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PREDICTIVE VALUE OF CUTTING-FORCE SIGNALS FOR MACHINE LEARNING-BASED SURFACE ROUGHNESS PREDICTION IN TURNING

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Abstract

This paper investigates the applicability of machine learning for surface roughness prediction in turning, with particular emphasis on evaluating the predictive value of measured cutting-force signals. Experimental data acquired between 2020 and 2023 for five material groups were processed using four regression approaches: Lasso regression, Random Forest, Extreme Gradient Boosting, and Multi-Layer Perceptron. The models were evaluated under different input scenarios combining machining parameters, material information, and measured cutting forces. The results show that the best performance was achieved by the Random Forest model without cutting-force inputs, reaching a mean absolute error of 0.523 micrometres, compared with 1.043 micrometres for the conventional geometric roughness model. Adding cutting-force signals did not improve the overall prediction accuracy under the stable cutting conditions represented in the dataset. The results indicate that machining parameters and material information can provide sufficient input for reliable data-driven roughness estimation, reducing the dependence on dedicated dynamometer-based sensing in stable turning operations.

Keywords: Surface roughness; Machine learning; Turning; Cutting-force signals; Virtual sensing

1. Introduction

Surface roughness is a key indicator of functional quality in machined components because it influences friction, fatigue behaviour, sealing performance and the ability of a surface to retain coatings or lubrication films. In turning, the arithmetic mean roughness Ra can be estimated from feed and tool nose radius by a geometric relationship. This calculation is valuable for process planning, but it represents an ideal kinematic surface and cannot describe all effects occurring during real cutting. Material heterogeneity, built-up edge, thermal effects, tool wear, vibration and measurement variability cause the measured surface to deviate from the theoretical profile. Consequently, predictive-quality research increasingly uses data-driven models to complement analytical machining models [1], [2].

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Machine learning is suitable for machining data because the relationship between process parameters and quality responses is nonlinear and strongly material dependent. Reviews of predictive quality and intelligent machining emphasize robust validation, physically meaningful features and careful treatment of sensor information [1], [3], [13]. Tree-based ensemble methods are frequently effective for tabular manufacturing data. Random Forest and gradient-boosting approaches have been successfully applied to machining-quality, tool-condition and cutting-force prediction [4], [5], [6], [7]. However, high predictive accuracy alone does not justify a monitoring architecture if additional sensors provide little information beyond the numerical-control parameters already available in the machine tool. Machine-learning decision trees have also been used to quantify the influence of workpiece material and technological parameters on machining torque, supporting the use of tree-based models for heterogeneous machining data [15].

Cutting-force measurement is attractive because the forces directly reflect the mechanical interaction between tool and workpiece. Sykora and Syrovatka [9] and Straka [10] reported relationships among cutting conditions, cutting forces and machining performance in turning. Demir et al. [11] identified feed as the cutting parameter with the strongest correlation with surface roughness, while Vukelic et al. [12] demonstrated that neural-network models can relate cutting-force information to surface-quality outputs. These findings motivate a more specific question: what predictive value do cutting-force signals add when the cutting conditions and workpiece material are already known? Valicek et al. [16] further demonstrated that experimentally selected cutting parameters can be related to surface roughness through predictive relations in machining.

This question has practical importance because a piezoelectric dynamometer, charge amplifier and data-acquisition chain increase system cost and require installation, calibration and signal processing. A recent 2026 study on Ti-6Al-4V found that process parameters alone were sufficient for several high-performing roughness models and that adding mean force values degraded four of six tested algorithms because of collinearity with process parameters [8]. The present study addresses the same general problem in a different experimental context: a heterogeneous multi-material database collected over four years by multiple laboratory groups using a common turning setup. The contribution is therefore not a new regression algorithm, but a controlled comparison of process-parameter-only and force-augmented input scenarios on historical machining data.

The present study focuses on the uncertain predictive value of cutting-force sensing for roughness estimation. Previous studies demonstrate the potential of machine learning and force monitoring, but less often isolate the incremental value of the force channels. Four regression families are therefore compared under three defined input scenarios and against the conventional geometric roughness model. The principal result is that the lowest MAE was obtained without force inputs, while the effect of force sensing depended on model architecture. Future work will extend the input space from mean force values to dynamic features describing chatter, tool wear and transient behaviour.

