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Predictive Modelling and Optimisation of Surface Roughness in Turning of AISI 1050 Steel Using Polynomial Regression

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An investigation has been conducted to address the surface integrity optimisation and prediction issue by applying the polynomial regression method for a variety of experiments and cutting conditions. A higher correlation coefficient (R^2) was obtained with a cubic regression model, which had a value of 0.9480 for Ra. The use of the response surface optimisation and composite desirability show that the optimal set of machining parameters values are (250m/min, 0.2398 mm/rev and 2.3383 mm) for cutting speed, feed and depth of cut, respectively. The optimised surface roughness parameter and productivity are Ra =2.7567 μm and Q = 95.341*10³ mm³/ min, respectively. Results show that the models developed can accurately predict the roughness on the basis of measured cutting conditions as input parameters, and can also be used to control the surface roughness by making a comparison between measured and estimated values. Furthermore, operators can benefit from the proposed models if the aim is the reverse determination of the cutting conditions corresponding to the requested roughness profile.

Keywords: Surface roughness, Cutting conditions, Polynomial regression, ANOVA, Optimisation

1 Introduction

A machined surface is the result of the geometric and kinematic reproduction of the shape and trajectory of the tool tip. As a result, the surface texture contains parallel lays (precisely helical texture) that characterises the surface roughness. Surface quality is one of the most relevant aspects of machining operations, since it represents the final phase in the production cycle for improving the degree of surface finish on mechanical parts. It is important, therefore, to be aware of the influence of the various factors involved in the cutting process in order to choose the appropriate parameters that achieve the desired quality of the surfaces and which depend on the geometry of the tool, cutting conditions and factors involved during cutting, because even small changes in any of these factors, however small they may be, are susceptible to have a significant effect on the produced surface[1]. Surface integrity considerations lead to the development of accurate predictive models of the surface roughness, thus significantly contributing to improving the surface quality of manufactured parts as well as reducing the total production cost. Accordingly, modelling and optimisation are necessary for understanding and controlling any process. It is therefore important for researchers to model and quantify the relationship between roughness and the parameters affecting it. Modelling with polynomial regression, surface response and neural networks have become the most appropriate methods. Several investigations have been made to model surface roughness as a function of various process parameters. One of the first empirical models to estimate surface roughness variation considers a combination of a geometric factor and a cutting parameter [1, 2]. A more elaborate empirical model for surface roughness takes the form of an exponential function of feed (f), tool nose radius (r), cutting speed (Vc) and depth of cut (Ap) as suggested by Fang and Safi-Jahanshaki[3]. However, the results of these empirical models were not very satisfactory, and cannot cater for the complex interactions of the various factors. For this reason, the use of new models and methods has become necessary to resolve the problem. Many models of surface roughness prediction, using Polynomial Regression, Surface Response, Taguchi methods, Statistical methods and Neural Networks have been developed. A study by Fang and Safi-Jahanshaki [3] was conducted for a new algorithm to establish general predictive surface roughness equations to cater for the effects of different tool chip breakers and work materials. They showed that the second order model is the most accurate model, compared to the developed linear and exponential models, giving the best fit to the experimental results. Choudhury and El-Baradie [4], have developed a model for surface

roughness prediction using the Response Surface Method (RSM) by combining their methodology with factorial design of experiments. Their results showed that the effect of the feed on the surface roughness, is much more pronounced than that of the cutting speed and depth of cut. Prediction and control of surface roughness in CNC (computer numerically controlled) lathe using artificial neural network was the aim of a study by Durmus Karayel [5] who developed a control system for surface roughness. Mathematical models that relate the roughness value, the cutting parameters and the hardness of the materials were established for different types of steel such as AISI 1020, AISI 1045 and AISI 4140, by Munoz and Cassier[6]. They found that surface finish could be improved by increasing cutting speed and tool nose radius and by decreasing the feed rate. The Taguchi method has been used by Paulo Davim [7] who showed that cutting speed had a greater influence on the roughness followed by the feed, while the depth of cut had no significant influence on surface roughness. With the intent to develop a surface roughness prediction model of AISI 410 steel in order to investigate the influence of machining parameters, based on a statistical method under various cutting conditions, using the response surface methodology and a (3^4) full factorial design of experiments, Makadia and Nanavati [8] have developed a quadratic model with a 95% confidence level. Özel and Karpat [9] used regression and artificial neural network models for predicting the surface roughness and tool wear in hard turning of AISI H11 steel with Cubic Boron Nitride (CBN) tools inserts. The results showed that decreasing the feed rate and increasing the cutting speed resulted in a better surface roughness . Hamdi Aouici et al. [10] have analysed the effects of the cutting speed, feed rate, work piece hardness and depth of cut on the surface roughness and cutting force components in the hard turning of AISI H11 steel hardened to (40, 45 and 50) HRC, using cubic boron nitride tool. Their results showed that the cutting force components are influenced principally by the depth of cut and work piece hardness. On the other hand, both the feed rate and the work piece hardness have statistically significant influence on the surface roughness. Optimising the turning of raw workpieces of low-carbon steel with low cold pre-deformation to achieve acceptable surface roughness was the object of a study by Kopac et al. [11]. They considered the cutting speed, cutting tool material, feed rate and depth of cut as cutting parameters in machining of C15 E4 steel on a lathe. They used the Taguchi orthogonal array methods and the quality determinant of (the smaller the better) to calculate the signal to noise ratio. They observed that the cutting speed is the most powerful control factor of the process and the depth of cut is the third most influential factor. Ilhan Asilturk and Harun Akkus [12]

