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Exploring Artificial Intelligence for Tool Wear Prediction in Turn-Milling

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Abstract. In modern precision manufacturing, optimizing complex processes like turn-milling is crucial for reducing production costs and ensuring high surface integrity. In this study the application of artificial intelligence, specifically machine learning (ML), for modeling turn-milling processes is investigated. The complexity of machining operations and the multitude of influencing input parameters often lead to time-consuming setups, particularly in single-part or small series manufacturing. Traditional process monitoring methods frequently fall short due to system complexity, prompting the exploration of ML for process optimization and automation. Focusing on orthogonal turn-milling, experimental data was collected to address regression problems such as tool wear and surface roughness, as well as tool condition classification. Three regression models - linear, polynomial, and support vector regression (SVR) - and four classification models - logistic regression, neural networks, support vector machines (SVM), and decision trees - were trained and validated using k-fold cross-validation. For regression models, root mean square error (RMSE) was used as the performance evaluation metric, while accuracy and F1-score were employed for classification problems. The results indicate that ML algorithms provide enhanced flexibility and accuracy compared to traditional statistical techniques, offering potential reductions in time and costs in process setups. By optimizing parameters iteratively, ML models demonstrate higher precision, reducing the need for extensive empirical research and the associated experimental costs. The developed models can be adapted to various manufacturing processes with minimal code adjustments, broadening their applicability and efficiency.

Introduction

The turn-milling process can be considered an alternative to turning and grinding. Compared to grinding, the turn-milling process allows for deterministic changes in the surface structure because a tool with geometrically defined cutting edges is applied [1]. This machining process also has ecological and economic advantages over grinding. Purchasing a separate grinding machine is unnecessary, and there is no need for the disposal of grinding sludge [2]. Moreover, turn-milling can be operated under dry conditions [1].

In contrast to turning, turn-milling utilizes a tool with multiple cutting edges. This reduces contact time and increases tool life [3]. Using orthogonal turn-milling, a tenfold improvement in surface quality can be achieved compared to turning, while maintaining the same productivity [4, 5]. Based on its kinematics, orthogonal turn-milling is more suitable for high-speed cutting (HSC) than conventional turning, where centrifugal force impedes the process [6, 7].

However, modeling the turn-milling process is challenging and expensive because extensive machining tests are required [8]. Furthermore, the material properties of both the workpiece and the tool significantly affect the accuracy of the model [4].

ML techniques are already widely applied to support critical decisions in medicine, financial markets, and the energy sector. Although ML is increasingly used in mechanical engineering, manufacturing technology is currently in an early phase of ML application [9]. This is due to the complex, dynamic, and even chaotic nature of manufacturing systems [10]. Traditional methods based on modeling cause-and-effect relationships are reaching their limits due to the rapidly growing complexity and high dimensionality of modern manufacturing processes [11]. ML techniques can address many of today's major challenges in complex manufacturing systems because they offer the following advantages:

- The ability to handle high-dimensional problems and data
- The ability to discover previously unknown (implicit) knowledge and identify implicit relationships in datasets
- Real-time processing
- The capability to handle various data types (numeric, nominal, text, and images)
- Enhanced user-friendliness of algorithms
- Reduced data requirements in certain cases

These advantages motivate the continued implementation of ML in manufacturing. However, several key issues create uncertainty and sometimes prevent companies from making meaningful investments in ML. These include unclear legal aspects regarding responsibility of decisions delegated from humans to machines and the time-consuming nature of data preparation [9].

Collecting relevant data can be challenging in manufacturing, as necessary data may not always be available, and high-dimensional data may contain large amounts of irrelevant and redundant information. This negatively impacts the performance of ML algorithms [12].

Another challenge is the interpretation of results. Not only does the representation of the output affect interpretation, but also the peculiarities of the chosen algorithm and hyperparameter settings must be considered [10].

Nevertheless, the general ability of ML algorithms to achieve desired results in a manufacturing environment has been successfully demonstrated [10].

