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Effects of cutting parameters during turning 100C6 steel

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Abstract. The objective of the paper is to evaluate the effects of cutting parameters in terms of cutting speed, depth of cut and feed rate on the influence of the surface roughness, consumed power, cutting time and tool vibrations during turning process. The material chosen in this case was 100C6 steel in dry conditions. The effects of the selected process parameters have been investigated using full factorial design of experiments (3^3) and the multiple linear regression (MLR). Thus, first-order empirical models were established. Analysis of variance (ANOVA) was employed to check the validity of the developed models within the limits of the factors that were being investigated and to test the significance of the above parameters. Results indicate that the feed rate is the only significant factor affecting the surface roughness. The cutting speed and feed rate are the most influential factors on cutting time. Estimated tool vibrations are functions of cutting speed, feed rate and depth of cut in decreasing order. Finally, the models obtained can be used for determination of optimal settings of cuttings parameters and this methodology should help us to obtain the best process parameters for dry turning of 100C6 steel.

1 Introduction

Even though the manufacturing industry has made an important progress, the metal cutting industries continue to suffer from a major drawback of not running the machine tools at their optimum operating conditions. Indeed, turning is one of the most commonly used machining processes in machining industry. Thus, the choice of optimized cutting parameters is very important to control the surface quality or surface roughness, a dimensional accuracy of a workpiece, the cutting time, tool life or the tool wear rates, to limit the consumed power of machine tool, to avoid high levels of cutting forces and tool vibrations. The problem of arriving at the optimum levels of the cuttings parameters has attracted the attention of the researchers and practicing engineers for a very long time. Unfortunately, the impact of the research work in this area does not seem to have reached a large majority of manufacturing engineers with the result that the operating conditions continue to be chosen on the basis of handbook values, manufacturers' recommendations or worker experience. Therefore, for lack of well defined rule, conservative cuttings conditions are usually chosen resulting in lower metal removal rates and a loss of productivity. A large number of analytical and experimental studies on surface roughness [1, 2], cutting tool wear [3], cutting forces [4] and tool vibrations [5], related to turning operations has been conducted. However in these studies, the interactions between the cutting parameters were not taken into consideration in the modeling process. But the key element for achieving high quality at low cost is Design of experiments (DOE). In this paper full factorial design of experiments approach is used to evaluate the effects of cutting parameters like cutting speed, depth of cut and feed rate on the resulting surface roughness, consumed power, cutting time and tool vibrations during a dry turning

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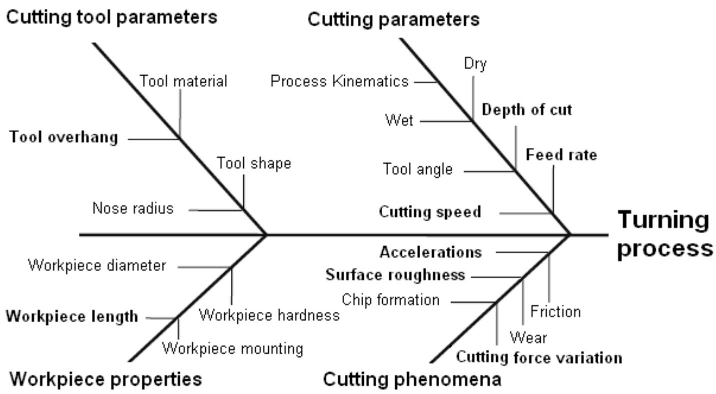
of 100C6 steel. Finally, this methodology should help us to obtain the best cuttings parameters for the optimization of the machining process.

2 Turning process parameters

In order to identify the cuttings parameters that may affect the machining characteristics of turned parts, an Ishikawa cause-effect diagram was constructed as illustrated in figure fig. 1. The process parameters affecting the characteristics of turned parts are: cutting tool parameters, workpiece properties, cutting phenomena and cutting parameters [6].

Fig. 1. Ishikawa cause-effect diagram of a turning process.



