INVESTIGATING THE IMPACT OF VIBRATION CHARACTERISTICS ON THE SURFACE ROUGHNESS USING MPU6050 SENSOR AT TURNING OF 11SMn30 STEEL

Namboodri Tanuj
student MSc, CAD/CAM
3515 Miskolc, Miskolc-Egyetemváros, e-mail: tanuj.namboodri@gmail.com

Csaba Felhő
associate professor, University of Miskolc, Institute of Manufacturing Science
3515 Miskolc, Miskolc-Egyetemváros, e-mail: csaba.felho@uni-miskolc.hu

Abstract
Manufacturing system automation is becoming more and more important in sectors due to the growing digital revolution (Industry 4.0) and economic competitiveness. One of the key criteria for making machines entirely automatic is the installation of sensors on the machine. Industrialists have used speed, temperature, and other sensors to offer real-time data and examine faults but sensors to interpret vibration are still being developed. One of the primary impacts of vibration is on the surface roughness. Surface roughness has an impact on several factors affecting the machine, including stress concentration, frictional wear, corrosivity, and so on. To prevent such failures, this study focused on identifying a correlation between vibration and surface roughness by adjusting the feed rate and it was found 92.2 % correlation is noted in *between vibration and arithmetic average surface roughness.*

Keywords: *vibration, turning operation, correlation, MPU6050 sensor, surface roughness.*

1. Introduction

The growing digital revolution (Industry 4.0) and economic competitiveness have driven industries to focus on manufacturing system automation. This requires the use of devices for inspection and data collection on the production process, as well as continuous reliability monitoring. One of the primary requirements to make machines completely automatic is the implementation of sensors on the machine. Over time, industrialists have implemented speed, temperature, and other sensors to provide real-time data and analyze defects, but sensors to understand vibration are still in research.

Chatter is a self-exited vibration of parts in machining system shown in Figure 1(a), that is caused by characteristics of a machining system under continuous action of a periodical external exciting force, it is widely present across a range of cutting processes and has an impact upon both efficiency and quality in production processing, typically due the strong relative vibration between a tool and the workpiece in metal cutting process. In figure 1. x, y, z, represents the orientation of tool and workpiece, which can be correlated with figure 4. in experimental setup. The first chatter problem was studied by Taylor in 1907 (Munoa et al., 2016). Despite chatter has been studied for more than a century, it is still an important subject in academia and industry, for automating machining processes such as turning. (Urbikain et al., 2015) reported chatter vibrations in heavy-duty turning operations restrain productivity and surface finish, (Deshpande and Fofana, 2001), predicted chatter using multimode analysis can help identify machine design features and threshold values for choosing good cutting parameters. One of the main effects of chatter is to reduce the quality of surface roughness (Hessainia et al., 2013; Kang, Derani and Ratnam, 2020), since the cutting tool is in direct contact with the workpiece during machining, self-excited vibration takes place as shown in Fig. 1 (Cherukuri et al., 2019), where (k) is the spring constant and (c) is damping coefficient which represents the level of damping. R(t) represents the surface roughness height in the surface profile created during turning operation.

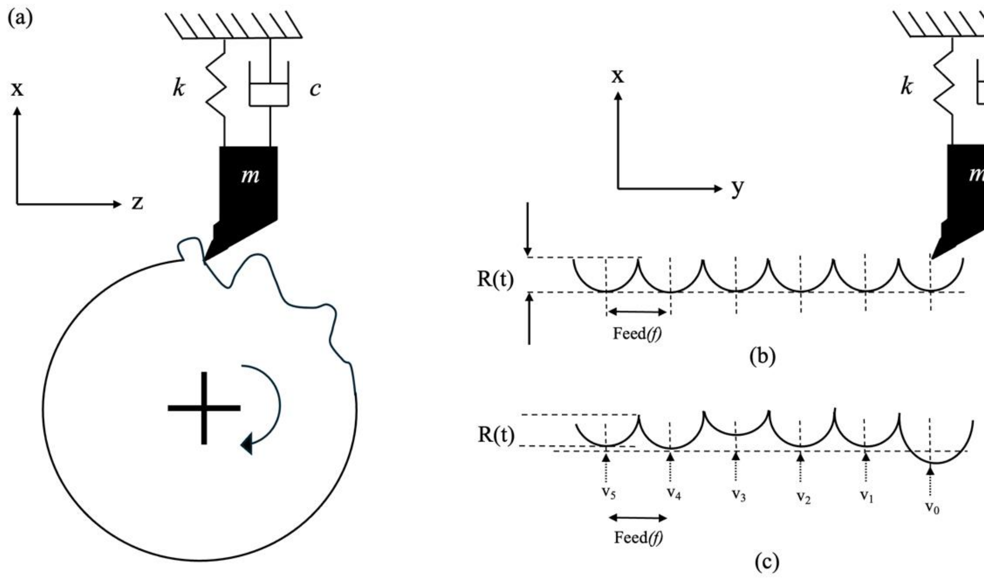

Figure 1. *(a) Magnified results of chatter in Turning (Cherukuri et al., 2019). (b) Ideal surface profile without vibration (c) Surface profile with vibration.*

