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Improved model to predict machined surface roughness based on the cutting vibrations signal during hard turning

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ABSTRACT

Purpose: The objective was to study the influence of cutting vibrations in hard turning of AISI 1045 steel.

Design/methodology/approach: A design of experiments using a complete factorial was used in the experiments. The specimens were tempered and quenched with 53 HRC. A piezoelectric dynamometer for turning with an acquisition data system was used in the measurements.

Findings: The results showed excellent correlation between the model and results and showed that the frequency amplitudes increase the model reliability by 5%.

Research limitations/implications: The instrumentation of machine and its correlation with the amplitudes of frequencies from data system acquisition could personalize the models for each experiment on the machines.

Originality/value: The paper uses a commercial piece and provides important information for the improvements in the roughness of hardened steel, which is an important factor for the components surface integrity.

Keywords: Machining; Turning; Vibration; Surface roughness

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SHORT PAPER

1. Introduction

Due to the interaction between the machining components, the relative vibration of workpiece and tool is an inextricable part during a machining process and it has detrimental effects on the machined surface [1].

Since surface quality is a great concern in the manufacturing industry, great attention has been paid to the effects of cutting vibration on surface finish. In machining processes, it is necessary to attain the desired surface quality in order to produce parts providing the required functioning. The surface quality also defines some mechanical properties of the product, such as wear resistance. Being such a considerable quality, surface quality is influenced by various parameters. It will be costly and time-consuming to acquire the knowledge of appropriate cutting parameters. At this point, surface roughness prediction will be helpful, which is mostly based on cutting parameters (cutting speed, feed rate, and cutting depth) and sometimes some other parameters [2].

The factors which result in cutting vibration are very complex, in which the dynamics of machine tool, workpiece materials, tool parameters and cutting parameters are all included. A simple structure with a simple degree of freedom system can be modelled by a combination of mass, spring and damping. If this system receives a hammer blow for a very short period, or when it is at rest and statically deviates from its equilibrium and leads the system to experiences free vibration. The amplitude of vibrations decays with time as a function of the system damping constant. The frequencies of the vibrations are mainly dominated by the stiffness and the mass and are slightly influenced by the viscous damping constant, which is very small in mechanical structures [3]. The cutting process dynamic model cannot predict the exact cutting vibration since most of them are great simplified and, to give a more reliable explanation of the correlation between surface generation and cutting vibrations, the vibrational state of the cutting process should be available.

At least two types of vibrations, force vibration and self-excited vibration were identified in the machining process. Force vibration is a result of certain periodical forces that exist within the machine. The source of these forces can be bad gear drives, unbalanced machine-tool components, misalignment of motors and pumps. Self-excited vibration, which is also known as chatter, is caused by the interaction of the chip removal process and the structure of the machine tool, which results in disturbances in the cutting zone. Chatter always indicates defects on the machined surface [4]. One of the factors that has the most influence on the machined surface and can deteriorate the surface quality is the presence of tool vibrations during the cutting process [5].

Precision hard turning has attracted great interest since the 1970s because it potentially provides an alternative to conventional grinding in machining high precision and high hardness components. This technology significantly reduces the production time, tooling costs and the capital investment for low volume finishing applications, such as dies, gears, shafts and bearings. In particular, it can often cut manufacturing costs, decrease production time, and improve overall product quality [6]. It concerns the removal of materials the hardness of which is higher than 45 HRC. This operation is performed with advanced tool materials, for example, cubic boron nitride (CBN) which induces a significant benefit such as short cutting cycle time, process flexibility, low cut surface roughness, high material removal rate and environment safe when machining without cutting fluid. It is also noticed that this process benefits from the motion capability of modern machine tools, which allow producing various contour geometries and generating complex forms [7].

The surface finish is an important factor for evaluating the quality of products. Surface roughness "Ra" is mostly used as an index to determine the surface finish in the machining process. Modelling techniques for the prediction of Ra can be classified into three groups which are experimental models, analytical models and artificial intelligence (AI)-based models [8].