conducted a parameters optimisation in CNC turning hardened AISI 4140 (51 HRC) with coated carbide cutting tools based on the Taguchi method to minimise surface roughness (Ra and Rz).The statistical methods of signal to noise ratio (SNR) and the analysis of variance (ANOVA) are applied to investigate the effects of the cutting speed, feed rate and depth of cut on the surface roughness. Results indicated that the feed rate has the most significant effect on Ra and Rz. In addition, the effects of two factor interactions of the feed rate-cutting speed and depth of cut-cutting speed appear to be important. They have also developed a model in order to determine the optimum cutting parameters for minimum surface roughness. The Taguchi optimisation of surface roughness and flank wear during the turning of DIN 1.2344 tool steel was used by Fuat Kara [13], where the optimum machining conditions were determined by investigating the surface roughness and flank wear depending on the machining parameters. The effects of the machining parameters on surface roughness and flank wear were found using the analysis of variance (ANOVA). Work by Abdul-lateef Al-Abdullah et al.[14], showed that the surface roughness measured on all tools increased in parallel with increasing feed rate. Increasing the feed rate causes the cutting forces and vibration to increase along with an escalation of the chip volume lifted by the unit, all of which lead to increased surface roughness. In addition, the increase in the feed rate causes the temperature at the cutting tool-workpiece interface to rise. As with the cutting speed, the temperature increase in the interface also causes tool wear and, consequently, leads to surface roughness and deformation.The study of Tourab Mohamed et al.[15] was conducted to determine a mathematical models statistically based on experimental design which allows to give the relationship between the two out parameters surface roughness and hardness, caused by the four internal roller-burnishing parameters called: burnishing speed, force, feed and number of passes of the tool. Their results showed that feed, burnishing force and speed are the most important and significant parameters to improve roughness surface, and feed, speed, burnishing force and number of passes are the most important and significant parameters to improve superficial hardness of S 355 J0 steel specimens. Analysis of the effect of machining parameters on surface roughness of stainless steel X153CrMoV12-1 in CNC milling of slope surfaces with sintered carbide tool was the object of the research of Ondřej Bílek et al.[16]. They have also determined linear regression models and probability dendrograms of similarities for cutting conditions, cutting tools and slope of machined surfaces.

In this paper, the principal objective is to predict and optimise the surface roughness values, of heat

treatable steel AISI 1050, in terms of cutting parameters such as the cutting speed, feed, and depth of cut with the search for the best appropriate models using Polynomial Regression, Surface Response and Statistical methods (ANOVA). It is also intended to determine the effects of the cutting parameters on the surface roughness. To calculate the constant and coefficients of these models, a calculation code on Matlab is used. From the above literature survey, it can be seen that no study has been carried out to study the effect of machining parameters using a third order polynomial model. The developed models (linear, quadratic and cubical) have been analysed and compared based on the increase of the correlation coefficient R^2, decrease of root mean square error (RMSE) and the analysis of the variance (ANOVA). At the end of the paper the cubic model of response surface optimisation was utilised to find the optimum cutting parameters values which correspond to the surface roughness and metal-removal rate optimal values.

2 Material and experimental conditions

2.1 Material

The tested material is a Heat treatable steel AISI 1050 for which the chemical composition is given in Table 1. The hardness is equal to 188 HV. The studied material is supplied in the form of 60 mm diameter cylindrical rolled bars. This steel is used in the mechanical engineering after normalisation, improvement and surface hardening, for a variety of parts (crankshafts, connecting rods, camshaft and pinions). In the normalised state, it has a high resistance compared to low carbon steel but its ductility is lower.

2.2 Machining of specimens and cutting tool used

Our work is based on obtaining experimental results and setting up resources for turning a heat treatable AISI 1050 steel with general purpose carbide insert tool P15 type DNMG 15-06-08 with three cutting edges and mechanically fixed. This turning insert has been used during the whole experiment by rotating it to minimise the effect of cutting edge wear.

The turning was carried out on a parallel universal lathe of the " MONDIALE GALLIC 16 N Center Lathe" type, with a maximum spindle rotation speed of 2000 rpm and a 7.5KW motor drive. The wortkpiece was mounted in a mixed assembly to ensure its good rigidity during machining (Fig.1). During this operation, lubrication is provided by means of an electric pump to preserve the mechanical and metallurgical characteristics of the material.

The machining tests are conducted considering three cutting parameters: the cutting speed (Vc), the feed (f) and the depth of cut (Ap) with 5 variation levels. In doing so, a total of (5^3 = 125) cutting experiments are carried out as shown in Table 2.

2.3 Roughness measurement

The surface roughness obtained after machining with the conditions mentioned above, is measured on the surfaces separated by grooves on the same test piece using a roughness tester of the SURFTEST SJ-310 type with electronic inductive diamond sensor (Fig.2). The measurements were carried out normal to the cutting direction. To avoid roughness measurement errors, the same path is used with only one direction of the left or right probe [17]. The center line average parameter Ra is used to characterise the roughness. It is defined as the average arithmetic mean deviation of the ridges and furrows. The length examined is 4.0 mm with a 0.8 mm basic span. This roughness was directly measured on the work piece, without dismounting from the lathe, to minimise measurement uncertainty due to carrying on operations. Each measurement was repeated three times at least to increase the average value accuracy. The experimental results and the standard deviation of the measured roughness Ra are shown in Fig.3. A low standard deviation can be seen which indicates that the values tend to be close to the mean of set.

Tab. 1 *Chemical composition of AISI 1050 Steel*

Elements	C%	Mn%	SI%	S%	P%
Composition in %	0.48	0.6	0.25	0.030	0.027

Tab. 2 *Cutting parameters*

Depth of cut (mm)	Feed (mm/rev)	Cutting speed(m/min)
0.5	0.05	50
1.0	0.1	100
1.5	0.15	150
2.0	0.2	200
2.5	0.25	250

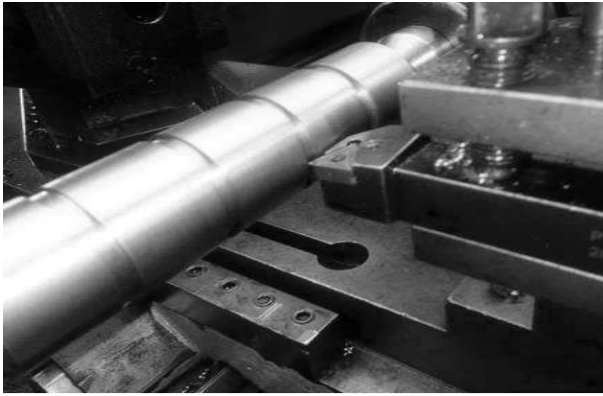
Fig. 1 *Tool-Piece assembly on the lathe*