A study (Zhang et al., 2015) reported the chatter in machining has an effect on surface roughness and machining precision, but also cutter life. (Shahabi and Ratnam, 2009) showed a decrease in average roughness (R_a) during the early stages of machining, followed by an increase in R_a as the machining was prolonged. Vibration has been proven to be a major element influencing surface roughness in all turning processes (En, Zhang and Huang, 2023). (Özbek and Saruhan, 2020) examined cutting tool vibration amplitude, temperature, tool wear, and surface roughness during dry and minimum quantity lubrication (MQL) turning of AISI D2 cold work tool steel. The average roughness decreased by 82%, demonstrating that vibration and tool wear have a considerable impact on surface roughness, with roughness increases with increasing vibration amplitude. (García Plaza and Núñez López, 2017) used singular spectrum analysis (SSA) on vibration data from workpiece-cutting tool interaction to assess surface roughness (R_a). A study (Sztankovics, 2023) shows that technological parameters have a complex effect on the surface roughness, which can be the result of chatter. Surface roughness is caused by the repetitive movement of the cutting tool tip along the workpiece at the proper feed rate during the machining process as shown in Figure 1 (b). This relative motion interacts in a complex manner, based on workpiece parameters, cutting circumstances, tool vibration, and metal shearing during chip production (Jang et al., 1996). (Salgado et al., 2009). Surface roughness have effects on several factors that effects the machine, like stress concentration, frictional wear, corrosivity etc. reason why in process surface roughness prediction is important. (Arola and Williams, 2002) reported, surface roughness increases fatigue strength, and the fatigue stress concentration factor (K_f) of machined surfaces ranges from 1.01 to 1.08. (Kubiak, Liskiewicz and Mathia, 2011) reported rough surfaces have a lower coefficient of friction and increase wear rate, while smooth surfaces have a decrease in wear rate and wear activation energy. (Li and Li, 2006) mentioned that surface roughness increases corrosion rate and decreases surface electron work function, contributing to corrosive wear, likewise many researchers has focused the effects of surface roughness on the functionality of the machine. As a result, understanding vibration signals is critical for avoiding such failures in manufacturing processes, to understand the chatter (Alzghoul, Sarka and Szabó, 2022) mentioned many types of models are found in the literature, Analytical chatter prediction techniques and experimental chatter prediction techniques in Analytical chatter prediction techniques, the primary three are the development of stability lobe diagrams (SLD), Nyquist plots, and the finite element approach. In experimental chatter prediction techniques, Researchers have focused on two key strategies for chatter prediction, online chatter classification, detection, and monitoring, and traditional experimental techniques for chatter avoidance. It especially refers to optimizing the cutting parameters of machining. Spindle speed variation (SSV) can be used to create a time-varying delay, or CNC controllers and other external devices can monitor vibration or process data in a time-efficient manner.

This work focused on to developing a method for monitoring vibration and analyses the effects of vibration on the surface roughness in a metal turning operation with MPU6050 sensor. To understand the relationship between surface roughness and vibration, the pearson correlation is used and to check the significance of the model ANOVA analysis was performed.

2. Experimental design

2.1. Workpiece preparation

Workpiece shaft used for experiment is of 11SMn30 grade steel, non-alloy quality not intended for heat treatment, according to EN 10277-3 standard, (EU Steel and Alloy Grades Number) was used for the experiment, the chemical composition of workpiece material is highlighted in Table 1., Mechanical properties of specimen is mentioned in Table 2.

Table 1. *Chemical composition in weight% of steel 11SMn30 (1.0715)*

C	Si	Mn	P	S
max 0.14	max 0.05	0.9 - 1.3	max 0.11	0.27 - 0.33

Diameter of workpiece specimen is 40 mm after machining which was reduced to 38 mm as shown in Figure 2, the specimen was divided in 5 equal parts of 16 mm length with partition by groove of 1.5 mm each, it was divided to test the vibrational signals at different feed rates to understand the relation between feed, vibration and surface roughness. Figure 2., represents the final machined part to analyse the corelation between feed, vibration and surface roughness parameters.

Table 2. *Mechanical properties of steel 11SMn30 (1.0715)*

Nominal thickness (mm)	Rm - Tensile strength (MPa) (+C)	$R_{p0.2}$ 0.2% proof strength (MPa) (+C)	Min. elongation at fracture (%) (+C)
40 - 63	400-650	305	9

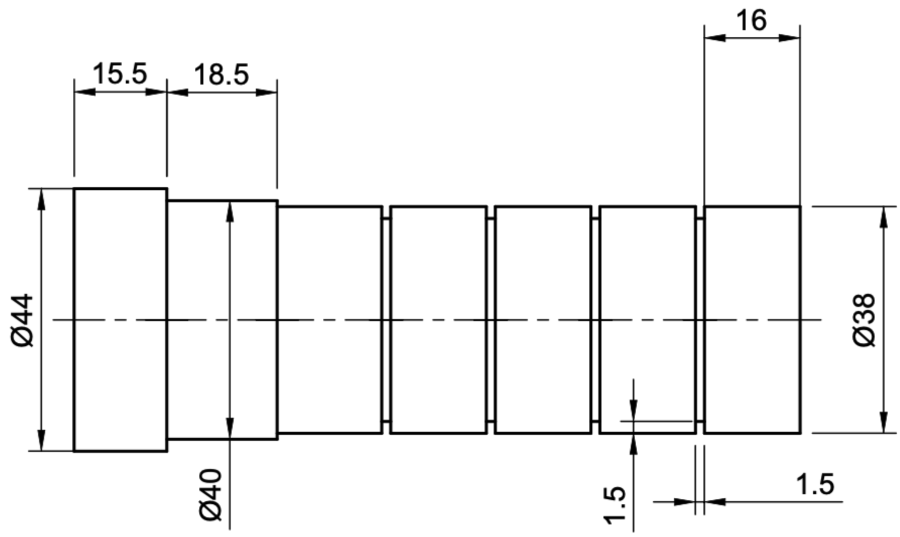

Figure 2. *Drawing of the final machined part.*

Vickers macro hardness test was performed on the specimen before machining to analyse the surface hardness, following ISO 6507 on the surface of the shaft the with HV 3 for a 10 s dwell time, the hardness tester used is Tukon 2100B Vickers/Knoop, at different points on the shaft specimen. The calculated average hardness is 211, as shown in Table 3.