The estimation of surface roughness by dynamic simulation of the system is very difficult because determining the machine tool parameters is not easy and parameters including damping and stiffness change in the course of time. The structure of surface roughness is very complicated and the calculation of its values through analytical equations is very difficult. Today, approximate solutions are totally inadequate for precision manufacture. Currently, it is approximately known which machining method can give what surface quality. Moreover, it is possible to obtain a desirable surface roughness value using conventional methods, but this approach is time-consuming because of repetitive and empirical processes [9].

The surface roughness greatly influences the surface integrity of products and it is controlled in most machined parts, mainly in hardened machining. The method of objective judgments and evaluation of the surface roughness has a long history. At first, a sinusoidal model of unevenness was used, when a quantity HSK (analogy of the effective value of alternating current) was used as a parameter for evaluation. Later, a parameter Ra (analogy of the mean value of alternating current) was preferred together with some further parameters [10]. In connection with a new conception of a geometrical specification of products, some more sophisticated systems for the assessment and evaluation of surface structure was created. This is the system which is regulated by currently valid standards. The surface structure is divided into components according to the pitch of overall unevenness. There are three components in the surface structure: a component with the smallest pitch creating surface roughness, a component called waviness of surface and a component with the greatest pitch of unevenness, called the basic profile. By the vibration acquisition signal, it is possible to try to predict what frequencies account for each one of these components.

The objective is to study the influence of the vibration signal on the surface roughness of machined parts.

2. Methods and materials

The hard turning testes had been carried out in cylindrical workpieces (Figure 1) of steel ABNT 1045 (Table 1), thermally hardened for quenching and tempering. The thermal treatment was carried out in a Lindberg oven with atmosphere controlled by vacuum pump. The initial hardness was measured with a digital Micron Hardness Tester Shimadzu, model HMV2. The measured values were near 53 HRC ± 2 HRC, for a load of 1.5 kN, with pre-load of 100 N.

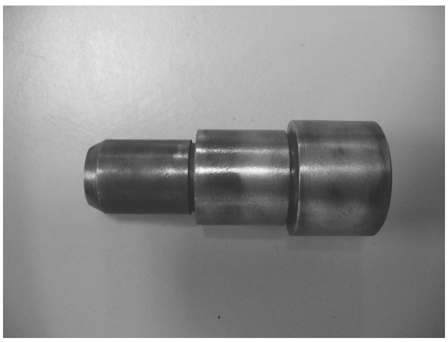

Fig. 1. Machined workpiece geometry

Table 1.
Chemical composition of steel ABNT 1045

	C	Fe	Mn	P	S
Minimum %	0.42	98.51	0.6	0.04	0.05
Maximum %	0.5	98.98	0.9		

Table 1 shows the chemical composition of the machined steel.

Hard steel turning demands a great rigidity from machining and great cutting speeds for the surface finishing of the machined materials that must be comparable to grinding operations. Aiming to fulfil with these requirements, a turning centre - Romi, Centur model 30D was used.

PCBN inserts VBGW160404S01020F (Sandvik), were used in the experimental work with PDJNR/L 2525M15 (Sandvik) clamp tool holder.

The cutting forces were measured using a PCB piezoelectric tri-axial load cell (model 260 A02) and mounted in the tool holder as shown in Figure 2. The data acquisition system used was the HBM Spider 8 with Catman Easy software (Figure 3). The data sampling frequency was kept at 9600 Hz per channel and the cutting vibration signals were evaluated by the measured cutting forces with the Catman software.