Fig. 2 *Roughness measuring tool assembly*

3 Polynomial regression

The aim of this section is to show details of the Bivariate and trivariate polynomial regression models (BPR and TPR) developed to estimate surface roughness using cutting conditions. When there are more than one independent variable, the model is called a multiple regression model and the regression is termed as multivariate regression. In the following, we develop the multiple regression models (BPR and TPR) and calculate their parameters. Two and three variables polynomial regression of total degree n models can be constructed respectively as follows [18]:

$$P(x,y) = \sum_{k=0}^{n} \sum_{i=0}^{k} \beta_{ik} x^i y^{k-i} , \qquad (1)$$

With $k > i$

$$P(x,y,z) = \sum_{k=0}^{n} \sum_{j=0}^{n} \sum_{i=0}^{k,j} \beta_{ijk} x^i y^{k-i} \beta_{ik} x^i y^{j-k} z^{k-i}, \quad (2)$$

With $k > i$ and $j > k$

Where: x, y and z represent the cutting conditions (Ap, f and Vc) and P represent the surface roughness Ra.

Using the above models we can estimate the surface roughness with Bivariate Quadratic Polynomial Regression Model, Bivariate Cubic Polynomial Regression Model, Trivariate Quadratic Polynomial Regression Model and Trivariate Cubic Polynomial Regression Model, shown in table 3 (appendix).
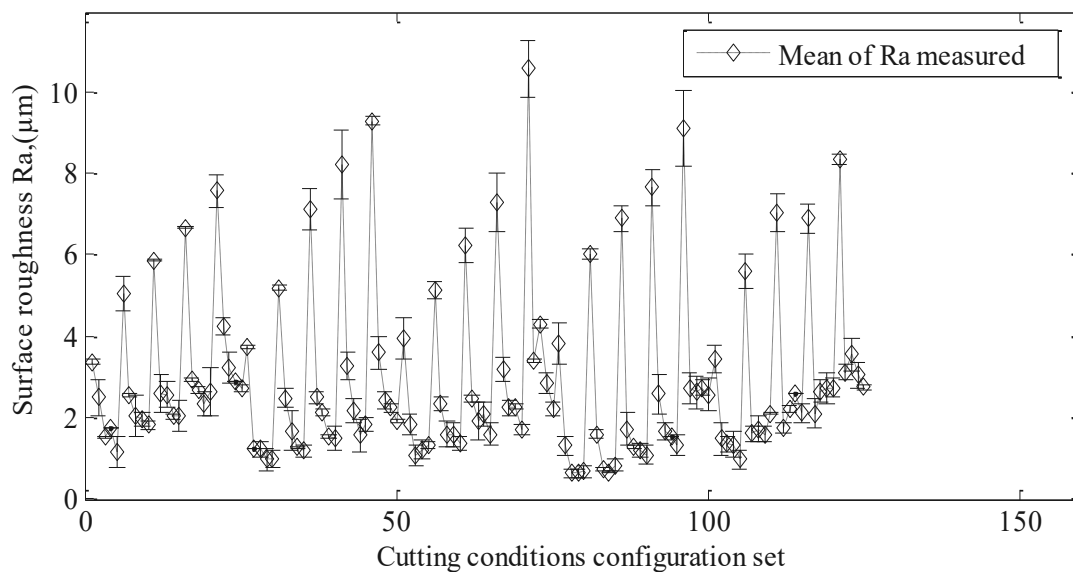

Fig. 3 *Standard deviations of surface roughness measurement*

4 Modeling, analysis and discussion of results

4.1 Modeling and analysis of experimental data

The models obtained take into consideration the linear, quadratic, cubic and interaction effects. The regression coefficients of these models allow the relationship between the surface roughness and the three studied parameters (feed f, depth of cut Ap and cutting speed Vc) to be expressed. These coefficients are obtained using a calculation code on Matlab.

Table 3 gives the set of models obtained and their coefficients of determination (correlation) R^2, which define the variation ratio of the results of the model and those of the experiment. When this coefficient (R^2) approaches unity, this means that the model is perfectly suited to the measurement results of the envisaged output responses. The Root Mean Square Error (RMSE) is also an evaluation factor for the model. Variables are gradually introduced into the model according to a criterion based on the increase in the coefficient R^2. Their selection can be challenged after introduction of a new variable according to the same (R^2) criterion.