Table 3. *Vickers hardness results of specimen.*

Load Capacity	Hardness Measured	Average
HV 3	217.7	211.06
HV 3	207.0	
HV3	208.5	

2.2. Tool specification

SVHBR2020K11 Walter Turn (Walter, no date) shank tool with screw clamping (S) as shown in Figure 3, was used, with positive basic shape inserts, this tool is suitable for low cutting pressures or small-diameter shafts, tool details are represented in Table 4.

Table 4. *Tool description.*

Description	Shank height	Shank width	Functional width	Functional length	Maximum projection length	Orthogonal rake angle	Inclination angle
Symbol	h = h1	b	f	l1	l4	γ	λs
Value	20 mm	20 mm	25 mm	125 mm	19 mm	0 °	0 °

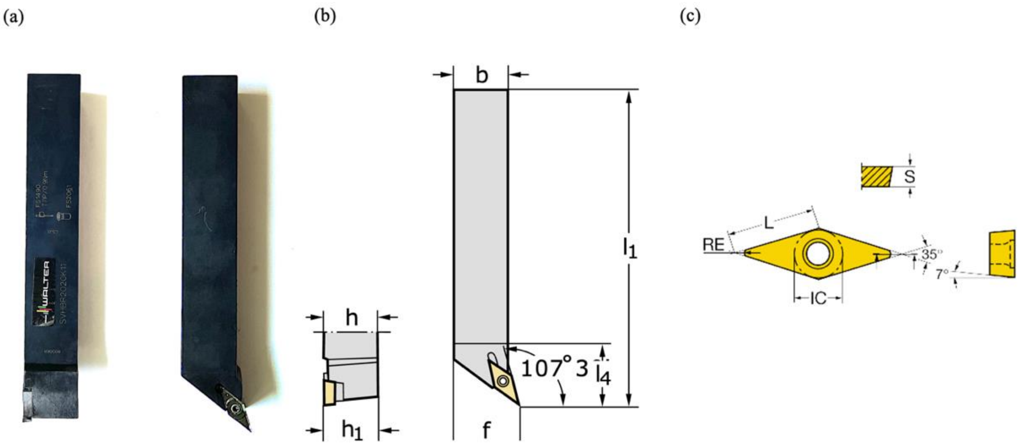

Figure 3. *(a) Tool (b) Tool Specification (c) Insert specification* ('Sandvik', no date).

Table 5. *Insert specification.*

Insert Style	Insert Shape	Clearance Angle	Cutting Edge Length	Corner Radius (Re)
VCGX	35° Diamond	7° Positive	11 mm	0.4 mm
Insert Material	Work Material	Machining Application	Insert Coating	Insert Thickness (S)
Carbide	High Temp+Cast Iron+Non-Ferrous	Roughing and Finishing	Uncoated	3.18 mm

VCGX style insert was used in the above-mentioned tool for the cutting process, insert specifications are given in Table 5.

2.3. Electronic setup

Vibrational signal was measured in each of the machining passes using MPU6050 sensor and ESP32 Microcontroller (Cameron, 2023), the microcontroller was used for the code to run, the data was collected using SD card module attached to the microcontroller. The electronic setup is shown in Figure 4. The MPU6050 sensor module is a comprehensive 6-axis motion tracking device. It combines 3-axis Gyroscope, 3-axis accelerometer and digital motion processor, The ESP32 microcontroller includes two 240 MHz cores, each with a tensilica xtensa 32-bit LX6 microprocessor. SD card module is connected to microcontroller to store the data, it is a breakout board used for SD card processes reading and writing the data.

2.4. Experimental setup

The rough turn OD turning operation was carried out to obtain experimental data in the dry condition, Optimum Opti Turn S600 CNC machine was used to perform the experiment, the sensor was connected with the tool to collect the vibrational data as shown in Figure 4. (a), the setup allowed electronic setup to be stationary with respect to machining process which provided the uninterrupted connection to the experiment. The direction of sensor with respected to tool direction is shown in Figure 4. (b), The machining operation was performed using different feed rate mentioned in Table 6. Experimental setup is highlighted in Figure 4. (a) workpiece, (b) 3 jaw chuck for clamping of workpiece (c) tool (d) MPU6050 sensor for data collection (e) electronic setup board consisting of microcontroller and SD card module (f) wire connection between sensor and microcontroller.

Tool and sensor position is shown in Fig. 4, monitor was also used to visualise the vibrational signals, monitor allows to validate the vibrational signal during the process to avoid any error. It is recommended to visualise the real time data. Sensor was attached to the tool with the help of a clip, the electronic setup was attached with the help of a screw to the tool holder in CNC machine. In case of movement of tool, the electronic setup will also move to keep the connection secure between sensor and microcontroller. The microcontroller was attached to monitor to provide the power supply and to visualise real time output vibration signals. The surface profile was measured by Alti Surf 520 using CL2 confocal chromatic sensor and to check the tool insert stereo discovery V8 microscope was used as mentioned in method section.

