euspen's 25th International Conference & Exhibition, Zaragoza, ES, June 2025
www.euspen.eu

Estimation of surface roughness on turned GG25 steel parts using IR thermography measurements

Ana C. Majarena[1,2*], Sergio Aguado[1,2], Saúl Remacha[1,2], Marcos Pueo[1,2], Jorge Santolaria[1,2],Raquel Acero[1,2]

[1] *Design and Manufacturing Engineering department, University of Zaragoza, Zaragoza 50018, Spain*
[2] *Instituto de Investigación en Ingeniería de Aragón (I3A), 50018 Zaragoza, Spain*

majarena@unizar.es

Abstract

This work examines the relationship between surface roughness and temperature during turning processes, aiming to develop a tool for the early detection of surface quality deterioration in machined parts. The material used is a pearlitic-ferritic laminar cast iron GG-25 (DIN 1691) and the cutting insert is ISO code TC.T 16T304. The process has been performed using a parallel lathe from the PINACHO CNC brand, RAYO 180 model. To do this, several tests have been carried out varying the cutting conditions of the process and different statistical analysis have been performed such as normality and variance tests, Welch analysis, Mood median or correlation analysis among others. The process has been monitored using an advanced thermal camera and a 3D focus variation optical microscope. Results show that the maximum temperature captured by the thermal camera increases following an exponential or asymptotic pattern in the vast majority of tests with increasing roughness values measured on the part. It is also stated a strong relationship with the turning tool life behaviour.

Keywords: surface roughness, turning, machining conditions, machining temperature, correlation

1. Introduction

Machinability is a complex process that must be evaluated considering technical objectives such as surface quality, tool durability or production speed and economics, such as productions costs and profitability [1].

Surface roughness is an essential parameter in machining processes affecting directly to functional and mechanical parts behaviour. Thus, it may be a good indicator of the process quality. It depends on six major categories: cutting parameters, tool properties, work piece properties, thermal parameters, machine tool properties and dynamic parameters [2]. Moreover, roughness changes along manufacturing due to changes on tool wear, vibrations on the MT and chip formation characteristics [3].

So, different approaches have been identified in the literature to estimate the surface roughness of machined workpieces, mostly based on analytical, numerical, empirical, hybrid and AI-based models [4, 5]. Thermal changes along manufacturing have an increase relevance as parameter of control. Changes based on PVD (physical vapor deposition) coatings, pyrometers offer some advantages such simplicity or low cost. However, they presents some limitations due to they tend to be slow and usually provide point measurements. Nevertheless, thermography is able to cover along time a larger measurementarea without contact; avoiding invasive techniques [6, 7]. So its relevance is growing on manufacturing sectors.

This work analyses the correlation between roughness and temperature in a turning process with the aim of obtaining a tool for early detection of deterioration in the surface quality of machined parts. The work is structured in different sections: section 2 introduces the experimental testing set-up and methodology carried out in the workshop, meanwhile sections 3 and 4 present the results and main conclusions of the study.

2. Materials and methods

2.1. Machine, workpiece, tool and cutting conditions

The machine tool used for turning the parts is a CNC lathe Pinacho Rayo 180 Ø 360 x 1000 mm. Its characteristics are the following: spindle power of 5.5 Hp, bed width of 250 mm, distance between centres of 1000 mm, diameter over head of 360 mm, a spindle hole diameter of 42 mm and a speed range between 100 and 2300 rpm.

Parts to be turned are made of grey cast iron GG-25 steel according to DIN 1691. This material is commonly used for appplications that require a balance between mechanics characteristics and machinability. Pieces used had a diameter of 60 mm and a length of 140 mm.

The experiments were carried out using a triangular insert ISO TC.T 16T304 from the Garant brand with a carbide grade of HB725-1 for finishing processes, a tip radius of 0.4 mm, and a cutting edge length of 16.5 mm.

