MM Science Journal | www.mmscience.eu
ISSN 1803-1269 (Print) | ISSN 1805-0476 (On-line)
Special Issue | TEAM 2024
Transdisciplinary and Emerging Approaches to Multidisciplinary Science
11.9.2024 – 13.9.2024, Ostrava, Czech Republic
DOI: 10.17973/MMSJ.2024_10_2024075

TEAM2024-00015

THE INFLUENCE OF THE CUTTING PARAMETERS ON THE SURFACE ROUGHNESS AND VIBRATION SIGNAL IN THE TURNING PROCESS

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Abstract
The performance of the final part of the turning process, a topic of practical importance, heavily depends on the cutting parameters. Surface quality, a crucial product attribute in manufacturing, often tops consumer demands during machining due to its significant influence on product functionality. This paper assesses the correlation between the detected vibration signal, statistical parameters (Crest, Kurtosis and I-kaz3D coefficient) and surface roughness and provides valuable insights for practical applications. When the tool experiences vibrations during material removal, these oscillations leave a ripple effect on the surface of the workpiece. We aim to determine the impact of cutting parameters on surface roughness while turning 42CrMo4 steel using a carbide tool insert. Cutting parameters, such as spindle speed, feed, and depth of cut, were used. Signal processing is carried out using different techniques to identify the effect of the cutting parameters on vibration signals. Finally, we delve into the interaction effects between the cutting parameters, vibration signals and surface roughness, offering a comprehensive understanding of real-world manufacturing scenarios. Higher I-kaz3D coefficients correspond to higher surface roughness values. The I-kaz3D coefficient decreases as the surface roughness measurements decrease, indicating that the I-kaz3D technique can accurately indicate an increase or decrease in surface roughness. On the other hand, the cutting force Fc was the component most strongly correlated with surface roughness (Ra), yielding the best results across all indices (adjusted R^2adj = 95.1%, er=.8 ± 2.3%).

Keywords:
Vibrations signal, Surface roughness, Turning, Cutting parameters

1 INTRODUCTION

Conventional processing operations, which include turning, milling, grinding and drilling, are among the most common processing operations in the metalworking industry. With the application of computer-aided design methods, computer-aided manufacturing (CAD/CAM) and open architecture control systems (OACs, which are control systems that allow for easy integration and modification of software and hardware components), technological and processing systems have reached a point where the need for flexibility and adaptability of production is at the peak of demand, and for a large number of companies whose technological systems are not equipped with state-of-the-art surveillance and management systems at the edge of cost-effectiveness.

The processing of materials by cutting is a complex task characterised by the dynamic behaviour of the system tool-workpiece-clamping device-machine. The system's dynamic behaviour is determined by the excitation forces acting on the system and the stiffness of the system itself. The oscillation in the system is highly undesirable, as it can directly impact the workpiece's quality and the tool's stability and even damage the system's elements and assemblies. The development and application of modern technologies, such as laser cutting, waterjet cutting, and plasma cutting, in obtaining products without subsequent processing is a limited domain. Even today, cutting processing remains the most used method in production practice. This highlights the urgent need for the metalworking industry to stay updated with the latest technologies to meet the evolving demands of the market. Turning is one of the most critical manufacturing operations because parts manufactured by casting, forming, or other shaping processes often require a further metal-cutting operation before they are ready for use.

The quality of surface roughness is crucial in achieving the desired product quality. Manufacturers specify the desired surface roughness to meet requirements such as fatigue strength, corrosion resistance, precision fits, tribological properties, and aesthetics. One commonly used model to assess surface roughness considers the feed rate and nose radius. While these factors significantly impact surface roughness, the model does not provide an accurate prediction. This is because factors such as machine tool rigidity, geometry and condition, use of cutting fluid, cutting parameters, and vibrations are not considered. Hence, estimating surface roughness in the metal-cutting process is becoming a significant research area. Unsurprisingly, many research papers on predicting surface roughness have been published based on regression modelling, artificial neural networks, fuzzy logic, and neuro-fuzzy systems. A predictive model for surface roughness based on cutting parameters using response surface methodology has been extensively documented in the literature [Cakir 2009] and [Bouacha 2010].