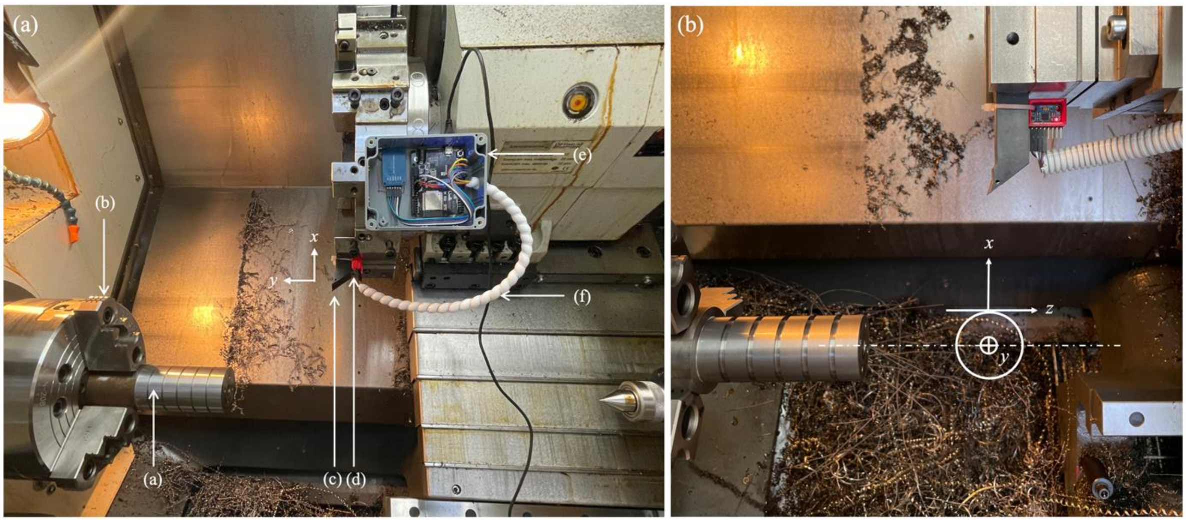

Figure 4. *(a)Experimental setup, (b) Orientation of sensor.*

2.5. Selection of parameters

Machining parameters used for experiment is mentioned in Table 6. Feed rate was intentionally varied to obtain relation between surface roughness, feed and also feed and vibration signals (Hardinsi, Novareza and As’ad Sonief, 2021; Yashwant Bhise and Jogi, 2022), workpiece was divided into 5 parts the surface number is mentioned in Figure 5. The feed was varied according to surface number as shown in Table 6.

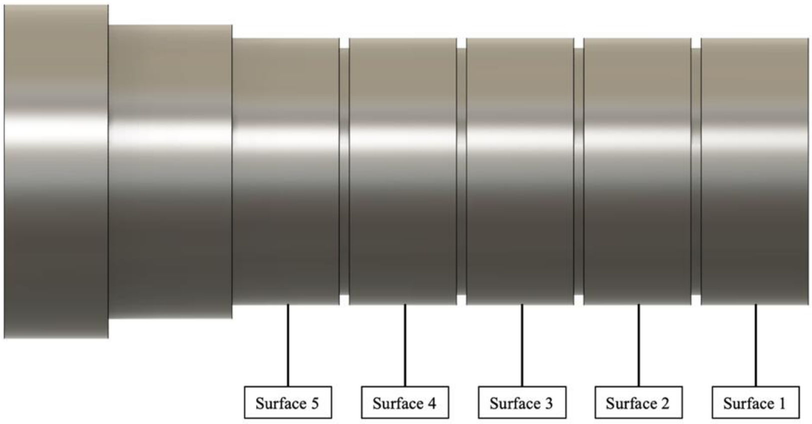

Figure 5. *Workpiece surface partition.*

Table 6. *Machining Parameters according to surface partition.*

Surface No.	5	4	3	2	1
Feed (*f*) mm/r	0.3	0.25	0.2	0.15	0.1
Depth of Cut (a_p) mm	1	1	1	1	1
Spindle Speed rpm	2000	2000	2000	2000	2000

3. Method

3.1. Processing data

The vibrational data was collected through electronic setup as mentioned in experimental setup, the data was saved in "[dot] csv" format with order time (ms) with sampling frequency 1000 Hz, acceleration in X direction (AccX) (m/s^2) which is radial , acceleration in Y direction (AccY) (m/s^2) which is axial, the acceleration in Z direction (AccZ) (m/s^2) which is tangential, AccY was kept zero intentionally because of the movement of tool in the Y direction. MATLAB academic licenced software was used to process the data, Figure 6 (a). represents the raw or unfiltered data from the sensor, where the vibrational signals in terms of acceleration in X direction is represented by blue line, and acceleration in Y direction is represented by red line, from the figure it can be visualised that the vibration peaks in Z, tangential direction are less in comparison to X, Radial (Rmili, Serra and Ouahabi, 2006; Renge, 2023). Figure 6 (b) represents the magnitude of the vibration. Equation (1) represent the magnitude of acceleration.

$$\text{Magnitude} = \sqrt{AccX^2 + AccY^2 + AccZ^2} \tag{1}$$

The data was separated according to surface to calculate the relation between each surface roughness and amplitude of vibration.

