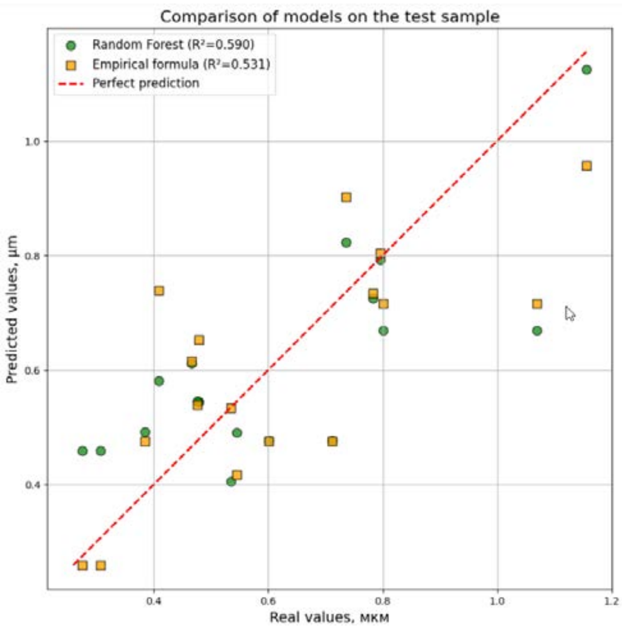

Figure 1. Comparison of predictions of the two models, $\overline{R_a}$

It can be seen that the points predicted by Random Forest cluster somewhat more tightly around the ideal prediction line (dashed line) than the points of the empirical formula.

Additionally, the importance of input parameters for the Random Forest model was analyzed (Fig. 2). The obtained values confirm the dominant influence of the feed rate f, which contributes the most to roughness variation. The tool nose radius r was the second most important factor, while the influence of the depth of cut d was the least significant. The cutting speed v manifested itself as a factor of medium significance.

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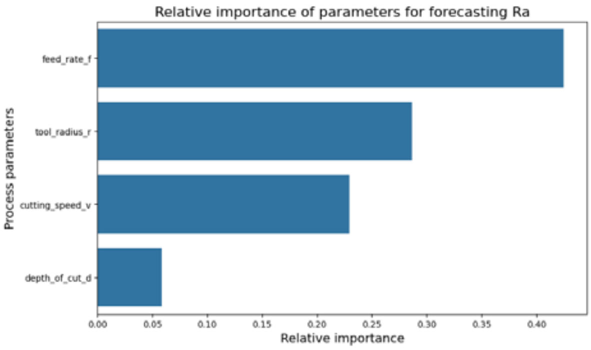

Figure 2. Feature importance for predicting $\overline{R_a}$

Process stability modeling, represented by the standard deviation of the roughness parameter S_{Ra}, was conducted separately. The results proved to be significantly less accurate compared to $\overline{R_a}$ prediction: for the Random Forest model, $R^2 = 0.139$ and MAE=0.0059μm were obtained. The empirical formula showed a negative value, indicating an inability to predict the data. The low value of the coefficient of determination is expected, as the variability of the S_{Ra} indicator is largely formed by stochastic factors (micro-vibrations, local microstructural differences, the initial state of the cutting edge, etc.) which are not represented in the dataset as input variables. The nature of the influence of the feed rate f on process stability is shown in Fig. 3.

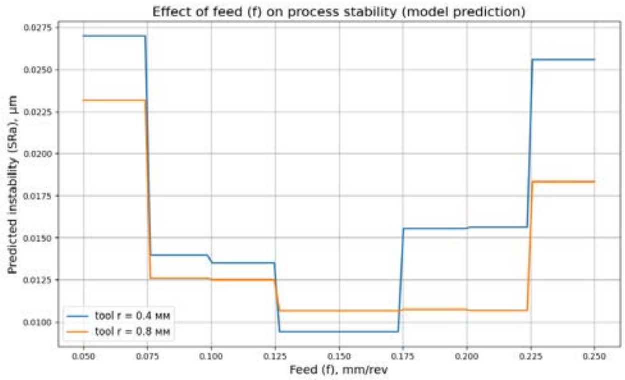

Figure 3. Influence of feed rate on S_{Ra}

An increase in S_{Ra} is observed with increasing feed, which corresponds to the complication of chip formation conditions and increased fluctuations in the load on the tool. The influence of cutting speed is shown in Fig. 4.