2. Materials and Methods

2.1. Experimental dataset and machining conditions

The dataset was assembled from laboratory measurements performed between 2020 and 2023 at the Department of Machining Technology, Faculty of Mechanical Engineering, University of West Bohemia. The experiments used longitudinal external turning on an EMCO MAXXTURN 25 CNC turning centre. Cutting forces were measured in three orthogonal directions using a Kistler 9119AA2 piezoelectric dynamometer integrated in the turret. The signal chain included a Kistler 5080 charge amplifier and a Kistler 5691A data-acquisition card, with recording in DynoWare. After each cut, surface roughness was measured using a MahrSurf LD 120 instrument. The cutting tool was an SCLCL 1212F-09 holder with a CCMT 09T304-SM IC807 insert and a constant nose radius of 0.4 mm.

Each experimental condition was measured in three repetitions. Cutting speed, feed per revolution and depth of cut were varied within material specific ranges selected to respect machine limits and stable cutting behaviour. The investigated materials and cutting-parameter ranges are summarized in Table 1.

Material	Cutting speed vc [m/min]	Feed f [mm/rev]	Depth of cut ap [mm]
12050	95-270	0.08-0.25	0.5-1.6
19573	70-200	0.10-0.25	0.5-1.25
42CrMo4	80-290	0.06-0.25	0.5-2.0
EN AW-6060	130-600	0.08-0.30	0.5-2.5
S235JR	100-250	0.10-0.25	0.5-1.3

Table 1. Cutting-parameter ranges for the investigated materials

For model development, the dynamic force records were reduced to mean values in the stable cutting region after the entry transient, and a 10 Hz low-pass filter was used to suppress high-frequency noise. Records with missing Ra or force components were removed and no imputation was applied. Material labels were numerically encoded. The resulting tabular record contained cutting speed vc, feed f, depth of cut ap, material class, mean force components Fx, Fy and Fz, and measured roughness Ra. The final evaluation set in the binding result summary contained 448 observations. Figure 1 summarizes the processing sequence.

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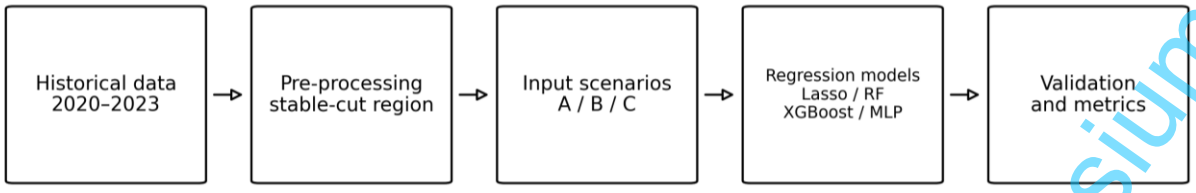

Fig. 1. Data-processing and model-evaluation workflow

2.2. Input scenarios and regression models

Three input scenarios were defined to separate the information provided by process settings and measured forces. Scenario A omitted feed and used cutting speed, depth of cut, material and the three force components. It tested whether force information can compensate for the absence of the most important kinematic roughness parameter. Scenario B used only variables normally available from the CNC process plan: cutting speed, feed, depth of cut and material. Scenario C used the complete set of technological parameters, material and all three measured force components. The comparison of Scenarios B and C directly evaluates the added value of the force-sensing system.

Four regression approaches were selected to represent different levels of model complexity. Lasso regression provided a regularized linear baseline; Random Forest represented bagged decision trees; XGBoost represented sequentially boosted trees; and a Multi-Layer Perceptron (MLP) represented a nonlinear neural-network approach. The retained configurations were Lasso with alpha = 0.1; Random Forest with 500 trees, minimum split size 5 and unrestricted tree depth; XGBoost with 300 estimators, learning rate 0.05, maximum depth 3 and subsample 0.7; and MLP with two hidden layers of 64 and 32 neurons, learning rate 0.001, 100 epochs, batch size 16 and alpha = 0.01. Model inputs were standardized within the training pipelines.

Validation was group based to prevent repeated measurements from the same experimental condition from appearing in both training and test data. The three repetitions of each condition shared an experiment identifier. Five-fold GroupKFold cross-validation was repeated ten times after permutation of the experiment-group labels with repeat-dependent random seeds, resulting in 50 evaluations for each model and input scenario. Performance was aggregated over these evaluations.

2.3. Reference model and evaluation metrics

The machine-learning results were compared with the conventional geometric estimate of arithmetic surface roughness for turning. With a constant tool nose radius $r_\varepsilon = 0.4$ mm, the theoretical roughness was calculated as:

$$Ra = \frac{f^2}{32 \cdot r_\varepsilon} \cdot 1000 \ [\mu m] \tag{1}$$

where f is feed per revolution in millimetres per revolution and r_ε is the tool nose radius in millimetres. The models were evaluated using mean absolute error (MAE), root mean square error (RMSE), mean absolute percentage error (MAPE) and the coefficient of determination R^2. MAE is used as the primary comparison metric because it is directly interpretable in micrometres and is less dominated by isolated large errors than RMSE.