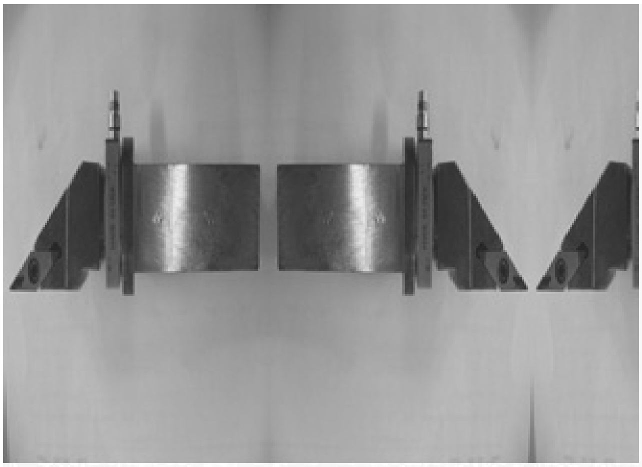

Fig. 2. Cutting force dynamometer

The average surface roughness measurements (Ra) were performed in the Mitutoyo Surftest – 301 (Cut-off = 0.8 and n=5). Three measurements of the surface roughness were taken at different locations and the average value was used.

The machining tests were carried out through an experimental planning composed by a central point; in order provide reliability to the results and to know the relation between the independent and the dependent variables. Twenty experimental runs composed of eight factorial points, plus six centre points and six axial points were carried out. Table 2 shows the experimental planning. Statistica® software was used for analysing the results.

Fig. 3. The data acquisition system

Table 2.
Experimental planning

Piece	Cutting speed [m/min]	Feed rate [mm/rev]	Cutting depth [mm]
1	120	0.08	0.025
2	120	0.09	0.15
3	120	0.16	0.025
4	120	0.16	0.15
5	210	0.08	0.025
6	210	0.08	0.15
7	210	0.16	0.025
8	210	0.16	0.15
9	89	0.12	0.0875
10	240	0.12	0.0875
11	165	0.05	0.0875
12	165	0.19	0.0875
13	165	0.12	0.0176
14	165	0.12	0.1926
15	165	0.12	0.0875
16	165	0.12	0.0875
17	165	0.12	0.0875
18	165	0.12	0.0875
19	165	0.12	0.0875
20	165	0.12	0.0875

3. Results and discussion

3.1. Acquisition and data treatment

In a visual inspection of a graph in function of time, even a signal that has information can be only a form of noisy wave. Thus, it is common to the same, convert signal to the frequency where it can be easier to distinguish what is information from what is noise. However, some cares are necessary so that the frequency spectre does not also mask the information.

Firstly, it is recommended to conduct an analogical filtering of the signal before it is shown by the data acquisition system. This consists in reducing the aliasing effect, that is, spectre overlapping. In this case, the sampling frequency of the acquisition system is 9600 Hz. Then an analogical filter low pass with cut frequency in 4800 Hz must be used to remove all the frequencies of this value.

The piezoelectric sensor used in the cutting forces measurements presents an exponential decline characteristic when submitted to a constant pressure. This behaviour is not desired, as it modifies the measure. Assuming that the cutting forces have a constant value measured during the machining, the decline effect can be removed numerically. In this work, the exponential decline is approached by a linear decline and the signal is restored during pre-processing data.

Aiming to prevent the emptying or tails in the rays of the spectre, a window in function of time must be applied. This emptying makes the spectre dirtier and must be minimized for the purposes of the signal analysis.

Another defect that can be present in the spectre is low resolution. When few points are used, a ray of the spectre is little characterized. In this situation, the values of amplitude and the frequency of the rays are inexact. To prevent this problem, the amount of points must be increased by “zeros” added to the original signal. Although this solves the resolution problem, the spectre will continue loaded by the spectral noise.

A solution to reduce the spectral noise is to divide the signal into segments and calculate the spectre for each one of these stretches that must be sampled individually. Thus, a spectre medium is generated that reduces the random error of a factor that is given by the square shaped root of the number of segments. In practice, it is common to use 100 segments. One alternative technique to reduce the spectral noise is to show the original signal, generating a spectre with high resolution and then apply a digital filtering low passes in the gotten signal, reducing the noise. In general, the first of the two alternatives is normally used.