To address these challenges, this study investigates the potential of Machine Learning to automate and optimize the modeling of orthogonal turn-milling processes. Based on experimental data, three regression models were developed to predict tool wear (flank wear) and surface roughness, alongside four classification models to evaluate tool condition. To ensure statistical reliability despite a limited dataset — a common constraint in small-series manufacturing — a k-fold cross-validation methodology was implemented. The main contribution of this work lies in demonstrating that classical ML algorithms can outperform traditional statistical methods in capturing non-linear process behaviors with high precision. Furthermore, the developed framework offers a flexible, code-agnostic approach that can be adapted to various manufacturing processes, significantly reducing the time and cost associated with empirical process setup.

Experimental Methodology

Cutting conditions in orthogonal turn-milling include tool and workpiece rotation speed, depth of cut, tool diameter, axial feed rate, eccentricity, and cutting speed. The arithmetic mean roughness and flank wear on two surfaces of the two inserts were selected as target variables because they characterize the quality of the produced components and the economic efficiency of the machining process. In this study, the axial depth of cut was varied to minimize the amount of data and allow for initial assessments of algorithm performance.

The following dependencies were examined:

- Flank wear on two surfaces of the tool as a function of depth of cut
- Surface roughness parameters as a function of flank wear
- Surface roughness parameters as a function of depth of cut

In Fig. 1 the experimental setup is shown in a DMG MORI CTX Beta 1250 TC. The tool used was a Ø 10 mm Sandvik CoroMill 390 milling cutter with two ISO 390R-070202M-PM 1130 P2.1.Z.AN indexable inserts with a maximum depth of cut of 5.8 mm and a feed per tooth of $f_z = 0.03$ mm - 0.1 mm. The tool was clamped in the intelligent tool holder ProMicron Spike. It is equipped with sensors for measuring cutting forces, bending moment, torsion and temperature. A workpiece made of 100Cr6 bearing steel was machined. In this experiment, a section with a diameter of Ø 65 mm and a length of 25 mm was machined. To ensure the objectivity of the wear measurements, the indexable inserts were replaced after each machining cycle, regardless of whether they were worn or suitable for further machining. In total 11 experiments were initially carried out. The axial depth of cut was changed each time and varied in the range ap = 0.05 - 0.45 mm. The cutting speed of 285 m/min recommended by the tool manufacturer was used.