Tab. 3 *Performance parameters of the developed models*

Models kinds	Linear			Quadratic			Cubic		
Variables	Model	R^2	RMSE	Model	R^2	RMSE	Model	R^2	RMSE
2 var (Ap,f)	Ra=11.5696 *f - 0.0916* Ap +1.2876	0.1571	1.9006	Ra = 0.1905*Ap^2 + 0.8616 *Ap.*f - 0.7924 *Ap +9.7829 *f^2 + 7.3423 *f + 1.9861	0.1595	1.8980	Ra=0.3533*Ap.^3-1.8640*Ap.^2*f-1.1199*Ap.^2+1.2457*Ap.*f.^2+6.07 99*Ap.*f+0.4753*Ap+376.2667*f.^3-161.4057*f.^2+26.8406*f+0.9105	0.1630	1.8940
2 var (Ap,Vc)	Ra= - 0.0199 *Vc - 0.0916* Ap +6.0077	0.4629	1.5172	Ra = 0.1905*Ap.^2 + 7.0400e-005 *Ap.*Vc- 0.6737 *Ap+ 2.2462e-004 *Vc.^2 -0.0874*Vc+10.2878	0.6704	1.1885	Ra=0.3533*Ap.^3+0.0070*Ap.^2*Vc -2.4459 *Ap.^2+ 3.5154e-005 *Ap.*Vc.^2- 0.0314 *Ap.*Vc+ 5.1654*Ap - 2.3456e-006*Vc^3+ 0.0012*Vc^2 -0.1978 *Vc+ 11.7175	0.7419	1.0517
2 var (f,Vc)	Ra=11.5696 *f - 0.0199*Vc+4.1349	0.6181	1.2794	Ra= 9.7829 *f.^2 - 0.0750 *f.*Vc)+ 19.8895 *f+ 2.2462e-004 *Vc.^2 - 0.0760 *Vc+6.5487	0.8573	0.7819	Ra = 376.2667 *f.^3 +0.0774 *f.^2.*Vc -171.1429*f.^2+8.1680e-004*f.*Vc.^2- 0.3433 *f.*Vc + 59.8650*f- 2.3456e-006*Vc^3 0.0012*Vc^2-0.1763 *Vc +8.3371	0.9303	0.5464
3 var (Ap,f,Vc)	Ra=11.5696 *f - 0.0916* Ap - 0.0199 *Vc+4.2723	0.6191	1.2777	Ra= 0.1905*Ap^2 + 0.8616*Ap*f + 7.0400e-005 *Ap*Vc - 0.8029 *Ap + 9.7829*f^2 - 0.0750 *f*Vc+ 18.5971*f + 2.2462e-004*Vc^2- 0.0761*Vc +7.2292	0.8602	0.7740	Ra = 0.3533 *Ap.^3) - 1.8640 *Ap.^2.*f + 0.0070 *Ap.^2.*Vc - 2.1663 *Ap.^2 +1.2457 *Ap.*f.^2 + 0.0093 *Ap.*f.*Vc + 4.6915 *Ap.*f + 3.5154e-005*Ap.*Vc.^2 - 0.0328 *Ap.*Vc + 4.4274 *Ap + 376.2667*f.^3 + 0.0774 *f^2.*Vc - 173.0114 *f.^2 + 8.1680e-004*f.*Vc.^2 - 0.3572	0.9480	0.4723

These models (linear, quadratic and cubic) generated for the same experimental data sets are compared and are shown in Fig 4. It should be noted that in models combining two variables (linear, quadratic and cubic) the two most influential factors are the feed (f) and the cutting speed (Vc).

For the models with all variables and their interactions, the cubical model given in eq.3 is the most appropriate model with a correlation coefficient R²=0.9480, AdjustedR²= 0.9385 and RMSE= 0.4723. This means that 93.85% of the roughness variations are explained by the model, and 6.15% consequently

remain unexplained. The value of the adjusted determination coefficient (AdjustedR²) of this surface roughness model represents a correction of R², which allows taking into account the number of variables used in the model. Both ratios show a good correlation between this model and the experimental data. So, The cubic model was, therefore used for further analysis. The second most appropriate model is still the cubic one with only two variables **f** and **Vc** (R²= **0.9303**, AdjustedR²= **0.9249** and RMSE= **0.5464**). This leads us to suggest that the feed and the cutting speed are the most influential parameters.

$$
\begin{aligned}
R_a = {}& 0.3533Ap^3 - 1.8640Ap^2f + 0.0070Ap^2V_c - 2.1663Ap^2 + 1.2457Apf^2 + 0.0093ApfV_c + \\
& 4.6915Apf + 3.5154e^{-005}ApV_c^2 - 0.0328ApV_c + 4.4274Ap + 376.2667f^3 + 0.0774f^2V_c - \\
& 173.0114f^2 + 8.1680e^{-004}fV_c^2 - 0.3572fV_c + 57.9538f - 2.3456e^{-006}V_c^3 + 0.001\text{l}V_c^2 - 0.1463V_c + 5.6658
\end{aligned}
\tag{3}
$$

In order to confirm the effect of the input parameters on the surface roughness, an analysis of variance (ANOVA) was applied on the selected model. The model is considered to be statistically significant if the probability (p-value) is less than 0.05 (95% confidence). A low p-value indicates statistical significance for the corresponding source of responses. The percentage contribution of machining parameters was estimated based on the sum of squares of responses. The relative importance of factor Ap

influencing the surface roughness was computed as the percentage contribution (PC_{Ap}) using:

$$
PC_{Ap} = \frac{SS_{Ap}}{SS_{Total}} \times 100
\tag{4}
$$

The sum of squares due to a factor is equal to its total squared deviation from the overall mean. In the present study, there were 25 experiments for each factor at each level. The sum of squares due to factor Ap (SS_{Ap}) was computed using:

$$
SS_{Ap} = 25\left(R_{aAp1} - R_{am}\right)^2 + 25\left(R_{aAp2} - R_{am}\right)^2 + 25\left(R_{aAp3} - R_{am}\right)^2 + 25\left(R_{aAp4} - R_{am}\right)^2 + 25\left(R_{aAp5} - R_{am}\right)^2,
\tag{5}
$$

Where, Ra_{Ap1}, Ra_{Ap2}, Ra_{Ap3}, Ra_{Ap4} and Ra_{Ap5} are the mean of Ra at the levels 1, 2, 3, 4 and 5 of the factor Ap, respectively, and Ram is the mean of responses. Similarly, the total sum of squares due to factor f (SS_f) and Vc (SS_{Vc}) and their respective percentage contribution PC_f and PC_{Vc} were computed as detailed

above.

The total sum of squares (SS_{Total}) was computed using:

$$
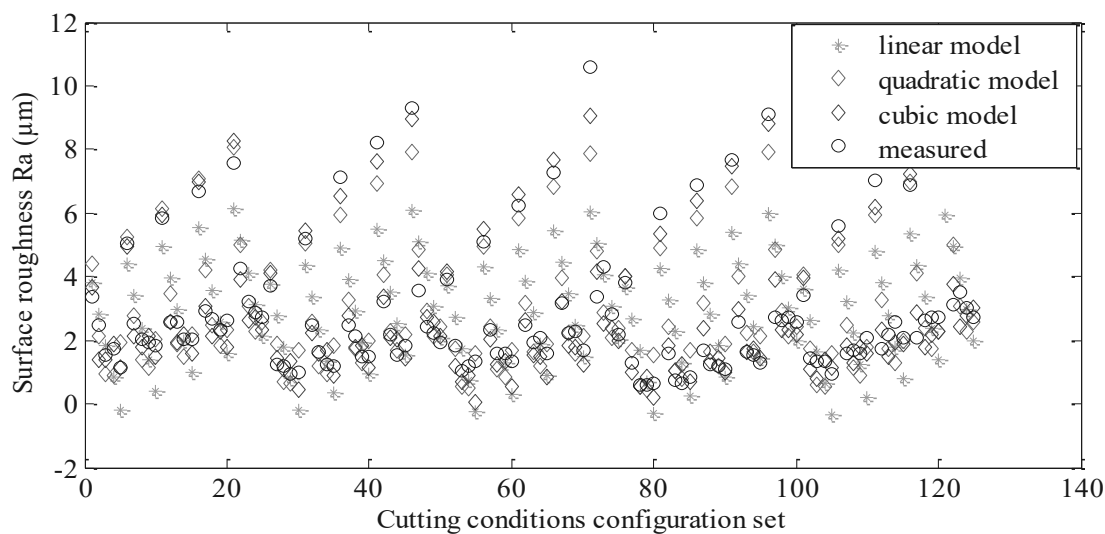SS_{Ap} = \sum_{1}^{125} \left(R_{aAp1} - R_{am}\right)^2 ,
\tag{6}
$$

***Fig. 4** Surface Roughness evolution with cutting conditions*

The results of the ANOVA are summarised in table 4. It is important to observe that the p-values are less than 0.05 in most of cases. So obtained model is

considered to be statistically significant. It can be seen that the terms chosen in the model have significant effects on the responses. More precisely, it is

established that the cutting speed and the feed are the most influential. This confirms the suggestion made in modelling and analysis (section 4.1). Some terms are less significant on generation of surface roughness: (f.^2, f^2.*Vc, f.^3, Ap.*f, Ap.*f.^2, Ap.^2.*f, Ap.^3 and Ap.*f.*Vc). Similar observations were also made by Dureja et al. [19], H. Aouici et al. [10]. and S. Benlahmidi, et al[20], especially for second order terms and bi- interaction parameters , except cutting speed Vc with Dureja and Aouici which is not significant parameter in their model. The result of the percentage contribution of cutting conditions on response surface roughness is shown in Fig.5.

The principal aim of this study is to predict the surface roughness values corresponding to the cutting parameters but we can also determine the effects of cutting parameters on surface roughness. The surface roughness obtained can be analyzed in three different states according to the variation of cutting parameters: Firstly the parameters were simultaneously variable as shown in Fig.6. In this case we have a complex representation which makes the interpretation difficult. The second state is that one of the parameters is variable while the other two are constant. This representation has been preferred for the analysis of the effects of cutting parameters on surface roughness, and some plots of surface roughness according to this configuration have been presented in Fig.7 (a–c), Fig.8 (a–c) and Fig.9 (a–c). Thirdly, one parameter is kept constant as the other two parameters are variable. It is thus possible here to plot 3D surface graphs for the surface roughness as shown in Fig.10 (a-c) and they are essential. The plots of these 3D surfaces can be used to approximate the surface roughness values for any appropriate combination of the input parameters such as cutting speed, feed and depth of cut.
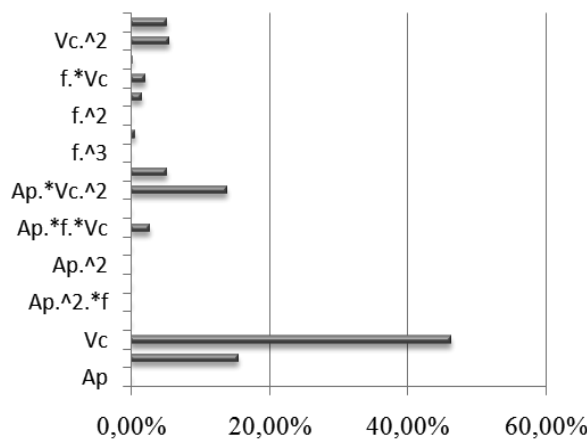

Fig. 5 *Percentage contribution of parameters*

Fig.7 shows that a good surface roughness can be obtained for a higher cutting speed and it is clear that the surface roughness decreases quickly with increasing cutting speed. In Fig.8 it can be seen that reducing the feed improves the surface roughness and

more particularly at a cutting speed of Vc=50 m/min.

The depth of cut has a slight effect on the surface roughness whose variation curve is roughly horizontal as shown in Fig.9.
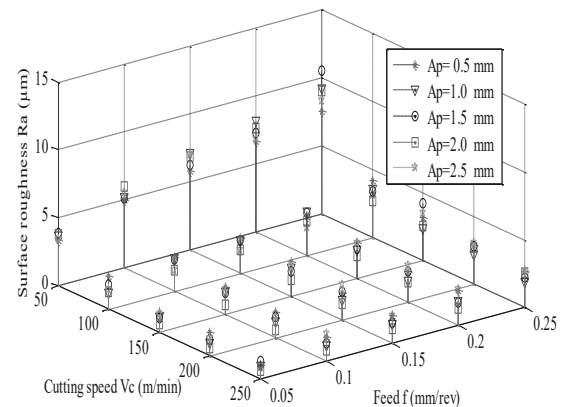
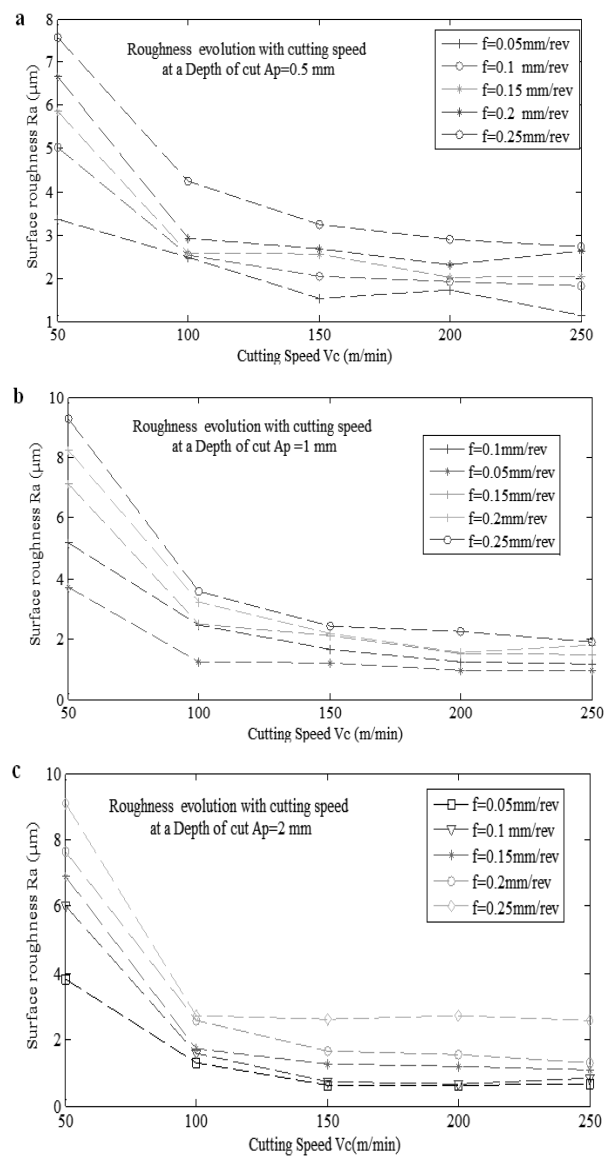