It is noticed that it is not trivial to infer the excellent information of this signal, and in this in case, it is more comfortable in the frequency domain

The graph in Figure (4b) shows the spectre of this signal, in which its amplitude is raised to the square to represent the power of each spectral component. The main component is observed to have a frequency near 30 Hz, whereas the two next ones have 60 Hz and 90 Hz.

Here the spectral information is gotten by the “Fast Fourier Transform” (FFT). The value of the amplitude of each ray was raised to the square to characterize the power of each contribution.

Later that the exponential decline was restored in the pre-processing data, the cutting forces signal has similar results to Figure (4a), in which Hz is one of the acquired signal of the tests with a frequency of 9600 Hz. .

Bernardos & Vosniakos [11] showed that the surface roughness refers to superimposed orders of deviation from the normal surface. These orders refer to forms and waviness (machine tool errors, setup errors, deformation of the workpiece, material workpiece inhomogeneity), to periodic grooves, cracks and dilapidations (connected to the shape and condition of the cutting edges, chip formation and process kinematics) and to materials workpiece structure (connected to slip, diffusion, oxidation, residual stress and other mechanisms) in accordance with [12].

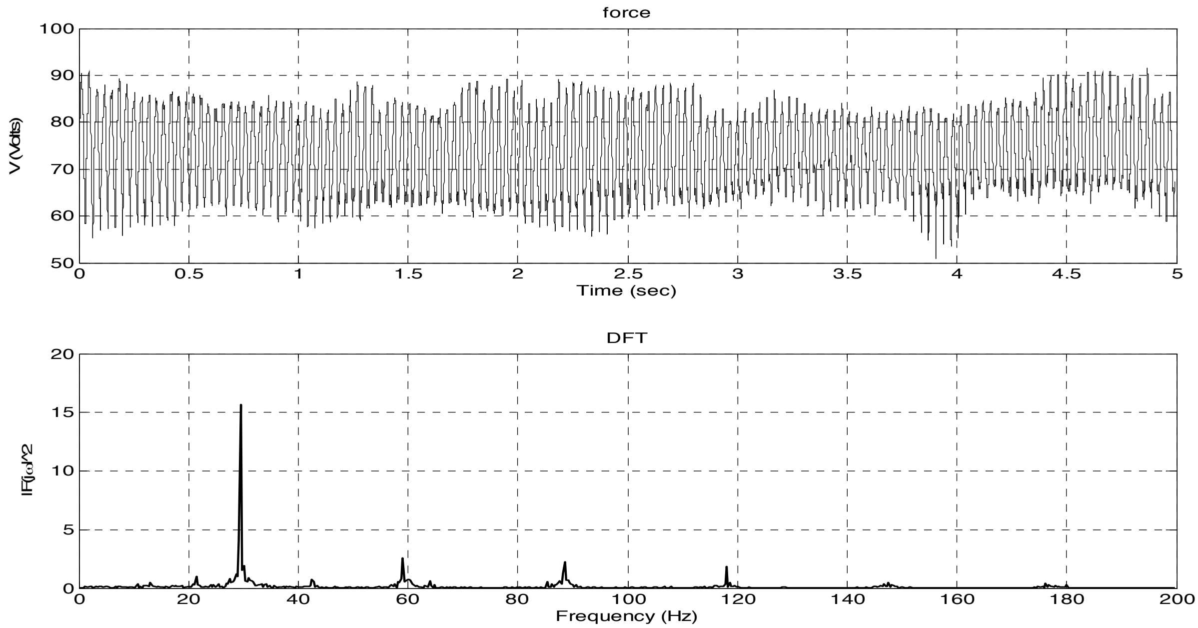

Fig. 4. Cutting forces in the time and frequency

Table 3.
Shows the results for all the experiments

Piece	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp	Freq [Hz]	Amp
1			10	0.34									24	0.97						
2			10										24	0.67						
3			10	0.17									24	1.44						
4			10										24	6.5						
5							17	0.7			21	0.5							42	1.57
6							17	0.86			21	0.36							42	1.78
7	8	0.84					17	0.71											42	5.22
8																			42	5.87
9	8	0.84					17	27.6											42	1.26
10									19	0.24			24	0.14			36	4.6		
11				0.1			17	0.62												
12				0.35											32	17.6				
13				1.1			17	0.61							32	2.47				
14				0.57											32	5.4				
15				0.77											32	1.5				
16				0.35											32	5.85				
17				0.56											32	5.51				
18				0.44											32	10.5				
19				0.91			17	0.42							32	4.94			42	0.3
20					15	0.52	17	0.32									36	1.18		

3.2. Experimental results and discussion