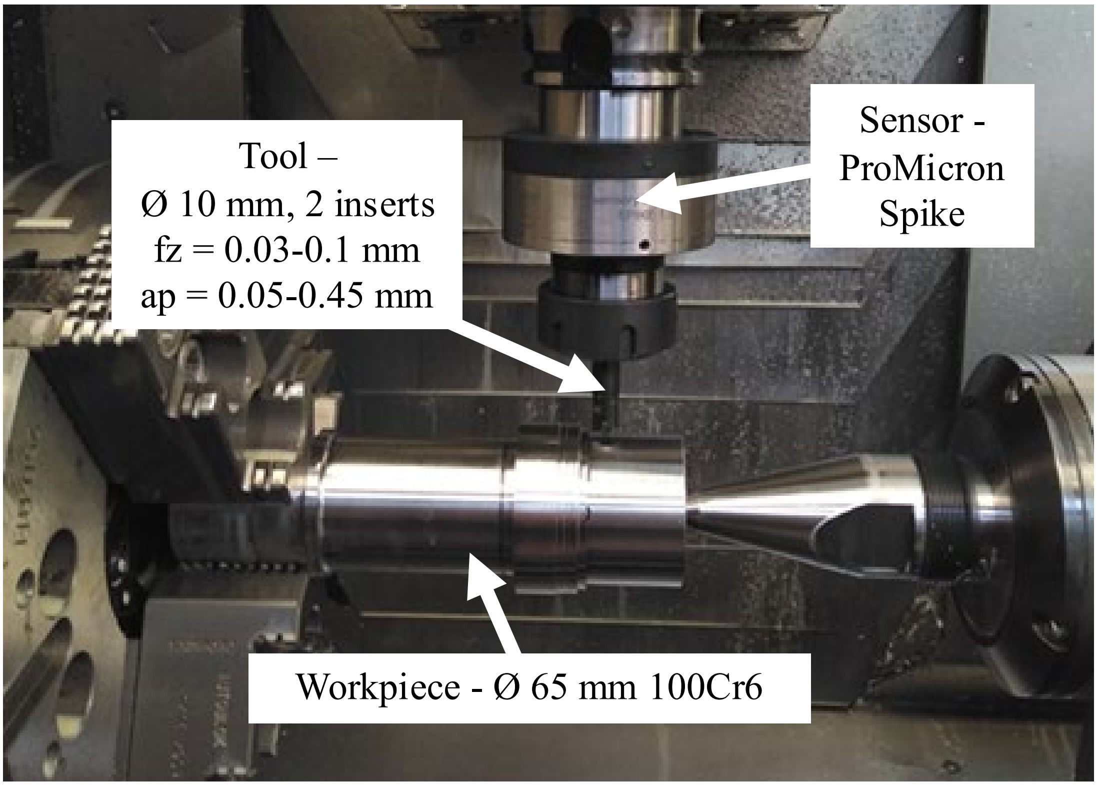


Fig. 1. Experimental setup in a DMG MORI CTX Beta 1250 TC lathe.

The resulting wear on the tool was measured on the main and secondary cutting edges. The Keyence VHX 5000 digital microscope was used for this purpose, see Fig. 2. W_{feed} represents the width of the flank wear land in feed direction and W_{ap} in axial direction respectively. The NanoFocus confocal microscope for three-dimensional optical surface measurement was used to measure the surface roughness of the workpiece. A photo of the measurement process is shown in Fig. 3.

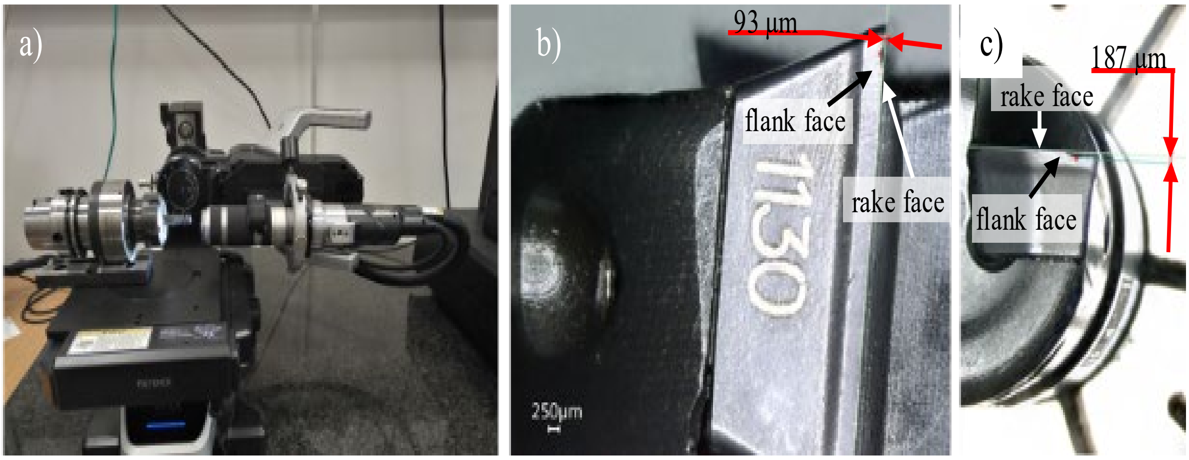
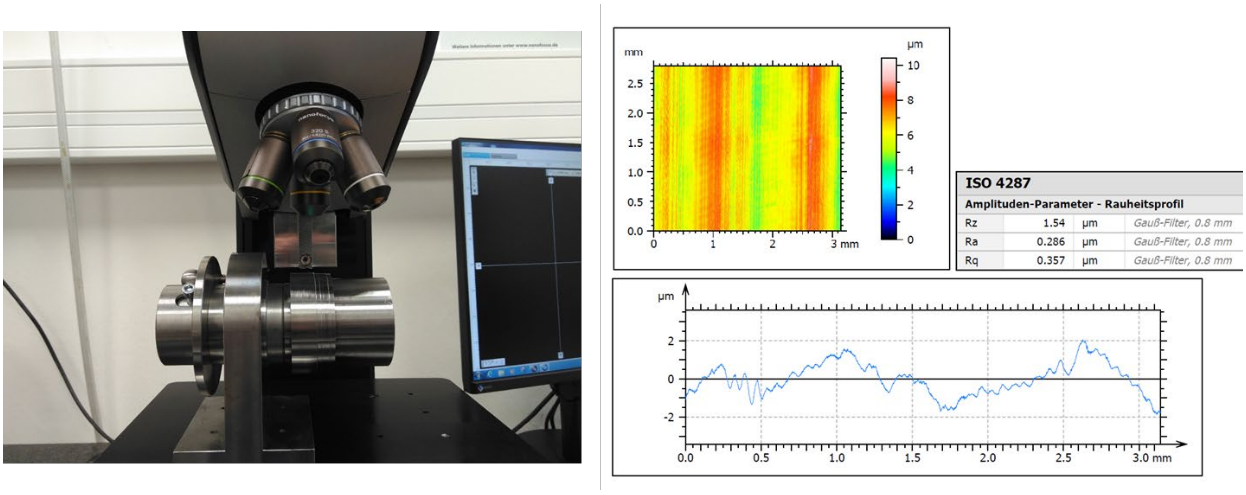