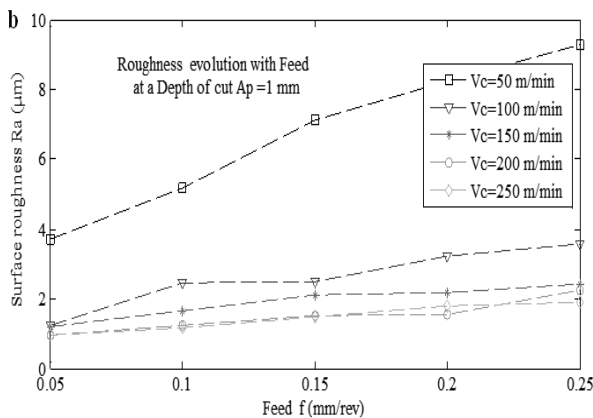**Fig. 6** *Effects of cutting parameters on surface roughness*

Fig. 7 *Effects of cutting parameters on surface roughness varying cutting speed while keeping depth of cut and feed are constant*

Tab. 4 *Analysis of Variance*

| Source	DF	Seq SS	Contribution%	Adj SS	Adj MS	F-Value	P-Value
Regression	19	507.825	94.8%	507.825	26.7276	100.67	0.000
Ap	1	0.524	0.1%	1.728	1.7275	6.51	0.012
f	1	83.66	15.62%	2.96	2.96	11.15	0.001
Vc	1	247.447	46.19%	18.864	18.8643	71.05	0.000
Ap.^3	1	0.959	0.18%	0.702	0.7023	2.64	0.107
Ap.^2.*f	1	0.102	0.02%	0.38	0.38	1.43	0.234
Ap.^2.*Vc	1	0.203	0.04%	5.323	5.3227	20.05	0.000
Ap.^2	1	0.593	0.11%	1.157	1.1567	4.36	0.039
Ap.*f.^2	1	0.445	0.08%	0.002	0.0017	0.01	0.936
Ap.*f.*Vc	1	14.808	2.76%	0.134	0.1339	0.5	0.479
Ap.*f	1	1.2	0.22%	0.121	0.1208	0.46	0.501
Ap.*Vc.^2	1	74.589	13.92%	1.352	1.3517	5.09	0.026
Ap.*Vc	1	27.921	5.21%	5.903	5.9029	22.23	0.000
f.^3	1	0.145	0.03%	0.796	0.7964	3	0.086
f^2.*Vc	1	3.562	0.66%	0.065	0.0655	0.25	0.621
f.^2	1	0.414	0.08%	0.738	0.7378	2.78	0.098
f.*Vc.^2	1	8.662	1.62%	7.297	7.2971	27.48	0.000
f.*Vc	1	11.112	2.07%	7.003	7.0027	26.38	0.000
Vc.^3	1	1.391	0.26%	30.948	30.9478	116.56	0.000
Vc.^2	1	30.089	5.62%	30.089	30.0895	113.33	0.000
Error	105	27.878	5.2%	27.878	0.2655		
Total	124	535.703	100.00%				
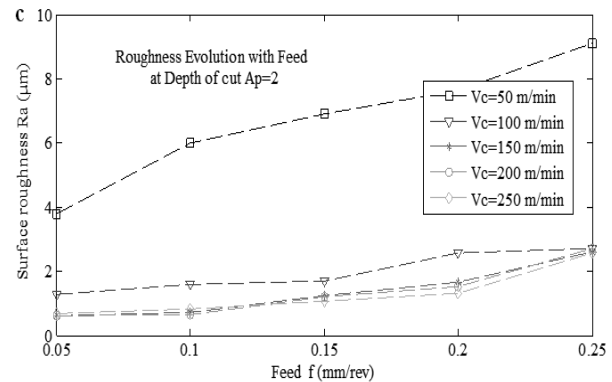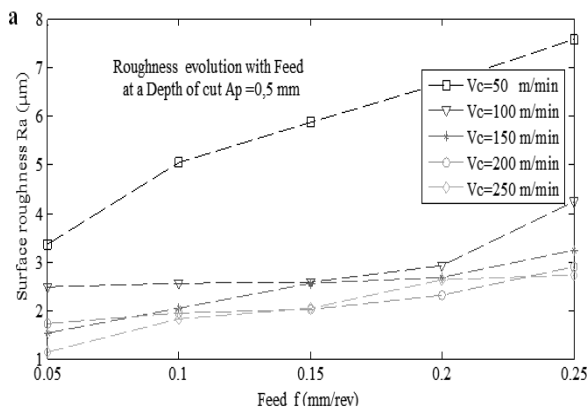
Fig. 8 *Effects of cutting parameters on surface roughness varying feed while keeping depth of cut and cutting speed constant*
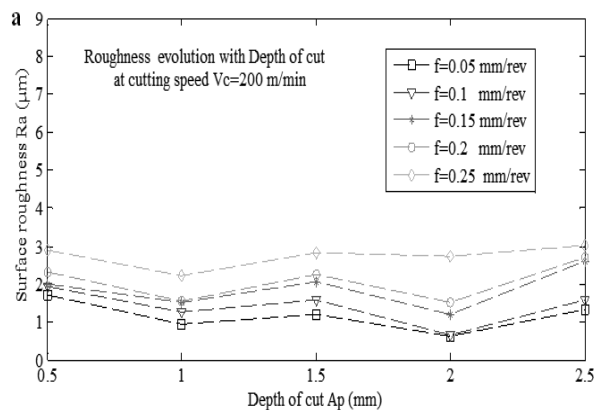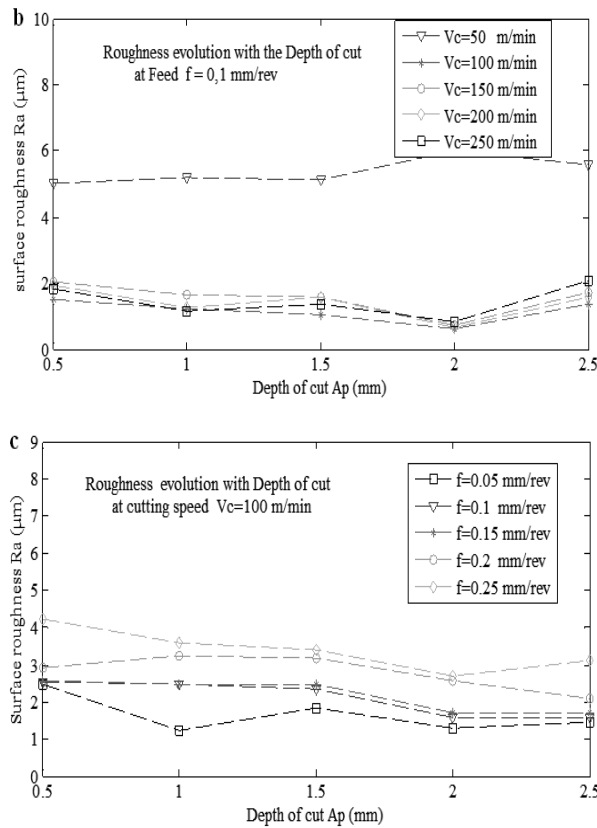
Fig. 9 *Effects of cutting parameters on surface roughness varying depth of cut while keeping cutting speed and feed constant*