Surface roughness varies during the machining process as the tool wears out. Consequently, signals representing the interaction between the tool and workpiece should be incorporated into the in-process surface roughness prediction model. To achieve this objective, the model can use the acceleration of the tool holder and cutting forces during the process as inputs. Developed in-process multiple regression surface roughness prediction system using feed rate and acceleration along the x, y and z-axis was presented in [Kirby 2004]. Upadhyay et al. [Upadhyay 2013] used the acceleration amplitude of tool vibrations in axial, radial and tangential directions to develop multiple regression models to prediction surface roughness. Plaza et al. [Plaza 2017] proposed two methods for enhanced surface roughness monitoring based on the application of singular spectrum analysis (SSA) to vibration signals generated in workpiece-cutting tool interaction in CNC finish turning operations and the grouping analysis of correlated principal components (G-SSA). A multi-sensor data fusion system was introduced for real-time surface quality control, incorporating cutting force, vibration, and acoustic emission signals, as presented in [Plaza 2018]. Four signal processing methods were analysed: time domain analysis (TDA), power spectral density (PSD), singular spectrum analysis (SSA), and wavelet packet transform (WPT). The mean deviation of the assessed profile (Ra) is the critical parameter for monitoring surface quality in machining processes. Ra indicates a product's surface quality and reflects the cutting process's behaviour. It is directly influenced by factors such as cutting parameters, tool geometry, cutting fluids, tool wear, and chatter. Time-domain analysis (TDA) is the most widely used signal analysis method for monitoring surface finish. Hessainia [Hessainia 2013] utilised TDA-processed vibration signals and cutting conditions to monitor the parameter Ra, employing a small sample of 27 data points for regression models and validating them with the same data. Kirby et al. [Kirby 2007] used a single component of vibration signals and cutting conditions to monitor Ra. They processed the vibration signal with TDA, using 87 data points for fuzzy logic predictive models and validated the models with seven workpieces selected under non-random cutting conditions. The experimental investigations on the influence of technological parameters on the machining accuracy and quality in the milling of cylindrical thin-walled structures are shown in [Sredanovic 2022]. The surface roughness of the workpiece under different cutting conditions in machining using acoustic emission (AE) and vibration signature in turning has been investigated in [Bhuiyan 2014]. The investigation has shown that the AE and vibration components can effectively respond to different occurrences in turning, including surface roughness. Asiltürk et al. [Asiltürk 2016] determined the effects of the cutting parameters on the surface roughness using ANOVA, surface response methodology and Taguchi orthogonal design.

The signal processing methods used in the presented literature are primarily based on different signal decomposition techniques (in the time and frequency domain). After that, the relationship between statistical parameters and the roughness of the treated surface is investigated. These techniques require much time and higher computer resources, which in actual production can lead to delays and interruptions in the production cycle. However, this method is complicated to apply in real-time. On the other hand, the connections between the vibration signals and the forces are analyzed individually in the presented literature.

This paper has been carried out to develop a more reliable condition monitoring system for surface roughness using vibration phenomena and statistical parameters. Three accelerometers and a triaxial dynamometer have been used to measure the acceleration and vibration generated by the cutting force. The raw signals (time domain analysis) have been used to correlate the sensor’s output with the different statistical parameters and with the surface roughness. We thoroughly analysed different methods for extracting features from the sensor signals, focusing on time-domain signal processing. We then studied how the statistical characteristics of the signals relate to the surface roughness by analysing multiple regression. This study's original contribution is determining the best sensor setup and signal feature extraction method in terms of their ability to predict surface roughness in real-time by statistical characteristics without needing offline parameters while ensuring reliability and processing efficiency.