Fig. 2. a) Wear measurement with a Keyence VHX 5000, b) Wear in feed direction W_{feed}, c) Wear in axial direction top (W_{ap}).



ISO 4287			
Amplituden-Parameter - Rauheitsprofil			
Rz	1.54	µm	Gauß-Filter, 0.8 mm
Ra	0.286	µm	Gauß-Filter, 0.8 mm
Rq	0.357	µm	Gauß-Filter, 0.8 mm

Fig. 3. Surface roughness measurement using confocal microscope NanoFocus and exemplary measurement results of the workpiece.

Features relevant for the defined target functions were selected. The goal was to remove irrelevant features that could impair model accuracy. The algorithms should be capable of creating regression models and accurately predicting targets after learning. Particularly with small datasets, a limited number of parameters was employed. Classification models for tool condition monitoring were developed to classify wear.

In data cleaning, missing, faulty, or redundant data were handled to ensure model accuracy. Problems with missing data were largely excluded thanks to attentive data collection. Results from experiments under different conditions or with peculiar outcomes were removed to avoid biases.
Datasets were processed and sorted using programming commands, with feature and target values stored as matrices or vectors for ML algorithms, and encoding was applied to transform categorical variables into binary form.

Data scaling with methods such as normalization and standardization was used to minimize negative effects of varying scales on model performance. Correlation between variables was evaluated using Pearson and Spearman correlation coefficients [13].
For evaluating model accuracy, the K-fold cross-validation method [14] was used in small datasets to avoid surveillance errors during model verification.

Results and Discussion

The resulting surface roughness Ra of the workpiece, the wear in feed direction W_{feed} and the wear in cutting axial direction W_{ap} are the targeted output parameters and are shown in Table 1 together with the corresponding input parameter ap.

Table 1. Experimental parameters and measured output variables (flank wear and surface roughness) for the orthogonal turn-milling tests.

#	ap [mm]	W_{feed} (Insert1) [µm]	W_{feed} (Insert2) [µm]	W_{ap} (Insert1) [µm]	W_{ap} (Insert2) [µm]	Ra [µm]
1	0.45	917	932	1018	1012	2.887
2	0.25	368	480	530	599	0.769
3	0.05	17	7	0	0	0.163
4	0.1	36	52	0	0	0.163
5	0.15	74	81	74	63	0.131
6	0.2	77	55	118	0	0.212
7	0.25	93	204	0	187	0.286
8	0.3	127	125	92	75	0.177
9	0.35	109	105	159	122	0.312
10	0.4	0	56	0	108	0.167
11	0.45	166	257	115	211	0.272

To utilize the results of the experiments, the data collected there was processed as described in [15] to make it usable for various machine learning approaches. This included selecting functions and characteristics, cleaning up the data, and partially converting the data into binary form—e.g., tool wear status—as worn (1) for a wear mark width > 100 µm or not worn (0). In addition, it was checked whether the recorded data correlate. Both Pearson and Spearman correlation coefficients [13] were determined for this purpose. It was found that surface roughness and tool wear correlate with depth of cut, see Fig. 4.