Cutting conditions were defined taking into account the cutting conditions recommendations provided by the tool manufacturer, the workpiece material, and the real limitations of the lathe used.

A series of eight experimental tests was planned, taking into account the following cutting conditions: cutting depth (ap) (1 - 2) mm, feed rate (f) (0.05 - 0.15) mm/rev and cutting speed (V_c) (200 - 250 m/min). Table 1 presents the different values established for each test.

Table 1 Experimental test cutting conditions

Test Id	V_c (m/min)	f (mm/rev)	a_p (mm)
1	200	0.05	1
2	250	0.05	1
3	200	0.15	1
4	250	0.15	1
5	200	0.05	2
6	250	0.05	2
7	200	0.15	2
8	250	0.15	2

2.2. Thermal camera

Process temperatures were measured using a thermal imaging camera FLIR-E64501. Its mainly characteristics are IR resolution of 320 x 240 pixels, thermal sensitivity < 0.05 °C, object temperature range of 0 °C to 650 °C and accuracy of ± 2 °C or ± 2 % of reading.

2.3. Experimental setup and data collection

To perform the experiments, the thermal camera was fixed to tool carriage, as shown in Figure 1. The temperature range was selected and reflected temperature of 21°C was established. A fixed emissivity of 0.6 was chosen as an approximation to ensure consistency in temperature measurement, since it is necessary to assess temperature variations and trends. This approach is suitable for industrial applications where fast estimations are required, allowing for effective comparison of temperature variations across different cutting conditions without the need for emissivity calibrations in each scenario. The piece was located in the claw plate and a roughing pass was performed.

Figure 1. Experimental setup

Then, the finishing passes were recorded by means of the FLIR Research IR software, extracting the frames from the video recording.

A region of interest (ROI) was defined, considering the contact area between piece and tool-tip, as shown in Figure 2. The maximum and mean temperature values were considered in this area for each image.

The surface roughness was measured for different passes by the optical 3D measuring device from Alicona InfiniteFocusSL using an objective of 10x. To performe the measurement process a measurement area was defined. Six measurements were taken, three at each end end of the piece rotated 120°. The profile length (L) was around 5 mm, and the cut off wavelength (L_c) was set to 800 µm for arithmetic average surface roughness (R_a) between 0.1 and 2 µm and to 2500 µm for R_a between 2 and 10 µm, according to ISO 4288 [8]. Figure 3 shows an example of roughness measurement.

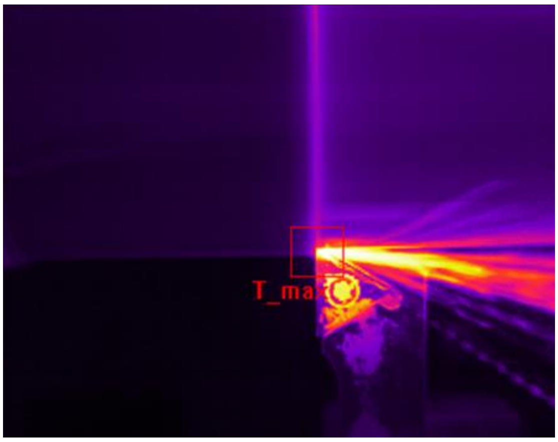

Figure 2. Thermal image capture in turning process

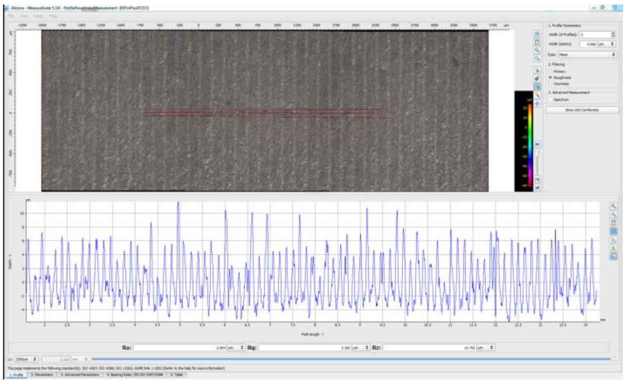

Figure 3. Roughness measurement with Alicona InfiniteFocusSL on the workpiece

3. Statistical analysis

A series of statistical techniques have been used to further analyse each dataset and the evolution of the turning process behaviour for every test. Since data patterns are yet to be identified, it is mainly necessary to determine how surface roughness and tool-tip temperature are related.