2 EXPERIMENTAL SETUP AND METHODOLOGY

This study aimed to examine the impact of cutting parameters and tool vibrations on surface roughness and establish a relationship between roughness parameters and signal characterisation parameters. Turning tests were performed under dry conditions using a numerically controlled INDEX GU600 lathe. The experimental setup is presented in Fig. 1.

The experiments utilised cemented ISO P-grade carbide inserts (SANDVIK TNMG160408). The workpiece material was 42CrMo4 steel, with dimensions of 30 mm in diameter and 60 mm in length and a cutting length of 40 mm (Figure 1). The nominal chemical composition of the workpiece was C = 0.34%, Si = 0.18%, Mn = 0.72%, P = 0.014%, S = 0.015%, Cr = 0.95%, Ni = 0.165%, Cu = 0.182%, Al = 0.005%, Co = 0.006%, and Ti = 0.002%. To avoid a clamping error and the resulting vibrations, the workpiece is pre-processed and clamped into soft clamps (Clamps machined for the workpiece's used diameter). The cutting edge was replaced after every twenty workpieces to minimise variability due to cutting-edge wear.

A sensor data system was developed using MATLAB to concurrently process cutting force (Fc, Fr, Fv) and mechanical vibration (ac, ar, av) signals. The system employed a Kistler 9021 dynamometer and three PCB 352C03 accelerometers (Figure 1). Acceleration vibration signals were sampled with a National Instruments (NI) USB 6281 data acquisition card at 51.2 kHz. In contrast, cutting forces were sampled using an NI PCI 6008 card at a frequency of 4 kHz. The experimental design followed a factorial approach with three factors at varying levels, resulting in 120 trial combinations (six levels of the cutting speed, four levels of the feed and five levels of the depth), as outlined in Tab. 1.

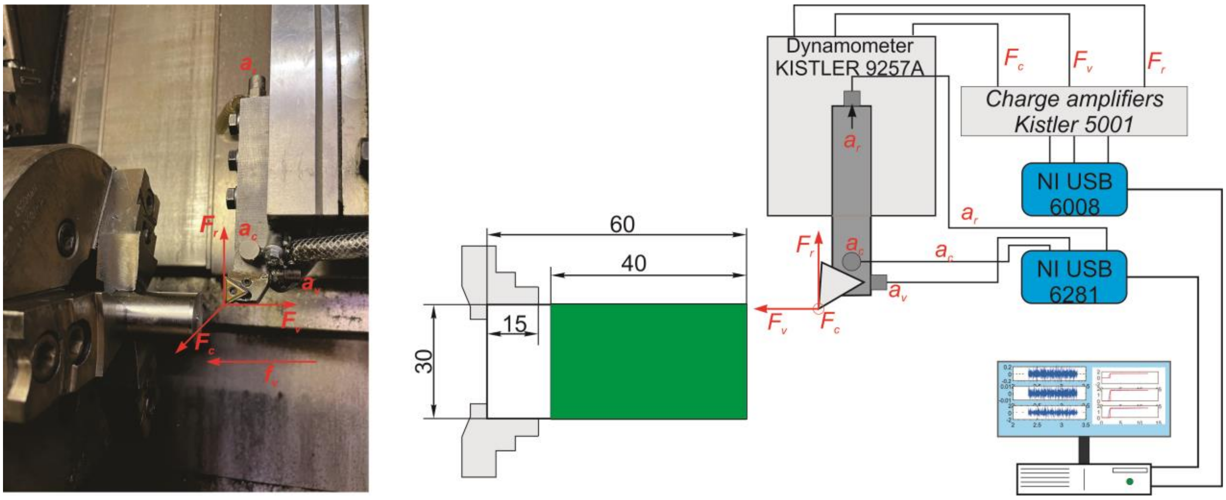

Fig. 1. Experimental setup and measurement flow of acceleration and force signals

Tab. 1. Cutting parameters for turning test.