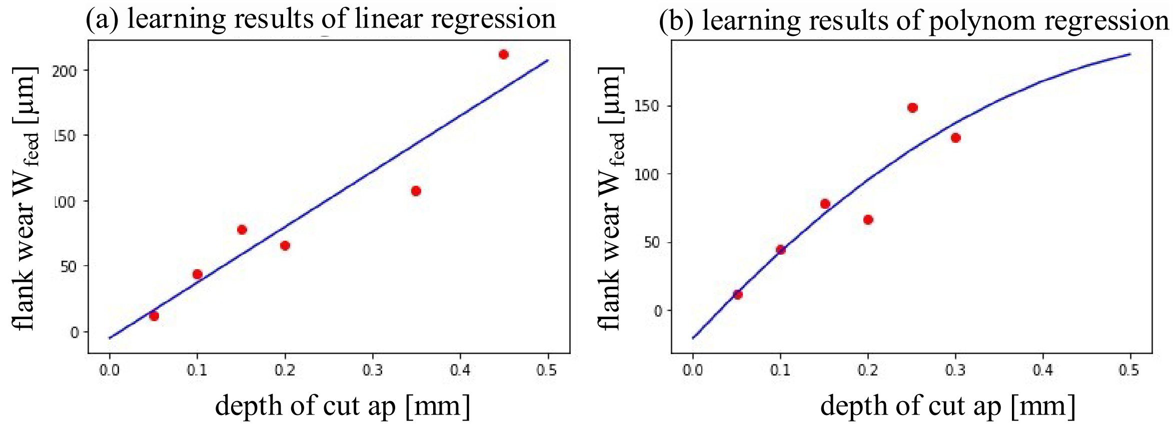


Fig. 4. Examples of training results: (a) linear regression; (b) polynom regression.

According to [14], the following criteria were used to select possible machine learning approaches: explainability, dimensionality of the data, non-linearity of the data and training and prediction speed. Machine learning regression algorithms such as linear regression [16], polynomial regression [17] and SVR [18] were compared with a statistical regression method. Fig. 5 shows an example of the training results of the linear and polynomial regression. K-fold cross-validation was used to validate the algorithms due to the small amount of data [14]. The RMSE was chosen as comparison value. The lower the RMSE value during validation, the more accurate the model is.

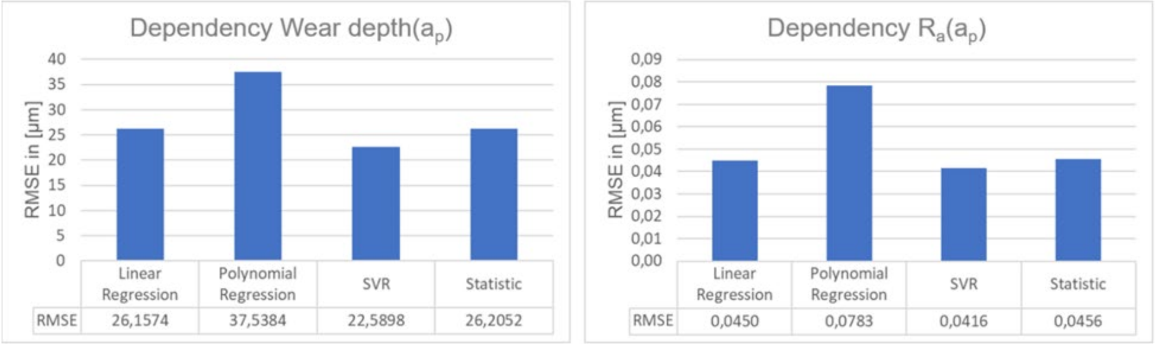


Fig. 5. Validation results for the dependence of wear (a) and surface roughness (b) on the axial depth of cut.

In all cases, a significantly higher RMSE value was achieved using polynomial regression. The possible reason for this is the high sensitivity of the polynomial function with small data sets. This means that the parameter values are very dependent on each point in the training set. Moreover, the Pearson coefficient values are high in the considered dependencies, which means strong linear correlation.

The models generated by the least squares method and linear regression using gradient descent are almost the same for all data sets. This confirms the accuracy of the ML algorithms developed.

For the dependencies wear of depth of cut and surface roughness of depth of cut, the SVR algorithm produced the best accuracy. However, the SVR algorithm is a "black box" algorithm and accordingly has a hidden model. Therefore, for further theoretical studies of these dependencies, the use of linear regression by optimization methods is recommended as an alternative to the least squares calculation method. However, the SVR algorithm is well suited for practical applications where only the model performance is important.