Here, an opposite trend is observed: stability deteriorates at low speeds, while increasing the cutting speed leads to a decrease in variability, corresponding to a more stable chip formation regime.

The influence of the tool nose radius on process stability is worth considering separately (Fig. 5).

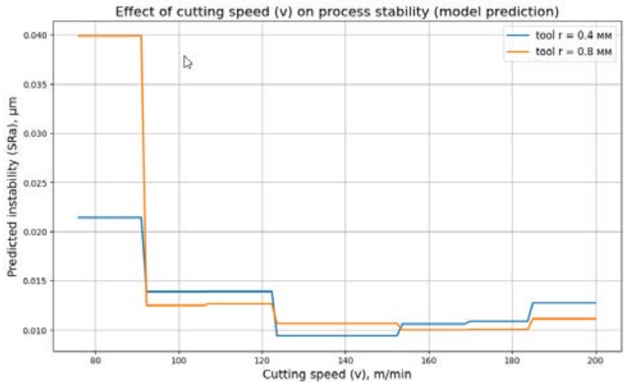

Figure 4. Influence of cutting speed on S_{Ra}

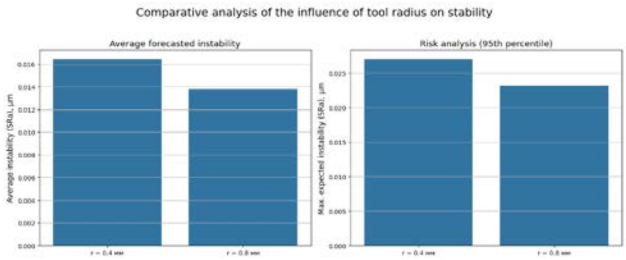

Figure 5. Comparison of S_{Ra} for r = 0.4 mm and r = 0.8 mm

The tool with a radius $r = 0.8$ mm showed significantly lower variability values than the tool with $r = 0.4$ mm, which can be explained by better load distribution and a reduction in local stress in the cutting zone. In particular, for certain combinations of regimes, a reduction in expected instability of more than 16 % is observed.

An important stage of the study was external validation on an independent set [15], which allowed for evaluating the generalizability of the constructed models. A comparison of the three approaches showed significant differences: the formula from [15] demonstrated a negative result ($R^2 \approx -0.675$), meaning it was unable to predicted the data. The modified power model obtained in this study showed a significantly more modest but non-zero consistency ($R^2 \approx 0.051$). The best result was provided by the Random Forest model with $R^2 \approx 0.525$, indicating its ability to transfer to other datasets without overfitting. A visual comparison of the three models relative to the ideal prediction is shown in Fig. 6.

As can be seen from Fig. 6, the points of the Random Forest model are located closest to the ideal prediction line, while the points of both empirical formulas are scattered across almost the entire range, indicating a complete inadequacy of prediction.

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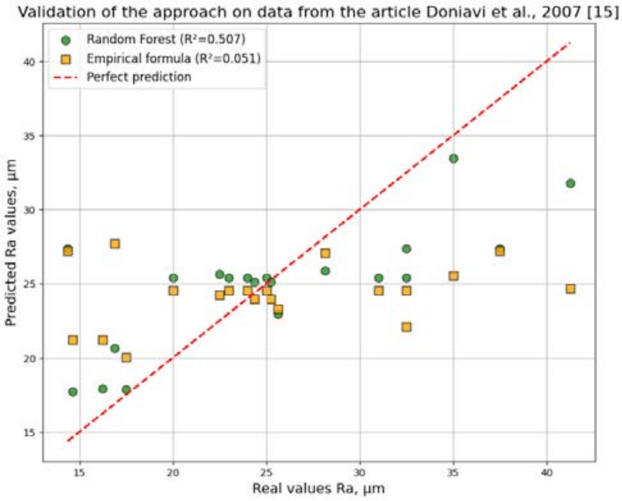