3. Results

3.1. Overall prediction performance

Table 2 presents the final and binding summary of the roughness-prediction results. The lowest MAE was obtained by Random Forest in Scenario B, without cutting-force inputs, at 0.523 micrometres. Random Forest with the full Scenario C was almost identical at 0.526 micrometres. XGBoost without force sensing followed at 0.531 micrometres. The conventional geometric model produced an MAE of 1.043 micrometres and an R^2 of -0.180. Thus, the best machine-learning configuration reduced MAE by approximately 49.9 percent relative to the geometric baseline.

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Model	Scenario	MAE	RMSE	R^2
Random Forest	B	0.523	0.881	0.578
Random Forest	C	0.526	0.891	0.569
XGBoost	B	0.531	0.879	0.580
XGBoost	C	0.557	0.912	0.548
MLP	C	0.624	1.002	0.454
Lasso	C	0.631	1.053	0.398
Lasso	B	0.642	1.059	0.391
MLP	B	0.657	1.049	0.402
XGBoost	A	0.753	1.130	0.306
Random Forest	A	0.766	1.147	0.285
MLP	A	0.813	1.173	0.252
Lasso	A	0.907	1.268	0.127
Geometric model	-	1.043	1.474	-0.180

Table 2. Final statistical results for surface-roughness prediction (N = 448)

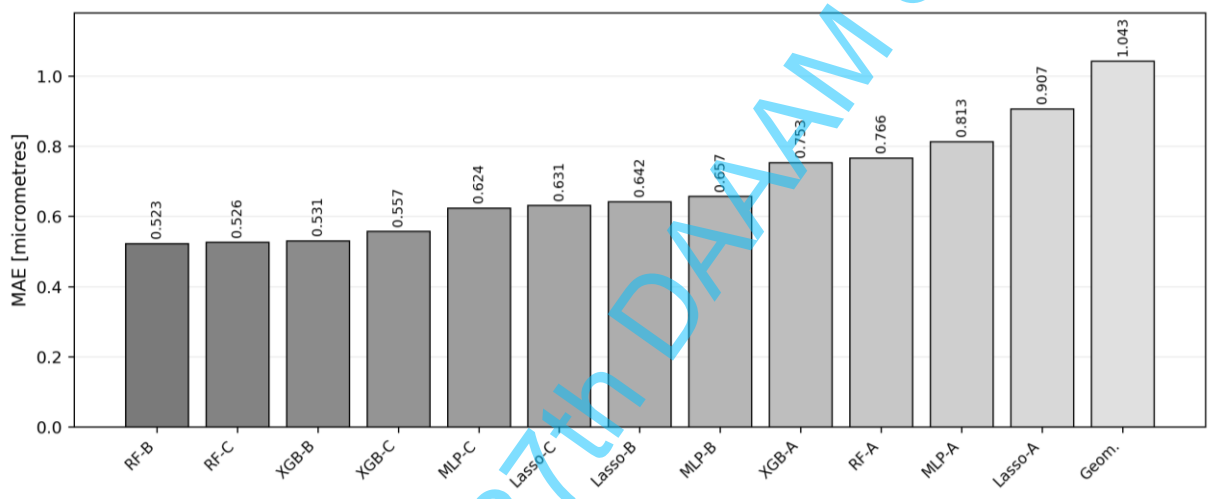

Fig. 2. Overall ranking of methods and input scenarios by mean absolute error

The ranking in Fig. 2 shows a consistent advantage of the tree-based models. Both Random Forest and XGBoost occupy the first four positions when feed is available. In contrast, all Scenario A configurations, where feed is deliberately omitted, move toward the lower part of the ranking. This confirms that feed contains information that cannot be reconstructed reliably from the mean force components alone. This result is consistent with Demir et al. [11], who reported feed as the cutting parameter with the strongest correlation with surface roughness in turning.

3.2. Added value of cutting-force sensing

The central question of this paper is answered by comparing Scenarios B and C. For Random Forest, adding Fx, Fy and Fz changed MAE from 0.523 to 0.526 micrometres, a relative deterioration of approximately 0.6%. For XGBoost, MAE increased from 0.531 to 0.557 micrometres, a deterioration of approximately 4.9%. The two simpler models behaved differently: force inputs improved Lasso from 0.642 to 0.631 micrometres and MLP from 0.657 to 0.624 micrometres. Cutting-force sensing is therefore not universally redundant; its contribution depends on model architecture. Nevertheless, the lowest overall MAE remained the Random Forest configuration based only on machining parameters and material information.