Cutting speed (*V*)	m/min	100	125	150	190	215	240
Feed rate (*f*)	mm/rev	0.08	0.11	0.15	0.2		
Depth (δ)	mm	0.5	0.8	1.1	1.4	1.7	

The surface roughness was characterised using the mean deviation of the assessed profile (Ra), measured with a Mitutoyo surftest SJ-210 device. The cut-off was 2.5 mm, and the evaluation length was 12.5 mm.

The methodology outlined in this paper involved analysing recorded signals (Fc, Fr, Fv, ac, ar, av) using signal extraction methods, shown in Fig.2. The processed signals with the Time Direct Method were characterised using statistical parameters (see Tab. 1). The method for extracting signal features was evaluated for each sensor. Multiple regression was then employed as a predictive modelling technique to establish the relationship between surface roughness and the signal characterisation parameters, which can be used in various industries.

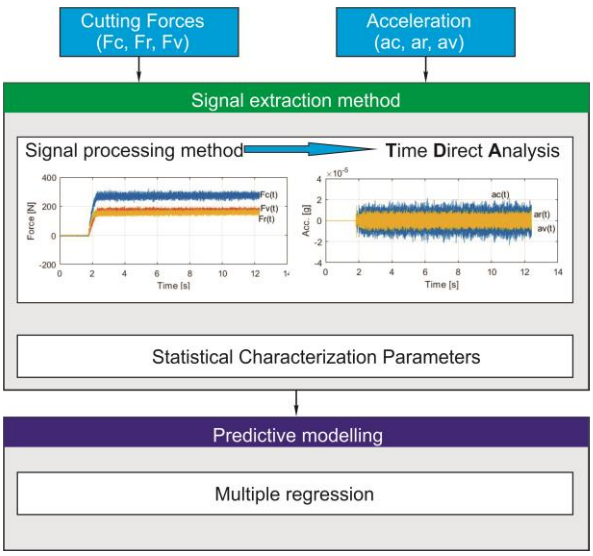

Fig.2. Methodology of the test

The TDA method analyses the signal registered by the sensor directly in the time domain, avoiding any transformation or decomposition. This approach ensures fast processing with minimal computational cost. Signal feature extraction in the TDA method involves parametric characterisation of the original signal, as captured by the sensor in the time domain. Statistical measurements used for this parametric characterisation are presented in Tab.2.

The multiple regression predictive models were evaluated in several ways, each method playing a crucial role in ensuring the accuracy and reliability of the results.

a) The goodness of fit to experimental data was assessed using the adjusted determination coefficient (R_{adj}^2);

b) The predictive power was evaluated by the mean relative error (e_r) in predicting the experimental validation data, along with the variability of e_r measured by the standard deviation (s_{er}); and,

c) The correlation between the data estimated by the predictive models and the experimental data (R).

Out of the 120 experimental data points obtained, a substantial 80% were used to build the models, ensuring a robust and comprehensive approach. The remaining 20% were randomly selected for model validation. The multiple regression models were adjusted stepwise to include only the significant characterization parameters (Tab. 2) according to ANOVA (p-value < 0.05). All regression models underwent a thorough diagnosis, analyzing typical values, independence and normality of residuals, and contrasts and hypothesis tests, ensuring their reliability.

Tab. 2 Statistical characterisation parameters

Feature	Equation
Kurtosis	$f_1 = \frac{1}{N}\sum_{i=1}^{N}\left(\frac{x_i-\mu}{\sigma}\right)^4$
Crest factor	$f_2 = \frac{max(\lvert x_i \rvert)}{RMS}$
I-kaz3D coefficient	$f_3 = \sqrt{\frac{\sum_i^N (x_{x,i}-\mu_X)^4}{N^2} + \frac{\sum_i^N (x_{Y,i}-\mu_Y)^4}{N^2} + \frac{\sum_i^N (x_{Z,i}-\mu_Z)^4}{N^2}}$

μ_X, μ_Y, μ_Z are the means of each signals in the X-, Y- and Z-axes respectively, and N is the number of data points. .