Cutting tests were carried out on a CNC SOMAB model 500 lathe machine (24kW power) under dry cutting conditions. Machining was performed dry because it has been considered as the machining of the future due to concern regarding the safety of the environment [7]. Because of its wide application, the 100C6 steel has been selected as the workpiece material in this study. The cutting power and time has been study to take into account the capacity of the lathe and productivity.

Process parameters selected for study are: depth of cut, feed rate and cutting speed. The range of the selected process parameters was selected after considering the recommendations given in the tool manufacturer's catalogue [8]. The process parameters, their designated symbols and ranges are given in Table 1.

Table 1. levels of independant variables

Parameter	Symbol	Unit	Levels		
			-1	0	1
Cutting speed	V_c	m/min	100	200	300
Feed rate	f	mm/rev	0.15	0.3	0.45
Depth of cut	a_p	mm	1	1.5	2

The following parameters were kept constant during entire experimentation: work material, cutting tool insert product by Safety Company of the standard designation CNMG 1204 08 5B (OR2500) and mounted on DCLNL 2525M 12 tool holder (standard designation), tool overhang and dry environment.

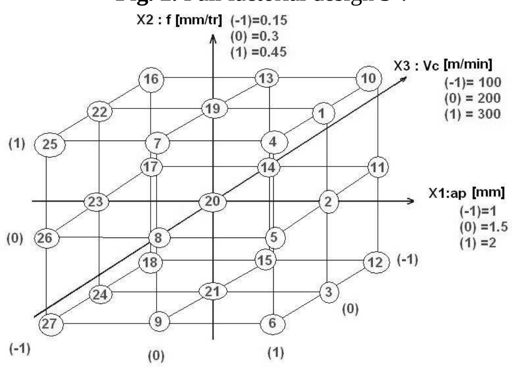
3 Methodology

3.1 Full factorial design of experiments

Experimental design is very important engineering tool for improving of process. Designed experiments can often be applied in the product design processes. This will produce information concerning which factors are most influential one and through use of this information the design can be improved [9].

In this case, a full factorial experimental design 3^3 has been selected with all combinations of the factors at three levels as illustrated in figure 2. Thus, 27 experiments were conducted at parameter levels as shown in Table 1 on the four measured dependant variables surface roughness, consumed power, cutting time and tool vibrations. The resolution of this full factorial design allows us to estimate all the main effects, factor interactions. Note that run orders are used randomly during the experiments.

Fig. 2. Full factorial design 3^3.



3.2 Multiple linear regressions

Multiple linear regressions attempt to model the relationship between two or more explanatory variables and a response variable by fitting a linear equation to observed data. By conducting experiments and applying regression analysis, a mathematical model of the response (Y) with independent input variables (X) can be obtained. Usually a lower-order polynomial in the region of interest is employed, like the first-order model seen in equation (Eq. 1):

$$Y = a_0 + a_1 X_1 + a_2 X_2 + a_3 X_3 + \varepsilon \tag{1}$$

where a_0 is constant, $a_{i,i=1,2,3}$ represent the coefficients of linear terms and ε is the experimental error. $X_{i,i=1,2,3}$ reveals the coded variables that correspond to the selected turning parameters. The coded variables are obtained from the following transformation equations:

$$X_1 = \frac{a_p - a_{p_0}}{a_{p_{+1}} - a_{p_0}} \quad , \quad X_2 = \frac{f - f_0}{f_{+1} - f_0} \quad , \quad X_3 = \frac{V_c - V_{c_0}}{V_{c_{+1}} - V_{c_0}} \tag{2}$$

where X_1, X_2 and X_3 are the coded values of a_p, f and V_c respectively. a_{p_0}, f_0, V_{c_0} and $a_{p_{+1}}$, f_{+1}, $V_{c_{+1}}$ are the values of a_p, f and V_c are zero level and +1 level respectively. The surface roughness, consumed power, cutting time and tool vibrations were analyzed as responses.

The ordinary least squares method is used to estimate the parameters $a_{i,i=0,1,2,3}$ within :

$$a = (X^T X)^{-1}(X^T Y) \tag{3}$$

where the calculation matrix of independent variables is X and the variance matrix is $(X^T X)^{-1} a$. The calculated coefficients or the model equation need to however be tested for statistical significance. In this respect, the following tests are performed.