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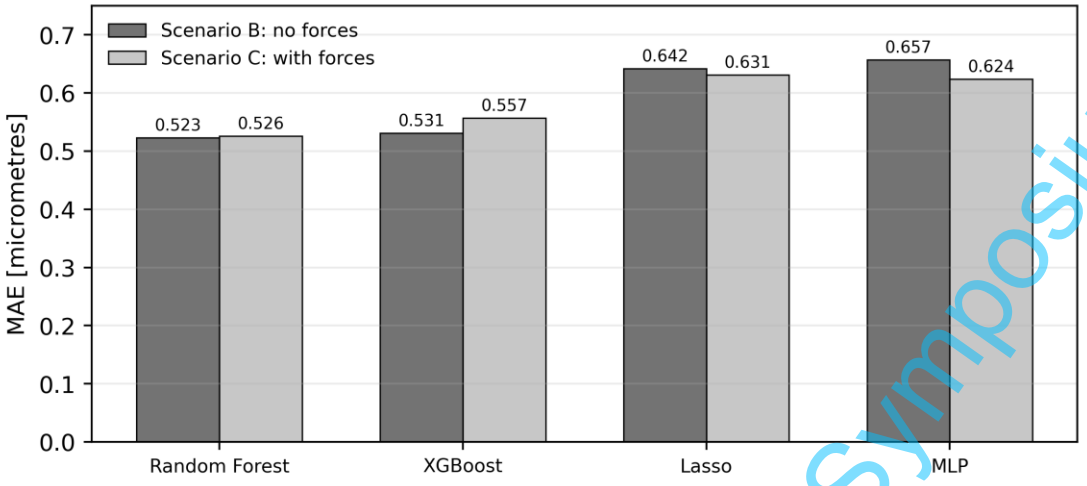

Fig. 3. Effect of cutting-force inputs on mean absolute error for each model family

This pattern can be interpreted in terms of information redundancy. Under stable cuts, mean force values are strongly governed by feed, depth of cut, material and cutting speed. Tree ensembles can already learn nonlinear interactions among these process variables, so measured forces may add correlated information together with sensor noise and inter-experiment variability. In simpler model structures, the force channels can still provide useful proxies for nonlinear physical effects that the model cannot represent from process settings alone. A recent Ti-6Al-4V study likewise found that process parameters alone outperformed force-augmented inputs for four of six algorithms [8]. The present multi-material results indicate that the same effect can also occur across different workpiece materials.

The conclusion is intentionally limited to mean force values under stable cutting conditions. It does not imply that force sensors are unnecessary for machining monitoring in general. Force signals remain valuable for detecting transients, tool breakage, vibration, chatter and progressive wear [2], [3], [13]. These effects are largely suppressed when a force time series is reduced to a single mean value from the stable-cut segment. The present comparison therefore concerns steady-state roughness estimation, not anomaly detection or closed-loop process control.

3.3. Material-dependent behaviour

The prediction error also depends strongly on the workpiece material. The best machine-learning configuration for S235JR achieved MAE = 0.3251 micrometres compared with 0.5942 micrometres for the geometric model. For steel 12050 the corresponding values were 0.3562 and 1.1599 micrometres, and for tool steel 19573 they were 0.3904 and 0.9791 micrometres. The highest best-model errors occurred for 42CrMo4 and EN AW-6060, with MAE values of 0.6271 and 0.6216 micrometres respectively. Figure 4 compares the best machine-learning result for each material with the geometric baseline.