ANOVA or analogous methods have been chosen as the main way to provide strong evidence about the significance of the effect of tool wear on surface roughness and tool-tip temperature. These statistical analysis methods should show significant differences in the behaviour of these indicators between the first and the latest passes of each test.

The parameter analysed for surface quality monitoring is the *Arithmetic Average Roughness*, noted as R_a. The main reason for choosing this parameter above other surface roughness descriptors is its condtion of “statistical descriptor” opposing to parameters such as R_z or R_{max}, which beheave as “extreme values descriptors”. R_a is also the most common reference value to establish the surface quality of a workpiece in machining processes.

Maximum temperature in the tool-part contact zone has been chosen as the main temperature indicator. Despite gathering data form different regions of interest during the turning process, a Pearson Coefficient analysis has shown that all these different temperature zones have a correlation coefficient of 1, which means a complete correlation between indicators. This indicates that, at first, choosing between any temperature indicator should not make a difference on the analysis results.

Once both indicators have been evaluated, a correlation analysis has been performed. This analysis includes a coefficient correlation analysis with Pearson Coefficient (linear) and Spearmean Rho (monotonic) in order to statistically verify the relationship between these two indicators. Right after the coefficient correlation analysis, a non-linear regression model has been developed for each test in order to better visualize the tendency of surface roughness with the registered increase of temperature during the turning process. Table 2 summarizes the analytical procedure.

Table 2 Summary of statystical techniques applied

Indicator	Statistical technique	Target
Roughness	Normality test	Verify normality of each data sample
	Equality of Variance test	Verify equal variance of each data sample
	Welch's ANOVA	Verify significant difference between first and latest values
Temperature	Normality test	Verify normality of each data sample
	Mood's median test	Verify significant difference between first and latest values
Roughness & Temperature	Correlation analysis	Verify direct relationship
	Regression analysis	Visual and analytical verification

4. Results

The tool used to perform the whole analysis is *Minitab 17* statystical software. Due to the extension of the manuscript, only the result of the first test will be shown for each statistical technique. A table containing the final results for every test will be added for each method.

A normality test has been performed for each part in every test to verify the normality of the gathered data. In this test, the null hypothesis states that the dataset follows a normal distribution. If p-values are higher than the significance level (α=0.05 for every test), the null hypothesis cannot be discarded. Therefore, for every part with a p-value over 0.05 will comply with the normality condition. Figure 4 shows the result for the first workpiece in the first test. Table 3 presents the global results as how many parts comply with the normality test.

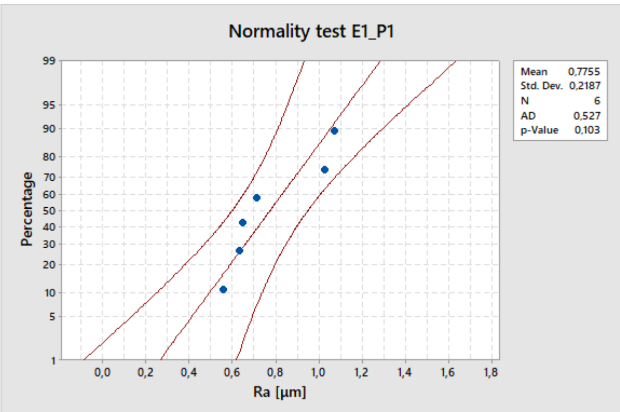

Figure 4. Normality test for Test 1 - workpiece 1

Table 3 Global results for normality test (R_a and *temperature*)