Table 3 shows the results of the FFTs signals for the experimental planning (only part of the results are shown and that is the most important, the continuation with higher values are multiples of the red values). The values are shown in crescent order from left to right. The red values correspond to the machine revolution, and are the largest values. The amplitudes values were adopted as an influence criterion on the dynamic of the process under the piece roughness. The values shown on the left side of the table are smaller than the red values and are relative to the error form of the piece. Only part of the results is shown and that is the most important, the continuations with higher values are multiples of the red values.

Table 4 shows the results for all the experiments.

3.3. Factorial modelling

With all the values shown in Table 4, a factorial modelling was made. The goal of this analysis was to evaluate the dependency of the roughness on all the parameters: cutting speed (V), feed rate (f), cutting depth and vibration amplitude (amp). The significance level was set to 0.05. Statistica® software was employed for the statistical analysis and the results are presented in Table 5 and Table 6. As shown in Table 5, the model had high square values of the regression coefficients which indicated high association with variances in the predictor values. The coefficients of the more significant variables and constants of the model are listed in Table 6.

Table 4.
Results for the roughness and frequency amplitudes

Piece	Cutting speed [m/min]	Feed rate [mm/rev]	Cutting depth [mm]	Roughness Ra [mm]	Amplitude
1	120	0.08	0.025	0.18	0.97
2	120	0.09	0.15	0.2	0.67
3	120	0.16	0.025	1.09	1.44
4	120	0.16	0.15	1.04	6.5
5	210	0.08	0.025	0.8	1.57
6	210	0.08	0.15	0.78	1.78
7	210	0.16	0.025	1.01	5.22
8	210	0.16	0.15	1.1	5.87
9	89	0.12	0.0875	0.96	27.6
10	240	0.12	0.0875	0.77	1.7
11	165	0.05	0.0875	0.14	3.82
12	165	0.19	0.0875	1.73	17.6
13	165	0.12	0.0176	0.71	2.47
14	165	0.12	0.1926	0.76	5.4
15	165	0.12	0.0875	1.11	1.5
16	165	0.12	0.0875	0.45	5.85
17	165	0.12	0.0875	0.46	5.51
18	165	0.12	0.0875	0.45	10.5
19	165	0.12	0.0875	0.89	4.94
20	165	0.12	0.0875	0.47	1.18

Table 5.
Factorial analysis with vibration amplitudes

Test of SS Whole Model vs. SS Residual					
Dependent variable	Multiple R	Multiple R^2	Adjusted R^2	F	P
Ra	0.902000	0.813000	0.764000	16.35000	0.00002

Table 6.
Coefficients of the model with vibration amplitudes

	Raparameter	Ra"t"	Ra"p"
V	-0.403	-1.726	0.105
V^2	0.00047	3.089	0.0075
f			
f^2	29.213	4.576	0.00037
ap			
ap^2			
amp			
amp^2			
v*f			
v*ap			
f*ap			
V*amp	-0.00069	-2.781	0.014
f*amp	0.67591	3.164	0.00642
ap*amp			

A different model, subtracting the vibration part (amplitude) from Table 4, was employed to verify the effectiveness of the vibration parameter in the model. Table 7 showed that are significant differences between accuracy values with vibration amplitudes and without vibration amplitudes.