The TDA method extracted the signal features of cutting forces and acceleration by directly characterizing the signals using the parameters listed in Tab. 2. Statistical parameters are critical in signal analysis because they provide information about peaks and spikes in a signal. Their use allows for more effective monitoring of machine conditions, early detection of potential problems, and optimisation of the machining process, which can significantly reduce costs and increase the reliability of operations. To ensure the accuracy of our findings, we employed a multiple regression predictive model with a high adjusted determination coefficient (R_{adj}^2) and a low mean relative error (e_r). This precision was crucial for our research. We analyzed the signals independently for each component to optimize the characterization of the signal sensors (dynamometer and accelerometer) and also examined the fusion of the three components (*Fc, Fr, Fv; and* a_c, a_r, a_v). This methodology helped identify correlations between components from each sensor, preventing information overload in the predictive model and preserving its accuracy.

3 RESULTS AND DISCUSSION

We analyzed the relationship between statistical parameters and surface roughness in the first step. Then, the multiple regression analysis was applied only to the most significant statistical parameter.

As shown in Tab. 3, the statistical analysis results reveal the complexity of the relationship between Kurtosis and crest factor in X-, Y- and Z-directions. The average of these values was calculated, with Kurtosis ranging from 3.99 to 5.94 and crest factor from 4.15 to 6.25 for acceleration signals. The average values for cutting tools sensors were calculated, with Kurtosis ranging from 0.12 to 0.22 and crest factor from 2.15 to 3.31 for acceleration signals. The slight difference between these factors underscores the intricate nature of the relationship to vibration signals, making it difficult to predict the surface roughness measurement. Due to the large amount of analyzed data, Tab. 3 presents only the results for one part of the analysis. The I-kaz3D technique significantly contrasts the I-kaz3D coefficients and surface roughness (Ra), as shown in Tab. 3. The I-kaz3D coefficients ranged from a minimum of $5.65\text{x}10^{-5}$ to a maximum of $11.24\text{x}10^{-5}$. In contrast, the surface roughness values varied between 0.855 µm and 2.553 µm for acceleration sensors. The I-kaz3D coefficients ranged from $0.16\text{x}10^{-5}$ to $0.82\text{x}10^{-5}$ for cutting tools sensors.

Higher I-kaz3D coefficients correspond to higher surface roughness values. The I-kaz3D coefficient decreases as the surface roughness measurements decrease, indicating that the I-kaz3D technique can accurately indicate an increase or decrease in surface roughness.

The results obtained for cutting force and acceleration signals with the TDA method, a key part of our methodology, are shown in Fig. 3. Using the TDA method, the individual analysis of vibration signal models (ai) showed an excellent fit to the data, with an adjusted R^2adj about 83% for all components. The two vibration components provided similar levels of information, with the feed vibration *af*(adjusted R^2adj = 78.4%) and cutting vibration *ac* (adjusted R^2adj = 86.9%) explaining most of the experimental data variability. At the same time, the *AR* percentage was slightly lower (64.8%). The combined vibration model (*af*+*ac*) and (*af*+*ac*+*ar*) significantly enhanced model prediction, improving both the fit to the data (92.4% and 90.5) and *er* (10.2 ± 3.6%). This demonstrates the effectiveness of the TDA method in analyzing vibration signal models *and* its contribution to our understanding of the relationship between statistical parameters and surface roughness.