3.2. Root Mean Square (RMS) of Vibration Magnitude (V_b RMS)

Vibration signals can provide many important information about the machining process, however, the most important analysis used to process the signal is Root Mean Square (RMS) value, thus the RMS can be calculated using Equation (2), (Pedro O.C. Junior, no date).

$$RMS = \sqrt{\frac{1}{n}\sum_i x_i^2} \tag{2}$$

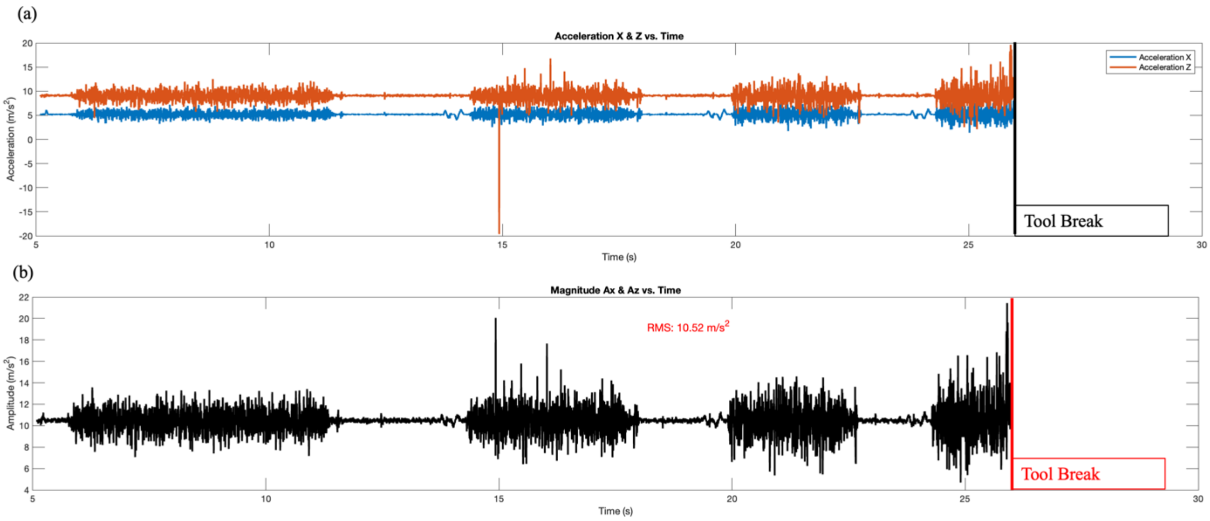

Figure 6. *(a) Raw vibration data from sensor, (b) Magnitude of vibration and RMS value.*

During the experiment the tool insert broke at the feed (*f*) 0.25 mm/r, depth of cut (a_p) 1 mm, and spindle speed 2000 rpm, insert was examined using stereo discovery V8 microscope equipped with camera and precise lens which provides the ability of high zoom rates. Image of tool insert was examined by a software axio vision, connected to the microscope. It can be suggested from Figure 7. that feed parameters for this VCGX style insert with above mentioned specification should be kept lower than 0.25 mm/r, although the same feed was used to check the outcome to verify the results. The same machining parameters were also used to understand the variation in results, by keeping the same machining parameters what outcomes are received for vibration RMS and the surface quality.

Vibration RMS value was calculated for each surface to understand the behaviour between feed and V_b-RMS. Table 7., represents the value of RMS vibration according to the surface and experiment. The workpiece's surface profile is measured to determine the relationship between V_b-RMS and the surface profile of the workpiece. The other parameters like depth of cut (DOC) and cutting speed may influence the vibration in machining however in this work the feed parameters was varied.

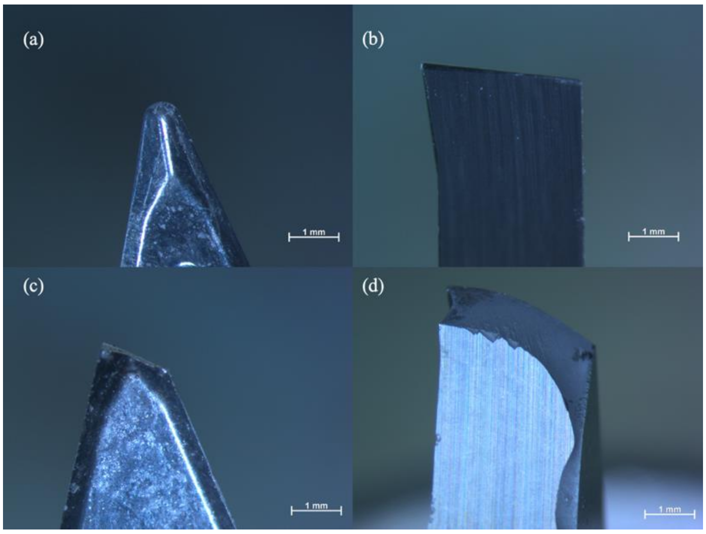

Figure 7. *(a),(b) New insert, (c),(d) Broken insert, microscopic image.*

3.3. Surface profile measurement

Surface values of the machined workpiece was measured by Alti Surf 520 as shown in Figure 8. The profile measured for all 5 machined surfaces for the sampling length of 10 mm at the scale of 100 µm using CL2 confocal chromatic sensor. The examined surface roughness parameters are R_a average surface roughness and R_z – mean surface roughness depth. Surface roughness is measured using the arithmetic roughness average (R_a) or arithmetic average roughness (R_a). This metric is often referred to as the arithmetic mean roughness value, arithmetic average (AA), or centreline average (CLA). The arithmetical average roughness is defined as the area between the roughness profile and its centre line, or the integral of the absolute value of the roughness profile height over the evaluation length (Nalbant, Gokkaya and Toktaş, 2007). Thus, R_a is given by the following Equation (3).