4.2 Response surface

The relationship between the different operating variables and the studied response is illustrated in the three-dimensional representations of the response surfaces below. Figs.10.a gives 3D surface graphs for the surface roughness while the feed and cutting speed vary and the depth of cut is kept constant at a value of Ap = 0.5 mm. It indicates that surface roughness decreases when cutting speed increases whereas it increases with increase in feed. It can also be deduced from this figure, that the surface roughness (Ra) is statistically significant (Table 4). Fig.10. (b and c) give the graphs of the area for surface roughness at a feed of 0.2 mm/rev and Vc= 50 m/min respectively. They indicate that the depth of cut generally has a small influence on the surface roughness, only for some case (f=1.5mm/rev) explained by tool wear or machine vibration. In Fig.10 (a and c) it can also be observe that while Vc =50 m/min, the effect of feed (f) is very important relatively to other cutting speed values. The cutting speed increase from 50 to100 m/min rapidly reduces the surface roughness due to the reduction in built up edge (BUE) formation tendency. which is in agreement with the results found by D. P. Selvaraj et al. [21]. Work conducted by Kopac et al. [11] showed that cutting speed is the most powerful controlling factor for achieving the desired surface roughness in fine turning process, higher cutting speeds resulting in

smoother surfaces. The effect of feed (f) on surface roughness is also very important. Similar results were also made by Paulo Davim [7]. He showed that cutting speed has a greater influence on the roughness followed by the feed, while the depth of cut has no significant influence on surface roughness.
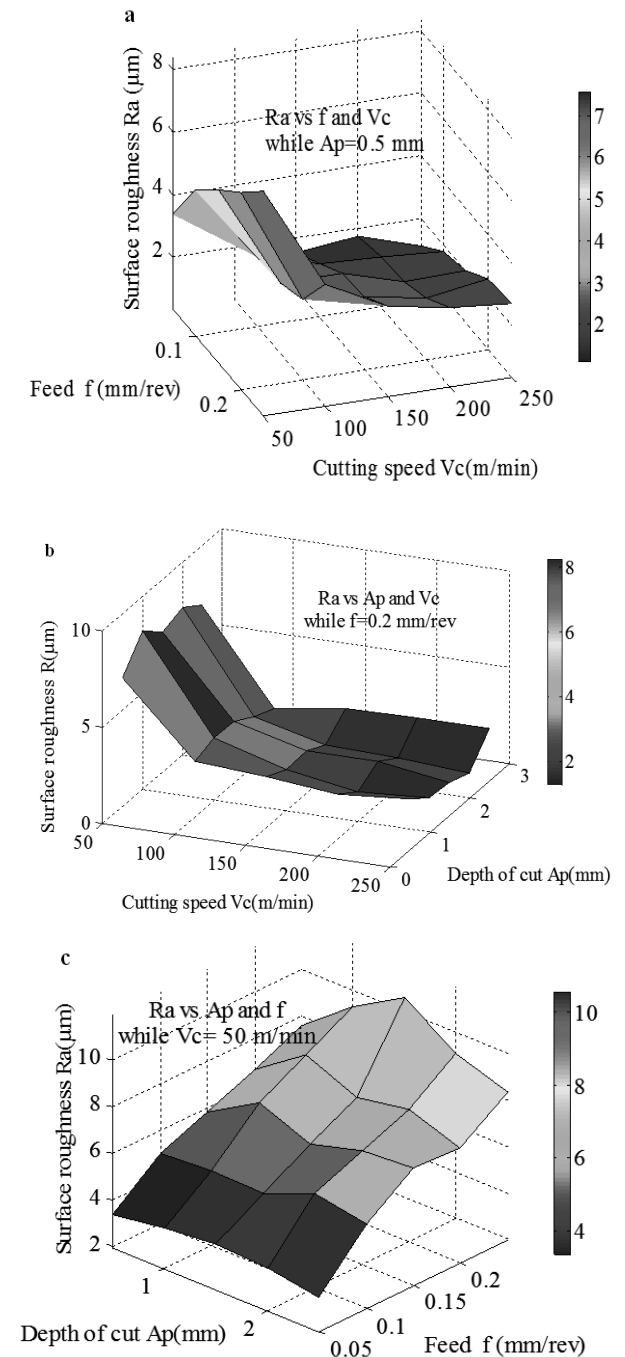