3.3 Test of significance

Tests of significance of the regression models are performed as an Analysis of variance (ANOVA) procedure by calculating the *F-ratio*, which is the ratio between the regression mean square and the mean square error. The *F-ratio* is the ratio of variance due to the effect of the factor (in this case the model) and variance due to the error term. This ratio is used to check the validity of the models under investigation with respect to the variance of all terms included in the error term at the desired significance level α. A significant model is desired.

Test for significance on individual model coefficients is the basis for model optimization. It involves the determination of the *P-value* or probability value, usually relating the risk of falsely rejecting a given hypothesis. For example, a $Prob. > F$ value on an *F-test* tells the proportion of time you would expect to get the stated *F-value* if no factor effects are significant. The $Prob. > F$ value determined can be compared with the desired probability or α-level.

The checks performed here include determination of the correlation coefficients R^2. These R^2 coefficients have values between 0 and 1. In addition to the above, the adequacy of the models is also investigated by examination of residuals [9].

4 Results and discussion

The results from the machining runs performed as per experimental plan is shown in Table 2.

Table 2. Design layout and experimental results.

N° data		Input factors			Coded factors			Output data					
Run	*N° exp.*	*ap*	*f*	*Vc*	X_1	X_2	X_3	*T*	*Pu*	*Ra*	A_x	A_y	A_z
1	27	1	0.15	100	-1	-1	-1	46.35	1	0.484	7.64	9.43	12.25
2	24	1	0.15	200	-1	-1	0	26.56	1.9	0.457	33.39	36.23	47.64
3	18	1	0.15	300	-1	-1	1	23.36	2.9	0.511	41.59	37.03	90.77
4	26	1	0.3	100	-1	0	-1	24.3	1.7	1.793	11.24	13.33	19.75
5	23	1	0.3	200	-1	0	0	13.85	3.2	2.049	49.59	65.83	66.95
6	17	1	0.3	300	-1	0	1	12.06	5.1	2.054	52.75	56.64	149.62
7	25	1	0.45	100	-1	1	-1	16.96	2.2	3.442	12.28	13.9	18.81
8	22	1	0.45	200	-1	1	0	9.61	4	3.652	59.91	81.49	89.43
9	16	1	0.45	300	-1	1	1	8.29	6.4	3.988	109.89	106.67	169.6
10	9	1.5	0.15	100	0	-1	-1	41.82	2	0.856	8.08	10.94	12.92
11	21	1.5	0.15	200	0	-1	0	29.96	2.7	0.598	27.77	31.01	47.98
12	15	1.5	0.15	300	0	-1	1	25.62	4.3	0.645	38.02	34.48	87.1
13	8	1.5	0.3	100	0	0	-1	22.61	2.5	3.082	12.01	16.23	19.36
14	20	1.5	0.3	200	0	0	0	15.83	4.6	1.967	47.00	53.33	73.33
15	14	1.5	0.3	300	0	0	1	13.38	7.1	2.516	73.65	82.99	119.71
16	7	1.5	0.45	100	0	1	-1	16.2	5.9	4.864	16.94	21.31	25.23
17	19	1.5	0.45	200	0	1	0	11.12	6.6	3.537	58.83	81.68	98.91
18	13	1.5	0.45	300	0	1	1	9.29	9.8	4.466	112.72	173.74	198.94
19	6	2	0.15	100	1	-1	-1	52	4	0.962	10.07	14.27	18.75
20	3	2	0.15	200	1	-1	0	32.78	3.4	0.583	27.82	32	49.58
21	12	2	0.15	300	1	-1	1	29.01	5.2	2.239	44.55	39.53	99.69
22	5	2	0.3	100	1	0	-1	28.26	3	1.165	18.18	25.36	35.24
23	2	2	0.3	200	1	0	0	17.52	6	1.135	42.6	54.2	68.63
24	11	2	0.3	300	1	0	1	15.26	9.1	0.974	89.34	110.59	164.27
25	4	2	0.45	100	1	1	-1	20.35	4.3	0.978	26.00	34	51.74
26	1	2	0.45	200	1	1	0	12.43	8	4.686	85.70	121.84	157.23
27	10	2	0.45	300	1	1	1	10.68	13.7	4.077	189.44	278.01	347.17

For a best discussion of results we have reorganized the 27 experiments (N°exp) to (run) in 3 blocks $(ap = 1, 1.5, 2)$.