The cutting force Fc was the component most strongly correlated with surface roughness (Ra), yielding the best results across all indices (adjusted R^2adj = 95.1%, er=.8 ± 2.3%). The cutting force is crucial for maintaining tool-workpiece contact stability and managing the flexing of the workpiece when machined in a cantilever setup, as this force acts perpendicular to the axis of rotation. These findings highlight the significant impact of the *Fc* component on surface roughness due to the interplay between tool and workpiece and the dynamic behaviour of the rotating workpiece. In contrast, the feed force *Ff*and radial force *Fr* showed weaker correlations with roughness, with adjusted R^2 values of 55.4% and 44.9%, respectively. Combining the force components (*Fc* + *Fv*+ *Fr* and *Fc*+*Fv*) small improved the results of the *Fc* force model, with data fit to 96.1% and 95.9, though the predictive power remained unchanged with an *er*of 7.9 ± 2.1%. The above confirms that the cutting force *Fc* accounted for a more significant portion of the variability in the experimental data, indicating it had the most significant impact on surface roughness (Ra). While the feed and radial forces added some value, their contribution to the combined model was relatively small.

Table 3 Results for signal statistical analysis and surface roughness

Cutting parameters			Kurtosis		Crest		I-kaz3D (10^{-5})		Ra (µm)
v (m/min)	f (mm/rev)	δ (mm)	*Acc.* K_{aave}	*Force* K_{Fave}	*Acc.* C_{aave}	*Force* C_{Fave}	Acceler.	Force	
100	0.08	0.5	4.51	0.17	4.85	3.16	5.71	0.168	0.855
240	0.08	0.5	4.58	0.19	4.87	3.18	5.65	0.164	0.884
100	0.11	1.1	3.99	0.19	4.15	3.13	6.02	0.254	1.106
240	0.11	1.1	4.12	0.22	4.99	2.15	6.0	0.199	1.099
100	0.15	1.4	4.64	0.16	4.98	2.88	6.85	0.362	1.699
240	0.15	1.4	4.49	0.12	5.2	3.07	6.11	0.285	1.282
240	0.2	1.7	5.12	0.22	6.01	3.16	7.23	0.451	1.853
240	0.2	1.7	5.94	0.15	6.25	3.31	11.24	0.826	2.553

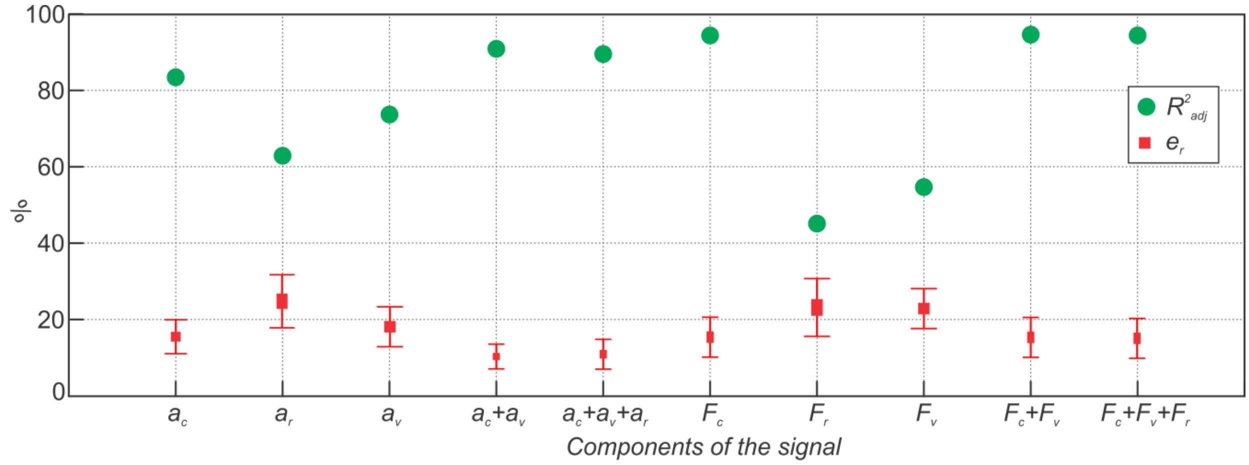

Fig.3 Analysis of signal results with the Time Direct Method.