Test	Parts which comply		%	
	Ra	Temperature	Ra	Temperature
1	9/12	2/12	75.00	16.67
2	15/16	5/16	93.75	31.25
3	8/10	1/10	80.00	10.00
4	8/8	3/8	100.00	37.50
5	18/22	3/22	81.82	13.64
6	12/13	2/13	92.31	15.38
7	13/13	0/13	100.00	0.00
8	4/5	0/5	80.00	0.00
Total	87/99	16/99	87.88	16.16

Once the normality of the roughness and temperature data is verified for every test, the Equality of Variance test is performed to check if ANOVA is set to be applied (Figure 5). This test provides information about the homoscestatic condition of surface roughness data for each test. The criteria to determine if each dataset is homoscestatic is a *p-value* higher than 0.05 on both tests (Multiple comparison and Levene test). If one of the tests is failed, the dataset cannot be declared as homoscestatic and therefore, conventional ANOVA cannot be used as a valid comparison technique.

Results shown in Table 4 indicate that only half of the tests comply with the homoscestatic condition, therefore, Welch's ANOVA technique will be applied to each dataset to determine if surface roughness data for first and latest passes of the same data set are show a statistical difference. Results of this test are presented in Table 5. It can be assumed that the process of tool wear is effectively reflected on the surface of the workpiece since results differ significantly from the first to the latest passes.

Table 4. P-value for Equality of Variance tests (R_a)

Test	Multiple comparison	Levene test
1	0.025	0.132
2	0.438	0.198
3	0.707	0.374
4	0.121	0.001
5	0.185	0.276
6	0.000	0.000
7	0.787	0.336
8	0.000	0.000

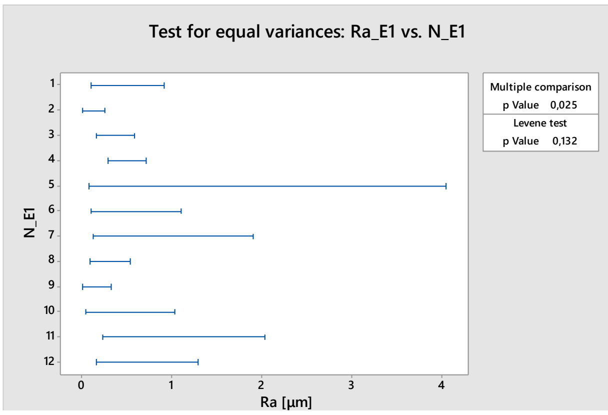

Figure 5. Equality of Variance test (R_a) for the first test

Table 5 Welch's Anova results (R_a)

Test	p-value	F value
1	0.000	69.82
2	0.000	381.72

3	0.000	23.67
4	0.000	111.96
5	0.000	14.07
6	0.000	518.84
7	0.084	1.91
8	0.000	33.62

The results of the Normality test performed on the temperature data are presented in Table 3.

It cannot be assumed that temperature during the machining process follows a normal distribution. Therefore, a Mood's median test is performed to determine the variability between first and latest passes of each test. This test is a nonparametric statistical method to effectively determine differences between the medians of each dataset relative to a workpiece in a test. The results are shown in Table 6.

Table 6 Mood's median test results (temperature)

Test	p-value	Chi-squared
1	0.000	4033.75
2	0.000	4297.89
3	0.000	6613.43
4	0.000	1211.62
5	0.000	13862.97
6	0.000	3833.77
7	0.000	8985.24
8	0.000	1267.94

Once both indicators roughness (R_a) and temperature (*Tº*) have been proven to accurately describe the effect of tool wear in the turning process as machining progresses, a correlation study has been performed on both indicators. The numerical correlation between these two indicators is shown in Table 7.