4.1 surface roughness model

The predictive linear surface roughness model *Ra* in terms of coded factors (Eq.4) was been transformed using (Eq.2) to provide the predictive surface roughness as a function of cutting parameters a_p, f and V_c (Eq.5) as follows:

$$Ra = 2.1393 - 0.0906\,X_1 + 1.4642\,X_2 + 0.2136\,X_3 \tag{4}$$
$$= -0.9444 - 0.1812\,a_p + 9.7611\,f + 0.0021\,V_c \tag{5}$$

Table 3. Analysis of variance of surface roughness model.

Source	Df	Sum of squares	Mean Squares	*F-ratio*	*Prob.* > *F*	R^2 adj.
Regression	3	39.5568	13.1856	17.8052	< 0.0001	0.6598
Residual	23	17.0326	0.7405			
Total	26	56.5894				
Effects	Df	Sum of squares	Contribution (%)	*F-ratio*	*Prob.* > *F*	
ap	1	0.1478	0.26	0.1996	0.6596	not significance
f	1	38.5881	68.19	52.1074	< 0.0001	significance
Vc	1	0.8209	1.45	1.1085	0.3033	not significance

In the table 3, the value of *Prob.* > *F* for the term of models are less than 0.05 (95% confidence), this indicates that the obtained model are considered to be statistically significant within the limits of factors studied, which is desirable. The other important regression coefficient of the model R^2 adjusted was found to be 0.6598. This shows that the model can explain the variation in surface roughness to the extent of 65.98% and it can be concluded that the first order model was adequate to represent this process. The analysis of variance results shows that the only significant factor on the surface roughness is the feed rate f. The depth of cut a_p and the cutting speed V_c don't impact the surface roughness in the studied range, which could be used to improve productivity if it would not worsen the surface microstructure of the workpiece and the dimensional accuracy. Thus, the insignificant terms can be removed so as to adjust the fitted first-order model (Eq. 6) which is in accordance with machining theory.

$$Ra = -0.9444 + 9.7611\,f. \tag{6}$$

Fig. 3. Comparison of predicted and measured values of surface roughness *Ra*

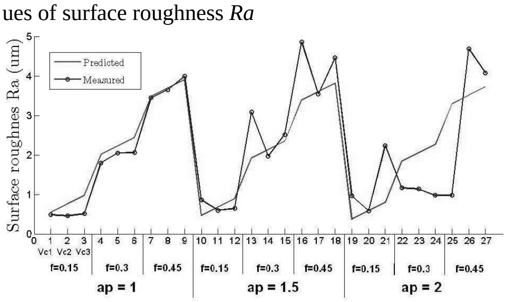
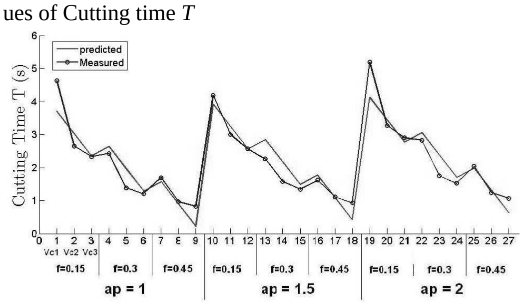


Fig. 4. Comparison of predicted and measured values of Cutting time *T*



4.2 Cutting time models T

To observe the influence of cutting parameters on productivity, we have studied the models of the cutting time T :

$$T = 21.6837 + 2.0528\,X_1 - 10.6961\,X_2 - 6.7722\,X_3 \quad (7)$$
$$= 50.4620 + 4.1056\,a_p - 71.3074\,f - 0.0677\,V_c \quad (8)$$

Table 4. Analysis of variance of cutting time model T.