The achieved accuracy of the developed algorithms is not yet sufficient to implement the generated models. To increase the accuracy, the training data set must be significantly enlarged.

The same was done with machine learning classification algorithms such as logistic regression, neural networks [19], SVM [20] and decision trees [21]. Two criteria were used to assess the accuracy of classification algorithms: Accuracy and F-Score. The accuracy shows how many examples out of the total number were correctly classified, see Table 2.When analyzing the two criteria, it was found that logistic regression, SVM and neural network perform with almost equal accuracy for the data set at hand. The highest accuracy was achieved using the decision tree, which is very suitable for theoretical research. For practical purposes, SVM is also a possible variant because it is trained much faster compared to the decision tree.

Overall, the average accuracy of the developed algorithms is not sufficient for validation. This is due to the fact that the data set under consideration contains a small number of data points. This means that algorithms are heavily penalized for each classification error during validation. The analysis performed can only be used to compare the algorithms. For the objective accuracy assessment of the obtained models, several data points must be tested during validation.

Table 2. Validation results of the classification algorithms.

	Logistic Regression	Neural Network	SVM	Decision Tree (ID3)
Accuracy	0.73	0.73	0.75	0.84
F-Score	0.64	0.64	0.63	0.78

Conclusion and Future Work

In this work ML was investigated as a tool for modeling of orthogonal turn-milling. The aim was to determine whether ML algorithms could optimize and automate the research process.

At the beginning, the relevant dependencies were defined, and experiments were conducted to collect data. The flank wear as a function of the axial depth of cut and the surface roughness as a function of the axial depth of cut were considered as regression problems. Additionally, the classification of the tool condition based on the machining parameters was examined. The data collected during the experiments were analyzed, processed, and prepared for use in the ML algorithms.

Three ML algorithms were developed to model the regression dependencies: linear regression, polynomial regression, and SVR. In parallel, four classification algorithms were implemented to predict the tool condition, including logistic regression, neural networks, SVM, and a decision tree. The trained models were validated using the k-fold method to assess their accuracy and generalization capability. Based on the validation results, the optimal algorithm for each dependency was selected.

A key difference between ML algorithms and traditional statistical modeling lies in the way parameters are determined. While conventional statistical methods calculate parameters using analytical formulas (e.g. the least-squares method), ML algorithms adjust these parameters iteratively through optimization techniques such as gradient descent. This iterative approach provides greater flexibility for adapting to different datasets and function types. Whereas traditional statistical modeling often requires extensive manual programming and is time-consuming, ML algorithms automate the model creation process and help to avoid programming errors. Furthermore, ML algorithms can be applied to various processes and data dimensions without requiring modifications to the source code.

When comparing the models generated by ML algorithms with those obtained using the least-squares method, it was found that in three out of four cases, the ML models were more accurate. SVR, in particular, achieved higher accuracy despite being based on different mathematical principles. However, the SVR algorithm is not suitable for examining theoretical relationships due to its black-box nature, meaning the structure of the final model is not interpretable. Nevertheless, it is particularly well-suited for practical applications, such as adaptive control and quality monitoring systems, due to its high accuracy and efficiency.

Although the developed classification models achieved relatively high prediction accuracy, they cannot yet be directly implemented in production. Further experiments are required to account for additional influencing factors, such as machining duration. In future developments, an optimized model could potentially detect tool breakage at an early stage, thereby increasing production safety. For this purpose, real-time data from sensors integrated into the manufacturing process must be processed. To handle this data, other data-driven approaches based on deep learning methods, as described in [22], can be used.

While the scope of this study is focused on a defined set of orthogonal turn-milling parameters, the results demonstrate a significant methodological advantage: the ability of ML algorithms to provide higher predictive accuracy than conventional methods even under data-sparse conditions. This suggests that the proposed framework is not merely a specific solution for one process, but a scalable approach for industrial environments where extensive empirical testing is economically unfeasible.

The results of this study highlight the potential of Machine Learning in modeling of orthogonal turn-milling. By using ML algorithms, the creation of empirical models can be automated, reducing the time and cost associated with investigating new machining processes. Furthermore, ML algorithms are more flexible and can produce accurate predictions even when traditional statistical methods reach their limits. This facilitates a more efficient design of research processes and reduces the number of required experiments, which in turn lowers overall costs.

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