The correlations between the estimated data and the validation data for the best model obtained with each sensor are illustrated in Fig. 4 and Fig. 5. The cutting force signals (Fig. 4) demonstrated the strongest correlation with a coefficient R = 0.965, indicating a high degree of agreement between the estimated and predicted values. This high correlation was consistent across all data ranges, meaning the model performed reliably regardless of the predicted value. However, it was noted that the model tended to slightly overestimate, as most of the estimated values were higher than the actual experimental validation values.

In contrast, the vibration model (Fig. 5) showed a weaker correlation with a coefficient R = 0.901. This lower correlation was due to more excellent dispersion observed in the data across all value ranges, indicating that the estimated values were more spread out and less consistently aligned with the actual validation values. This dispersion weakened the model's reliability compared to the cutting force signals, which exhibited more uniform and accurate behaviour.

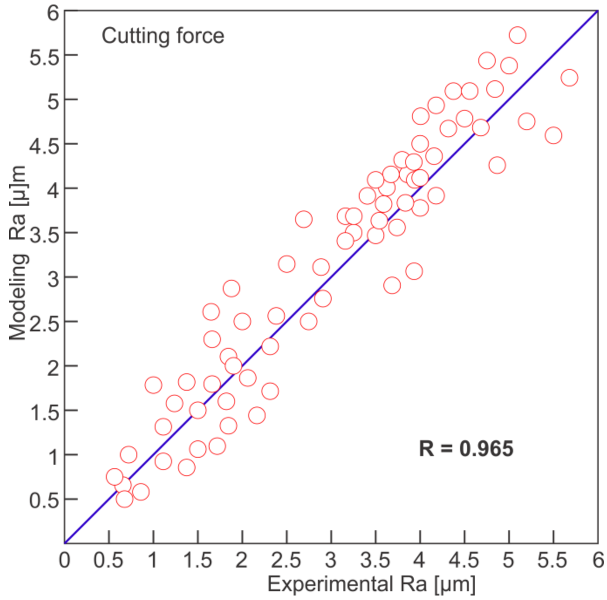

Fig.4. Determined values versus experimental validation values for the parameter Ra with cutting force sensor

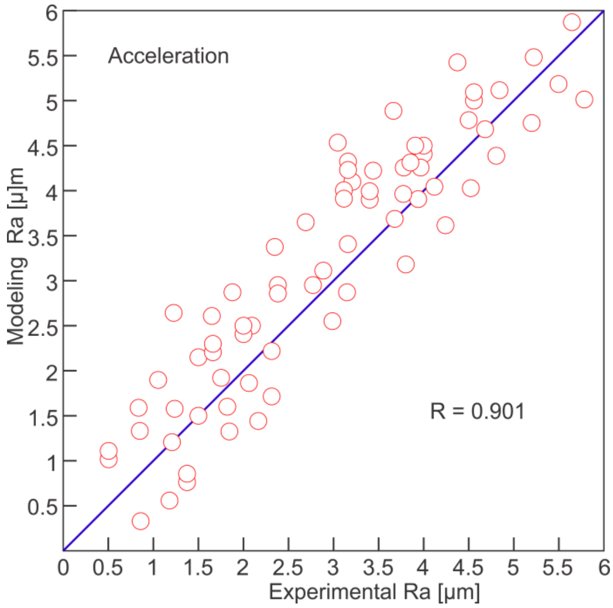

Fig.5. Determined values versus experimental validation values for the parameter Ra with acceleration sensor

Simulations were also performed to study the influence of the cutting parameters on surface roughness (Ra). The curves are plotted according to the v parameter, and the results are concluded in Fig. 6 and Fig 7.

Figure 6 demonstrates a clear relationship between cutting speed and Ra values. The best Ra values are achieved at a cutting speed v higher than 140 m/min with a feed rate f = 0.08 mm/rev. Notably, the minimum Ra value of 0.55 µm is obtained at a cutting speed of 150 m/min. Conversely, a feed rate of f = 0.2 mm/rev consistently yields high Ra values above 1.5 µm. Intermediate Ra values are observed with a feed rate of f = 0.11 mm/rev.