$$R_a = \frac{1}{L}\int_0^L |Y(x)|dx \tag{3}$$

when evaluated from digital data, the integral is normally approximated by a trapezoidal rule.

$$R_a = \frac{1}{n}\sum_{i=1}^{n} |Y_i|, \tag{4}$$

where R_a is the arithmetic average deviation from the mean line (µm), L is the sampling length, and Y is the ordinate of the profile curve. R_z is average absolute value of the five highest peaks and the five lowest valley is defined on the sampling length, this parameter is frequently used to check whether the profile has protruding peaks that might affect static or sliding contact function. R_z is evaluated using Equation (5), (Ferencsik and Varga, 2022).

$$\frac{\sum y_{p_i} + \sum y_{v_i}}{5} \tag{5}$$

After the calculation of R_a and R_z, the Pearson correlation analysis method was used to understand the effects of variables like vibration, feed on the surface quality of the machined product.

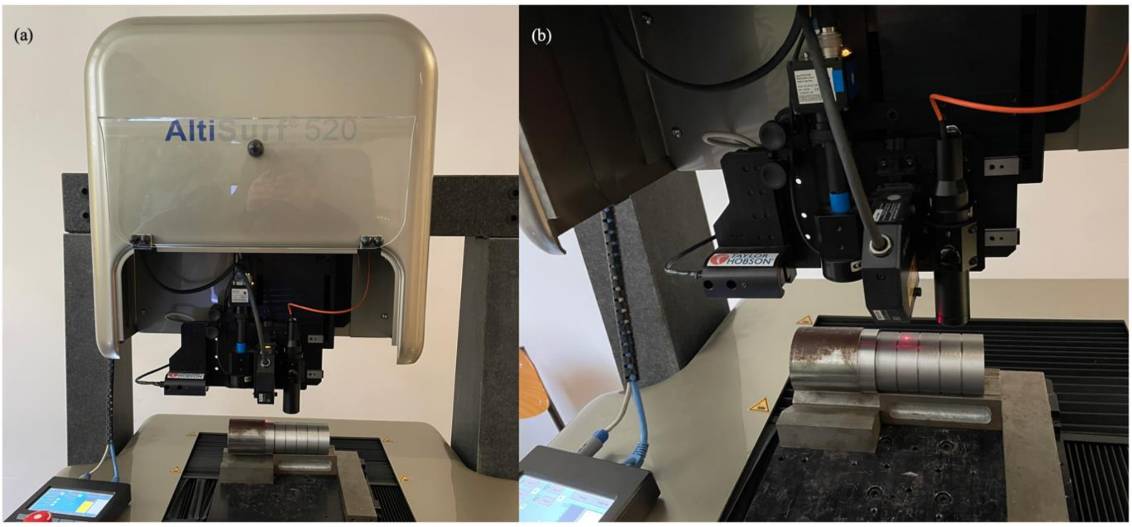

Figure 8. *(a) Setup for surface profile measurement, (b) Working area of the Alti Surf 520.*

3.4. Correlation analysis

Pearson correlation analysis is widely used technique to investigate the correlation between two quantitative variables (Mukhtar et al., 2020; Abidi and Boulanouar, 2021), In this study it was applied to understand the relationships between the machining parameters and the quality of finished product.

Specifically, the analysis examined the correlation between the feed rate *f (mm/r) and* arithmetic average surface roughness (R_a) (µm), as well as feed rate (*f*) (mm/r) and mean surface roughness depth (R_z) (µm), additionally the correlation analysis between root mean square of vibration (V_b *RMS)* and arithmetic average surface roughness R_a (µm), as well as root mean square of vibration (V_b *RMS)* and mean surface roughness depth (R_z) (µm).

4. Results and discussion

4.1. Vibration analysis

The V_b – RMS value obtained from the vibration signal during experiment was noted 10.52 m/s^2, with change in feed rate the V_b – RMS was changed as shown in Table.

Table 7. *Feed and V_b RMS value for experiments.*

Surface No.	5	4	3	2	1
Feed (mm/r)	0.3	0.25	0.2	0.15	0.1
V_b – RMS (m/s^2)	10.81	10.71	10.51	10.52	10.48

4.2. Confocal microscopy results

The surface 2D profile was measured according to ISO 4287, Gaussian filter (λ_c) was applied in accordance with the Table ISO 4288, ASME B 46.1 to reduce the noise.

Table 8. *Surface profile measurement results.*

Surface No.	5	4	3	2	1
Feed (mm/r)	0.3	0.25	0.2	0.15	0.1
R_a (μm)	9.95	6.474	4.263	2.55	1.233
R_z (μm)	61.457	34.421	23.778	14.376	5.786

4.3. Correlation analysis

Correlation analysis results represent the relationship between two variables, in this study Pearson correlation was studied, correlation coefficient is lies between -1 and 1. In case of coefficient of relation $r > 0$ shows a positive correlation between the two variables, the value of r is near to +1 means the correlation is strong positive correlation, when the value is near to 0 it shows the correlation is weak. If $r < 0$ there is a negative correlation between the variables which shows that by changing the value of the variable will not have the direct effect on the other.

Table 9. represents the results of correlation between the variables, the correlation coefficient between feed rate (*f*) and AA surface roughness (R_a) is 0.981, this results explains the strong correlation between both variables. The correlation between feed rate (*f*) and mean surface roughness depth (R_z) *is given by* correlation coefficient (r) 0.964 this results shows strong correlation between feed rate and mean surface roughness depth (R_z), which can be predicted from the relationship between *f* and R_a.