Table 7.
Differences between accuracy values with vibration amplitudes and without vibration amplitudes

Test of SSWhole Model vs. SSRedidual					
Dependent variable	Multiple R	Multiple R^2	Adjusted R^2	F	P
Ra	0.864000	0.746000	0.699000	15.68000	0.00 005

Analysing the results, it is possible to conclude that, when the vibration amplitudes were considered in the model the reliability was better at minimum 8% for the multiple R^2 and the adjusted R^2 analysis.

Then, an empirical model for predict the roughness Ra was created, in accordance with Equation 1.

$$Ra=-0.403+0.0047*cs+29.21*f^2-0.00069*cs*amp +0.6759*f*amp \quad (1)$$

4. Conclusions

Only the amplitudes related to the machine rotation were found; the other ones were smaller and related to the error piece form.

A factorial analysis was performed and it shows that the vibration amplitudes provide improvements of at least 8%.

The surface roughness model shows that the square of feed most significantly influences the surface roughness.

Cutting depth has no significant effect on surface roughness.

Cutting speed has no significant effect on surface roughness.

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References

[1] H. Jiang, X. Long, G. Meng, Study of the correlation between surface generation and cutting vibrations in peripheral milling, Journal of Materials Processing Technology 208 (2008) 229-238.

[2] M.C. Cakir, C. Ensarioglu, I. Demirayak, Mathematical modelling of surface roughness for evaluating the effects of cutting parameters and coating material, Journal of Materials Processing Technology 209/1 (2009) 102-109.

[3] Y. Altintas, Manufacturing automation, metal cutting mechanics, machine tool vibrations and CNC design, Cambridge University Press, 2000.

[4] L. Huang, J. Chen, A multiple regression model to predict in-process surface roughness in turning operation via accelerometer, Journal of Industrial Technology 17 (2001) 2-8.

[5] M. Arizmendi, F.J. Campa, J. Fernández, L.N. Lópes de Lacalle, A. Gil, E. Bilbao, F. Veiga, A. Lamikiz, Model for surface topography prediction in peripheral milling considering tool vibration, CIRP Annals – Manufacturing Technology 58/1 (2009) 93-96

[6] J. Rech, G. Kermouche, W. Grzesik, C. Garcıa-Rosales, A. Khellouki, V. Garcıa-Navas, Characterization and modelling of the residual stresses induced by belt finishing on a AISI52100 hardened steel, Journal of Materials Processing Technology 208 (2008) 187-195.

[7] K. Bouacha, M.A. Yallese, T. Mabrouki, J.F. Rigal, Statistical analysis of surface roughness and cutting forces using response surface methodology in hard turning of AISI 52100 bearing steel with CBN toll, International Journal of Refractory Metals and Hard Materials 28/3 (2009) 349-361.

[8] A.M. Zain, H. Haron, S. Sharif, Prediction of surface roughness in the end milling using artificial neural network, Expert Systems with Applications 37 (2010) 1755-1768.

[9] D. Karayel, Prediction and control of surface roughness in CNC lathe using artificial neural network, Journal of Materials Processing Technology 209 (2009) 3125-3137.

[10] J. Valicek, J. Mullerova, S. Hloch, Interpretation of the rough roughness measurement spectra of the surface profiles, Machines Technologies Materials (2008) 22-24.

[11] P.G. Bernardos, G.C. Vosniakos, Prediction surface roughness in machining: a review, International Journal of Machine Tools and Manufacture 43 (2003) 833-844.

[12] Ch. Lu, Study on prediction of surface quality in machining process, Journal of Materials Processing Technology 205/1-3 (2008) 439-450.