Table 7 Roughness and temperature correlation results

Test	Pearson Coefficient		Spearman Rho	
	Ra [µm]	p-value	Ra [µm]	p-value
1	0.875	0.000	0.245	0.443
2	0.300	0.259	0.468	0.068
3	-0.471	0.169	-0.491	0.150
4	0.894	0.007	0.643	0.119
5	0.518	0.013	-0.160	0.476
6	0.864	0.001	0.882	0.000
7	-0.671	0.017	-0.783	0.003
8	0.921	0.026	0.800	0.104

This study shows an unclear correlation between both indicators. Linear correlations can only be accepted if Spearman Rho shows that both variables are related. Otherwise, the data is distorted by outliers. Only test 6 presents a clear correlation between surface roughness and tool-tip temperature.

Since this analysis does not comprehend the complete process behaviour, an additional non-linear regression test has been performed for each test. Figure 6 shows the results of this test for machining test one. A clear exponential relationship between both indicators even though the numerical coefficient analysis did not provide favourable results. This pattern is repeated along almost every test (six out of eight tests). Consequently, it leads to the conclusion that the tool failure is a complex phenomenon of exponential character and, therefore, challenging to periodically sample

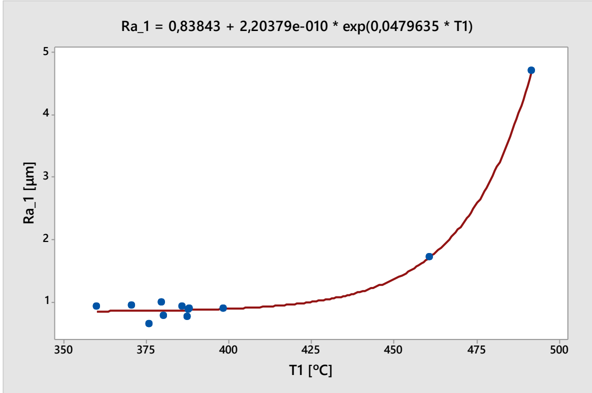

Figure 6. Non-linear regression analysis (roughness vs. temperature) for the first test

5. Conclusions

Statistical results have shown that turning is a complex mechanical process which involves countless variables. However, by only monitoring final surface roughness and tool-tip temperature it has been possible to establish the path for a possible model to predict surface roughness depending on online temperature monitoring.

It is worth noting that the behaviour shown in the non-linear regression models is strongly linked to the combination of both cutting speed and feed as input parameters. Tool wear speed is also influenced by high feed and cutting speed values. Feed rate has also been determined to be the most influential parameter in surface quality.

Although a correlation between machining temperature and workpiece roughness seems to exist, this model is complex and depends on multiple process factors. As future work, it is proposed the use of neural networks to predict surface roughness, based on machining temperature measurements and variables that influence the process, due to its ability to approximate complex models without a detailed knowledge of all the variables involved in the system.

References

[1] Rao R V 2013 Decision making in manufacturing environment using graph theory and fuzzy multiple attribute decision *Ed. Springer* Vol.2

[2] Khorasani A M 2012 Analysis of machining parameters effects on surface roughness: A review *Int J Comput Mat Sci and Surf Engin*. **5** 68- 84

[3] Davim J P 2010 Surface integrity in machining *Ed. Springer*

[4] Korkmaz M E et all 2024 Analytical modelling methods in machining: A state of the art on application, recent challenges, and future trends *Arabian J Sci and Engin*. **49** 10287 - 326

[5] Attia H et all 2024 Physics based models for characterization of machining performance – A critical review *CIRP J Manuf Sci and Tech*. **51** 161-189

[6] Suhail A H 2011 Workpiece surface temperature for in-process surface roughness prediction using response surface metrology *J Appl Sci* **11 (2)** 208-315

[7] Pereira, B M et all 2022 Cutting temperature measurement and prediction in machining processes: comprehensive review and future perspectives *Int J Adv Manuf Tech*. **120** 2849-78

[8] ISO 4288:1996 Surface texture: Profile method - Rules and procedures for the assessment of surface texture. 1998.