Table 9. *Correlation coefficient between variables.*

Variables	Feed	V_b – RMS	R_a	R_z
Feed	1	0.922*	0.981**	0.964**
RMS	0.922*	1	0.957*	0.945*
R_a	0.981**	0.957*	1	0.995**
R_z	0.964**	0.945*	0.995**	1

The correlation coefficient between feed rate (*f*) and vibration RMS suggests that there is very strong correlation between both variables with correlation coefficient 0.922, this value also indicates that there will be certain effects of vibration on the surface roughness. The correlation coefficient between V_b *RMS* and AA surface roughness (R_a) is 0.957 the value suggests strong correlation between the V_b *RMS* and R_a, similarly the Correlation between V_b *RMS* and R_z shows the strong correlation with correlation coefficient 0.945. The one streak "*", suggests correlation is significant at the 0.05 level (2-tailed). This indicates a moderately strong piece of evidence that the observed correlation is not due to chance. There is a 95% chance that a real relationship exists between the variables. The two streak "**" suggests correlation is significant at the 0.01 level (2-tailed). There is a 99% chance that a real relationship exists between the variables.

Table 10. *ANOVA results R_a and RMS.*

	Sum of Squares	df	Mean Square	F	Sig.
Regression	43.374	1	43.374	32.683	.011[b]
Residual	3.981	3	1.327		
Total	47.355	4			

[a] Dependent Variable - R_a, [b] Predictors - (Constant), RMS, "df" is degrees of freedom which shows the number of independent variables in the model. According to experimental results the analysis of variance (ANOVA) of regression using SPSS Statistics academic licence software was evaluated. The model is found statically significant, based on the significance level 0.011 which is below 0.05, It can be noted that V_b – RMS is a statistically significant predictor of R_a.

5. Summary and conclusion

This article presents a successful methodology based on the analysis and feature extraction of the vibration signal to monitor the quality of workpiece surfaces during OD Turning operation for metal work. Based on the results following conclusions can be derived.

1. The vibrational value indicates that with changing the feed rate the amplitude of vibration also changes and 92.2 % correlation is noted in between both variable, which shows the feed has significant effects on the V_b – RMS.
2. The correlation between the feed rate (f) and AA surface roughness (R_a) is significant, as indicated by the correlation coefficient. In summary, since the feed rate (f) parameters directly affect surface roughness, it is important to choose them properly in order to obtain smooth surface roughness.
3. The correlation coefficient between V_b *RMS* and AA surface roughness (R_a) is 0.957, it can be concluded that vibration have significant effects on the quality of product.

6. Acknowledgements

This research was supported by project No. 2020-1.2.3-EUREKA-2022-00025 which was realized with financial help of the National Research Development and Innovation Fund of the Ministry of Culture and Innovation of Hungary.

References

[1] Munoa, J., Beudaert, X., Dombovari, Z., Altintas, Y., Budak, E., Brecher, C., & Stepan, G. (2016). Chatter suppression techniques in metal cutting. *CIRP Annals - Manufacturing Technology*, *65*(2), 785–808. **https://doi.org/10.1016/j.cirp.2016.06.004**

[2] Urbikain, G., Campa, F. J., Zulaika, J. J., López De Lacalle, L. N., Alonso, M. A., & Collado, V. (2015). Preventing chatter vibrations in heavy-duty turning operations in large horizontal lathes. *Journal of Sound and Vibration*, *340*, 317–330. **https://doi.org/10.1016/j.jsv.2014.12.002**

[3] Deshpande, N., & Fofana, M. (2001). Nonlinear regenerative chatter in turning. *Robotics and Computer Integrated Manufacturing,* *17*(1-2), 107–112. ISSN 0736-5845. **https://doi.org/10.1016/S0736-5845(00)00043-0**

[4] Kang, W. T., Derani, M. N., & Ratnam, M. M. (2020). Effect of vibration on surface roughness in finish turning: Simulation study. *International Journal of Simulation Modelling*, *19*(4), 595–606. **https://doi.org/10.2507/IJSIMM19-4-531**

[5] Hessainia, Z., Belbah, A., Yallese, M. A., Mabrouki, T., & Rigal, J. F. (2013). On the prediction of surface roughness in the hard turning based on cutting parameters and tool vibrations. *Measurement: Journal of the International Measurement Confederation*, *46*(5), 1671–1681. **https://doi.org/10.1016/j.measurement.2012.12.016**

[6] Cherukuri, H. et al. (2019). Machining chatter prediction using a data learning model. *Journal of Manufacturing and Materials Processing*, *3*(2), 45, pp. 1-15. **https://doi.org/10.3390/jmmp3020045**

[7] Zhang, S. J., To, S., Zhang, G. Q., & Zhu, Z. W. (2015). A review of machine-tool vibration and its influence upon surface generation in ultra-precision machining. *International Journal of Machine Tools and Manufacture, 91*, 34–42. Elsevier Ltd. **https://doi.org/10.1016/j.ijmachtools.2015.01.005**

[8] Shahabi, H. H., & Ratnam, M. M. (2009). In-cycle monitoring of tool nose wear and surface roughness of turned parts using machine vision. *International Journal of Advanced Manufacturing Technology*, *40*(11-12), 1148–1157. **https://doi.org/10.1007/s00170-008-1430-8**

[9] En, X. N., Zhang, Y. M., & Huang, X. Z. (2023). Reliability analysis of regenerative chatter stability in turning tool systems by modified control variate method. *International Journal of Advanced Manufacturing Technology*, *128*(9-10), 4535–4550. **https://doi.org/10.1007/s00170-023-12228-w**