Source	Df	Sum of squares	Mean Squares	*F-ratio*	*Prob.* > *F*	R^2 adj.
Regression	3	2960.7063	986.9021	47.5229	< 0.0001	0.8429
Residual	23	477.6383	20.7669			
Total	26	3438.3446				
Effects	Df	Sum of squares	Contribution (%)	*F-ratio*	*Prob.* > *F*	
ap	1	75.8501	2.21	3.6525	0.0685	not significance
f	1	2059.3223	59.89	99.1638	< 0.0001	significance
Vc	1	825.5339	24.01	39.7524	< 0.0001	significance

As expected, the cutting time T model is function of cutting speed V_c (m/min) and feed rate f (mm/rev). Depth of cut a_p is not significant.

4.3 Consumed power models Pu

The evolution of the consumed power Pu models in function of cutting parameters have studied :

$$Pu = 4.8370 + 1.5722\,X_1 + 1.8611\,X_2 + 2.0556\,X_3 \quad (9)$$
$$= -7.7130 + 3.1444\,a_p + 12.4074\,f + 0.0206\,V_c \quad (10)$$

Table 5. Analysis of variance of consumed cutting power model Pu.

Source	Df	Sum of squares	Mean Squares	*F-ratio*	*Prob.* > *F*	R^2 adj.
Regression	3	182.8967	60.9656	41.3066	< 0.0001	0.8230
Residual	23	33.9463	1.4759			
Total	26	216.8430				
Effects	Df	Sum of squares	Contribution (%)	*F-ratio*	*Prob.* > *F*	
ap	1	44.4939	20.52	30.1464	< 0.0001	significance
f	1	62.3472	28.75	42.2428	< 0.0001	significance
Vc	1	76.0556	35.07	51.5307	< 0.0001	significance

In accordance with the machining theory, the consumed cutting power Pu is affected by the selected parameters: cutting speed V_c, feed rate f and depth of cut a_p in decreasing order.

4.4 RMS accelerations models

The three models of RMS cutting axial (X), radial (Y) and tangential (Z) accelerations are described below:

$$Ax = 48.4074 + 8.6344\,X_1 + 24.0433\,X_2 + 34.9728\,X_3 \quad (11)$$

Fig. 5. Comparison of predicted and measured values of Consumed cutting power *Pu*

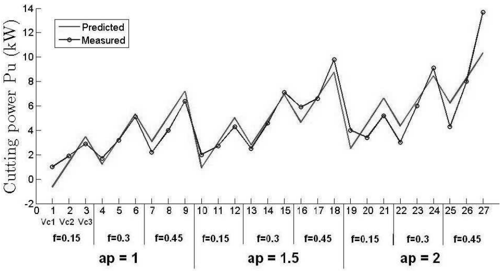
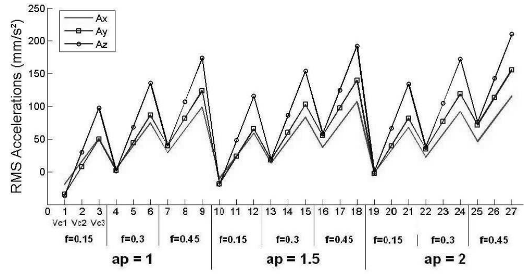


Fig. 6. Predicted values of RMS accelerations A_x, A_y, A_z



$$= -95.5281 + 17.2689\, a_p + 160.2889\, f + 0.3497\, V_c \quad (12)$$

$$Ay = 60.5948 + 16.0694\, X_1 + 37.0956\, X_2 + 42.2728\, X_3 \quad (13)$$

$$= -146.3502 + 32.1389\, a_p + 247.3037\, f + 0.4227\, V_c \quad (14)$$

$$Az = 86.6889 + 18.1933\, X_1 + 38.3544\, X_2 + 67.3789\, X_3 \quad (15)$$

$$= -179.3578 + 36.3867\, a_p + 255.6963\, f + 0.6738\, V_c \quad (16)$$

In these models, the order of effects is respected: first the cutting speed, then the feed rate and finally the depth of cut.