Figure 6. Comparison of predictions of three models on the external dataset [15]

Discussion

The obtained results confirm that classical power regression models, although providing a basic level of forecasting, are insufficiently flexible to describe the complex interrelationships between cutting process parameters. Machine learning models, particularly Random Forest, demonstrated a significantly higher capacity for generalization, especially under conditions of heterogeneous or noisy experimental data.

An important practical implication is the possibility of transitioning to multi-objective optimization, which simultaneously considers:

- low surface roughness;
- process stability and repeatability;
- productivity (via the possibility of increasing the depth of cut).

Stability analysis allowed for the identification of specific risk zones that are usually not revealed in works focusing solely on $\overline{R_a}$.

Conclusions

A methodology for predictive modeling of turning based on machine learning, which simultaneously forecasts process quality and stability, has been developed and validated.

The Random Forest algorithm provided significantly higher accuracy compared to classical regression.

It was established that the feed rate and tool nose geometry are the most influential factors on $\overline{R_a}$.

The first process stability model for S_{Ra} was built, allowing for the assessment of result repeatability.

Critical zones of instability were identified: low cutting speeds and extreme feed values.

A tool with a cutting edge radius of r = 0.8 mm ensures a tangible reduction in process variability (up to 16%) relative to tools with r = 0.4 mm.

Validation on an independent dataset confirmed the robustness of the machine learning approach.

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ЗАСТОСУВАННЯ МЕТОДІВ МАШИННОГО НАВЧАННЯ ДЛЯ МОДЕЛЮВАННЯ ЯКОСТІ ТА СТАБІЛЬНОСТІ ПРОЦЕСУ ТОКАРНОЇ ОБРОБКИ

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Мета роботи. *Розробка та валідація методики предиктивного моделювання, що дозволяє проводити багатоцільовий аналіз технологічного процесу точіння шляхом одночасного прогнозування двох ключових параметрів: середньої якості поверхні та стабільності (варіабельності) процесу.*

Методи дослідження*. Порівняльний аналіз моделей на основі множинної лінійної регресії (емпірична формула) та алгоритму Random Forest. Моделі навчалися на відкритому наборі експериментальних даних для сталі 42CrMo$_4$+QT. Точність оцінено за метриками R^2 та MAE на тестовій вибірці. Проведено валідацію на незалежному наборі даних.*

Отримані результати*. Модель Random Forest продемонструвала дещо вищу прогностичну здатність для середньої шорсткості (R^2=0.59 проти 0.53) та особливо для стабільності процесу (R^2=0.139 проти негативних значень для формули). Встановлено домінуючий вплив подачі та радіуса інструменту на якість, а також ключову роль швидкості різання та геометрії інструменту на стабільність.*

Наукова новизна. *Запропоновано підхід до одночасного моделювання якості та стабільності процесу точіння. Кількісно доведено суттєву перевагу гнучких ML-моделей над класичною регресією для аналізу стохастичних аспектів процесу, таких як його варіабельність процесу токарної обробки.*

Практична цінність. *Розроблена методика є інструментом для багатоцільової оптимізації режимів різання. Сформульовано рекомендації для підвищення надійності процесу: збільшення глибини різання для підвищення продуктивності, уникнення низькошвидкісних режимів ($v < 95$ м/хв) та використання інструменту з радіусом r=0.8 мм, що знижує максимальну очікувану варіабельність процесу більш ніж на 16%.*

Ключові слова: *машинне навчання, алгоритм Random Forest, шорсткість поверхні, стабільність процесу, оптимізація, токарна обробка, багатоцільовий аналіз.*

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