In Figure 7, with δ = 1.7 mm, the best surface roughness (Ra) values are achieved at a feed rate of 0.11 mm/rev, resulting in Ra = 1.15 µm at a cutting speed higher of 160 m/min. An intermediate Ra is observed at f = 0.15 mm/rev at a cutting speed between 100 to 190 m/min. Notably, a feed rate of f = 0.2 mm/rev consistently yields higher Ra values, highlighting the reliability and predictability of the results.

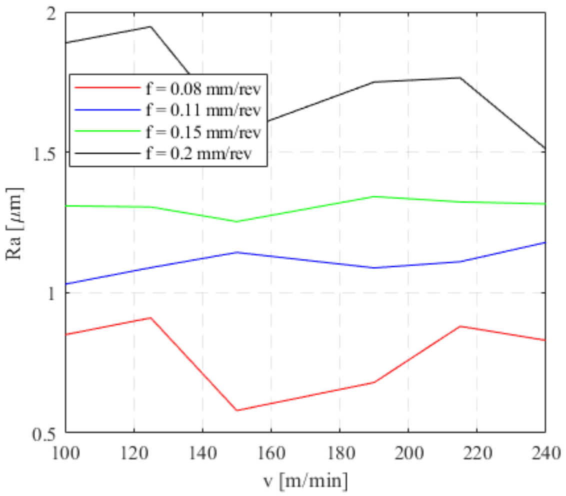

Fig. 6. The influence of v and f on the Ra with δ= 0.5 mm

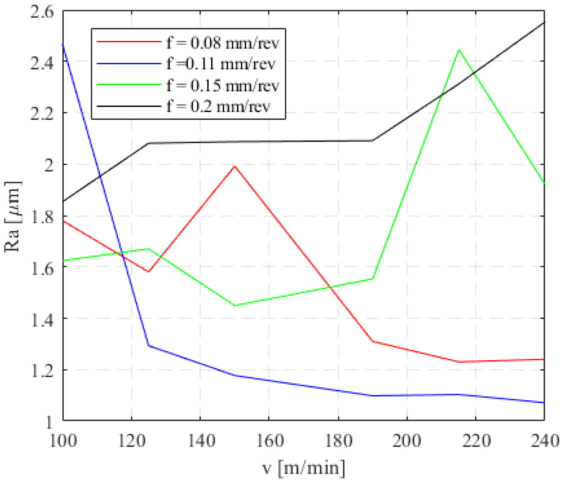

Fig. 7. The influence of v and f on the Ra with δ= 1.7 mm

4 SUMMARY

This study successfully developed a more reliable condition monitoring system for surface roughness using vibration phenomena and statistical parameters. Our approach used raw time-domain signals to correlate sensor outputs with statistical parameters and surface roughness. An essential contribution lies in determining the optimal sensor setup and signal feature extraction method for predicting surface roughness in real-time. This method uses statistical characteristics without relying on offline parameters, ensuring reliability and processing efficiency. Among the components analysed, the cutting force (Fc) exhibited the strongest correlation with surface roughness (Ra), with an adjusted R^2 of 95.1%. The correlation between estimated and validation data for the best model obtained with each sensor showed that cutting force signals had a high degree of agreement with a coefficient R of 0.965. However, vibration signals exhibited a weaker correlation due to more excellent data dispersion.

In summary, our findings highlight the effectiveness of the TDA method in real-time surface roughness prediction, emphasising the importance of cutting force in achieving reliable and accurate predictions. This study contributes to advancing condition monitoring systems by optimising sensor setups and signal feature extraction methods, paving the way for more efficient and precise surface roughness predictions in machining processes.

5 ACKNOWLEDGMENTS

The paper presents a part of the research results of the project "*Management of machining process parameters using artificial intelligence tools in production*" No. 000827481 2024 09418 003 000 000 001 01 001, supported by the Provincial Secretariat for Higher Education and Scientific Research of the Autonomous Province of Vojvodina.

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