[10] Özbek, O., & Saruhan, H. (2020). The effect of vibration and cutting zone temperature on surface roughness and tool wear in eco-friendly MQL turning of AISI D2. *Journal of Materials Research and Technology*, *9*(3), 2762–2772. **https://doi.org/10.1016/j.jmrt.2020.01.010**

[11] Jang. D., Choi Y. J., Kim, H.-G., & Hsiao, A. (1996). Study of the correlation between surface roughness and cutting vibrations to develop an on-line roughness measuring technique in hard turning. *International Journal of Machine Tools & Manufacture, 36*, 453–464. **https://doi.org/10.1016/0890-6955(95)00074-7**

[12] Salgado, D. R., Alonso, F. J., Cambero, I., & Marcelo, A. (2009). In-process surface roughness prediction system using cutting vibrations in turning. *International Journal of Advanced Manufacturing Technology*, *43*(1-2), 40–51. **https://doi.org/10.1007/s00170-008-1698-8**

[13] Arola, D., & Williams, C. L. (2002). Estimating the fatigue stress concentration factor of machined surfaces. *International Journal of Fatigue, 24*(9), 923–930. ISSN 0142-1123. **https://doi.org/10.1016/S0142-1123(02)00012-9**

[14] Kubiak, K. J., Liskiewicz, T. W., & Mathia, T. G. (2011). Surface morphology in engineering applications: Influence of roughness on sliding and wear in dry fretting. *Tribology International*, *44*(11), 1427–1432. **https://doi.org/10.1016/j.triboint.2011.04.020**

[15] Li, W., & Li, D. Y. (2006). Influence of surface morphology on corrosion and electronic behavior. *Acta Materialia*, *54*(2), 445–452. **https://doi.org/10.1016/j.actamat.2005.09.017**

[16] MATLAB. (n.d.). https://matlab.mathworks.com

[17] Alzghoul, M., Sarka, F., & Szabó, F. J. (2022). Analytical and experimental techniques for chatter prediction, suppression and avoidance in turning: Literature Survey. *Design of Machines and Structures*, *12*(2), 33–43. **https://doi.org/10.32972/dms.2022.011**

[18] Sztankovics, I. (2023). Preliminary study on the function-defining 3D surface roughness parameters in tangential turning. *International Journal of Integrated Engineering*, *15*(7), 72–81. **https://doi.org/10.30880/ijie.2023.15.07.007**

[19] EU *Steel and Alloy Grades Number*. (n.d.). http://www.steelnumber.com/en/

[20] Walter. (n.d.). https://www.walter-tools.com/en-us

[21] Sandvik. (n.d.). https://www.sandvik.coromant.com/en-us

[22] Cameron, N. (2023). ESP32 Microcontroller. In *ESP32 Formats and Communication: Application of Communication Protocols with ESP32 Microcontroller* (pp. 1–54). Apress. **https://doi.org/10.1007/978-1-4842-9376-8_1**

[23] Hardinsi, F. A., Novareza, O., & As'ad Sonief, A. (2021). Optimization of variable helix angle parameters in CNC milling of chatter and surface roughness using Taguchi method. *Journal of Engineering and Management in Industrial System*, *9*(1), 35–44. **https://doi.org/10.21776/ub.jemis.2021.009.01.4**

[24] Yashwant Bhise, V., & Jogi, B. F. (2022). Effect of cutting speed and feed on surface roughness in dry turning of Inconel X-750. *Materials Today: Proceedings*, *61*, 587–592. **https://doi.org/10.1016/j.matpr.2022.04.098**

[25] Renge, S. et al. (2023). *Tool wear prediction device using vibrational analysis*. Project Report, PES's Modern College of Engineering 2023, Pages 61. **https://doi.org/10.13140/RG.2.2.10757.12003**

[26] Rmili, W., Serra, R. and Ouahabi, A.: *Tool wear monitoring in turning process using vibration measurement*, 2006 13th International Congress on Sound and Vibration 2006, 5, pp. 4117-4123. https://www.researchgate.net/publication/257297972

[27] Pedro, O. C. Junior. (n.d.). Feature extraction using frequency spectrum and time domain analysis of vibration signals to monitoring advanced ceramic in grinding process. *LET Science, Measurement & Technology*, *13*, 1–8. **https://doi.org/10.1049/iet-smt.2018.5178**

[28] Nalbant, M., Gokkaya, H., & Toktaş, I. (2007). Comparison of regression and artificial neural network models for surface roughness prediction with the cutting parameters in CNC turning. *Modelling and Simulation in Engineering*, *2007*. 2007, 92717. **https://doi.org/10.1155/2007/92717**

[29] Ferencsik, V., & Varga, G. (2022). The influence of diamond burnishing process parameters on surface roughness of low-alloyed aluminium workpieces. *Machines*, *10*(7), 564. **https://doi.org/10.3390/machines10070564**

[30] Abidi, Y., & Boulanouar, L. (2021). Correlation analysis between tool wear, roughness and cutting vibration in turning of hardened steel. *Engineering Transactions*, *69*(4), 403–421. **https://doi.org/10.24423/EngTrans.1263.20211210**

[31] Mukhtar, N. F. H., Zawawi, F. N., & Ismail, M. A. (2020). Pearson correlation analysis between radius and surface roughness (Ra) measurements during turning processes. *International Journal of Advanced Trends in Computer Science and Engineering*, *9*(1.1 S I), 237–241. **https://doi.org/10.30534/ijatcse/2020/4291.12020**