Table 6. Analysis of variance of RMS acceleration model in tangential direction A_z.

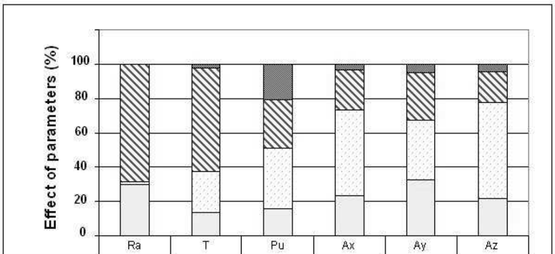
Source	Df	Sum of squares	Mean Squares	*F-ratio*	*Prob. > F*	R^2 adj.
Regression	3	114155.56	38051.8527	27.5929	< 0.0001	0.7542
Residual	23	31718.04	1379.0452			
Total	26	145873.60				
Effects	Df	Sum of squares	Contribution (%)	*F-ratio*	*Prob. > F*	
ap	1	3957.953	4.08	4.3203	0.0490	significance
f	1	26479.141	18.15	19.2011	0.0002	significance
Vc	1	81718.464	56.02	59.2573	< 0.0001	significance

The tool vibrations are greater in the tangential direction compared with the others directions axial and radial as illustrated in figure 6. The tangential accelerations A_z are analyzed in table 6, the effect of cutting speed (56%) is more important than the two other effects: feed rate (f) and dept of cut (ap) respectively (18%) and (4%).

4.5 Discussions

In this study, globally, depth of cut is not a significant parameter. It's due to the range chosen. Thus, depth of cut has not a significant effect on surface roughness, thus indicating that a minimum cutting tool vibration can be obtained by decreasing the depth of cut without significant change in the value of surface roughness, but the decrease of depth of cut has an effect on cutting time and consumed cutting power, so the operator must choose this parameters depending on the surface roughness and productivity desired. Feed has major contribution on surface roughness (68%) and cutting time (around 60%). The others process parameters are affected at the lowest level (around 25%). The cutting speed although highly significant for the tool vibrations on X and Z directions (around 50%) and minor significance on Y direction and consumed power of machine tool (35% each one). The lowest significant level is obtained for the cutting time (24%).

Fig. 7. Percentage contribution of cutting parameters on various process parameters (Ra, T, Pu, A_x, A_y, A_z).



	Ra	T	Pu	Ax	Ay	Az
depth of cut	0,26	2,21	20,52	3,03	5,11	4,08
Feed rate	68,19	59,89	28,75	23,53	27,21	18,15
Cutting speed	1,45	24,01	35,07	49,78	35,33	56,02
residual	30,1	13,89	15,66	23,66	32,35	21,75

In the Fig. 7, it is clear that each selected parameters affect one or more process parameters in a significant manner.

5 Conclusions

Regression analysis is performed to find out the effects of selected cutting parameters like cutting speed, depth of cut and feed rate on the resulting surface roughness, consumed power, cutting time and tool vibrations during a dry turning of 100C6 steel.

The results of ANOVA have proved that the proposed mathematical models could adequately describe the performance indicators within the limits of the factors that are being investigated with 95% confidence interval.

The analysis of models results show that the surface roughness is influenced only by the feed rate, the cutting time increase principally with the feed rate, the consumed power is affected by a combination of cutting parameters and the tool vibration increase principally with cutting speed. The models found in this study will be used in a second part for optimizing of cutting parameters using a genetic algorithm.

This study should help the operator to choice the cutting parameters depending on the surface quality (surface roughness *Ra*) desired productivity (Cutting time T) and used machine (cutting time T and consumed power *Pu*) with controlling vibrations (tool accelerations A_x, A_y, A_z).

The results of this study are valid for 100C6 steel and selected parameters and their specified ranges. Any extrapolation must be confirmed through further experimentation.

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