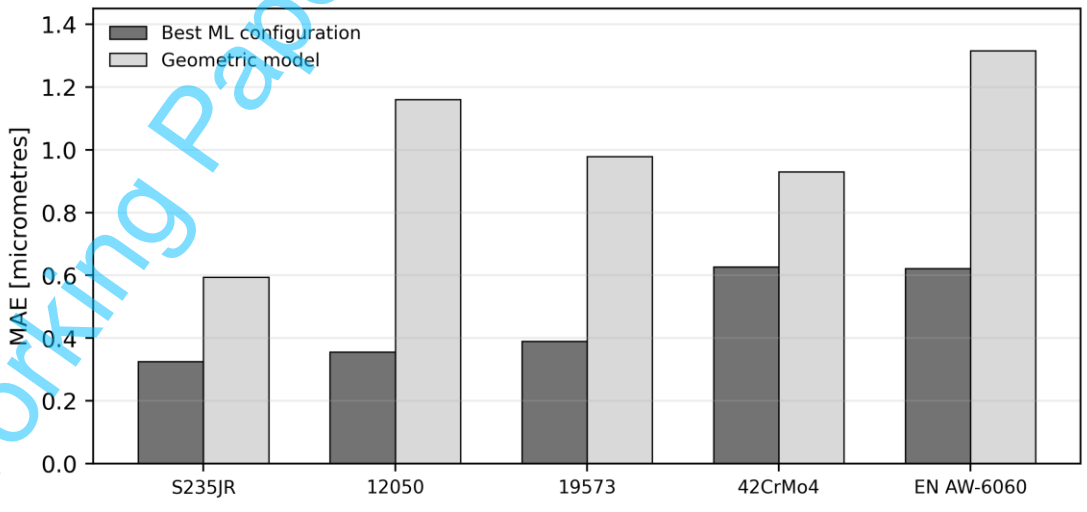

Fig. 4. Material-specific MAE of the best machine-learning configuration and the geometric model

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The larger error for EN AW-6060 is physically plausible because aluminium alloys are prone to built-up edge and adhesive effects that introduce stochastic changes in the effective cutting geometry. The 42CrMo4 results also show greater variability, which may reflect higher mechanical and thermal loading. In contrast, the narrower parameter domain for material 19573 produced a comparatively homogeneous dataset and lower prediction errors. These observations illustrate an important limitation of purely data-driven roughness prediction: accuracy reflects not only model capability but also the process domain represented in the training set. A model can perform well inside a restricted parameter region without necessarily extrapolating reliably beyond it.

4. Discussion

The main technical implication is that roughness prediction and process monitoring should not automatically be treated as the same sensing problem. If the objective is to estimate Ra during stable turning and the numerical-control parameters and material are known, the present results show that the best prediction in this dataset did not require force inputs. This supports a lower-cost virtual quality-sensing architecture [14], because the relevant inputs can be obtained from the NC program and production database while dependence on a dedicated dynamometer is reduced. Force sensing can then be reserved for monitoring tasks where dynamic process information is essential.

At the same time, R^2 values of approximately 0.58 for the best configurations show that the problem is not fully solved. The unexplained variance can contain tool wear, local material heterogeneity, built-up edge, vibration, temperature, measurement uncertainty and differences among historical experimental groups. Recent tightly controlled single-material studies have reported higher cross-validated R^2 values for roughness prediction [7], [8]. The more moderate performance obtained here should therefore be interpreted in the context of a heterogeneous database collected over multiple years and operators. Such variability is also relevant to the practical transfer of predictive-quality models from laboratory development to shop-floor use.

The findings also clarify the role of force information. Cutting-force signals remain physically informative, as demonstrated by machining research on turning and force prediction [5], [6], [9], [10], [12]. Their limited benefit in the best steady-state roughness model is related to the representation used here: three mean scalar values. Dynamic features in the time, frequency and time-frequency domains can capture chatter onset, transient contact, tool degradation and instability that mean values discard [2], [3], [13]. Future work should therefore compare process-parameter-only inputs with force-derived dynamic features and should include uncertainty estimates capable of identifying operating states outside the validated domain.

A further limitation is that the present paper uses the aggregate final values from the validated summary table as the binding result set. The small differences between Scenarios B and C are therefore interpreted descriptively and are not presented as statistically significant. Future studies should retain the fold-level predictions together with the raw force time series so that paired statistical tests, bootstrap confidence intervals and model-calibration analyses can be performed.

5. Conclusion

This study assessed the predictive contribution of cutting-force signals to machine-learning surface roughness estimation in turning. Lasso, Random Forest, XGBoost and MLP were evaluated using multi-material data from 2020–2023 under three input scenarios. Random Forest without force inputs achieved the lowest MAE (0.523 micrometres), compared with 1.043 micrometres for the conventional geometric model, a reduction of approximately 50%.

Feed proved essential: the mean force components did not compensate for its omission. Adding force inputs slightly degraded the results of Random Forest and XGBoost but improved Lasso and MLP. This does not mean that cutting-force sensing lacks value; rather, it was not required for the most accurate steady-state roughness model in the investigated dataset. Roughness can thus be estimated from machining parameters and material information while dynamic sensing remains valuable for unstable and transient process states.

Future research will preserve synchronised three-component force time series and evaluate dynamic descriptors in addition to mean force values. Planned time-domain features include root-mean-square amplitude, variance, peak-to-peak force and transient peaks. Fast Fourier transform (FFT) spectral power and energy in frequency bands will be considered alongside wavelet coefficients to capture short-duration disturbances. Their incremental value will be assessed using group-wise validation, tool-wear and vibration information, and calibrated prediction-uncertainty estimates. Independent validation on production data will precede any proposed closed-loop quality control.

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