Fig. 10 *3D Surface graphs for (Ra): (a) as the cutting speed and feed vary, (b) as the depth of cut and cutting speed vary, and (c) as the depth of cut and feed vary*

5 Response optimisation

One of the most important aims of the experiments is to optimise values of cutting parameters (cutting speed, feed and depth of cut) which corresponds

to optimal surface roughness and productivity (metal-removal rate MRR). To this regard, the use of the response surface optimisation and composite desirability is an ideal technique to identify the combination of input variable settings (cutting parameters) that jointly optimise the surface roughness and productivity values in the turning process. In the present study the goal is to minimise surface roughness (Ra) and maximise the metal-removal rate. The Metal Removal Rate (MRR) Q (mm3/min) was calculated by the relationship below.

$$Q = 1000 \times Ap \times f \times V_c \qquad (7)$$

The RSM optimisation results for the surface roughness parameter (Ra) and productivity are shown in Fig.11 and Table.5. The optimal set of cutting parameters values are (250m/min, 0.2398 mm/rev and 2.3383 mm) for cutting speed, feed and depth of cut, respectively. The optimised surface roughness parameter and productivity are:

Ra =2.7567 μm and Q = 95.341*103 mm3/ min.

Tab. 5 *Response optimisation for surface roughness parameter and productivity*

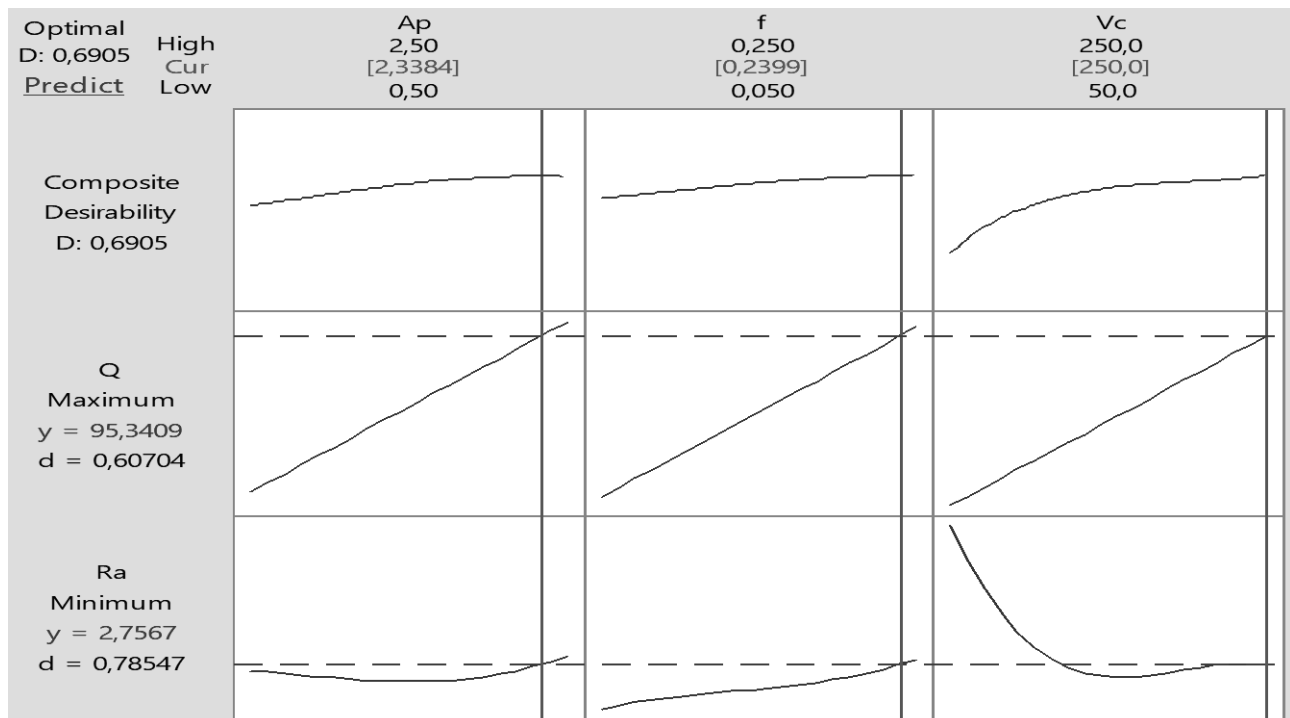| Parameters	Goal	Optimum Combination			Lower	Target	Upper	Predict response	Individual desirability d
		Ap	f	Vc					
Ra(μm))	Minimum	2.3383	0.2398	250		0.62	10.58	2.7567	0 .785
Q(mm³/min)	Maximum				1.25*10³	156.25*10³		95.341*10³	0.607
Composite desirability D = 0.6905									

Fig. 11 *Plot of response optimisation for surface roughness parameter and productivity*

6   Conclusion

The objective of developing surface roughness models is to provide a quantifiable reference so that the effects of different cutting conditions can be quantified. In the present study an attempt has been made to investigate the effect of cutting parameters on surface roughness and to develop models for predicting the surface roughness. Different models have been developed, namely linear, quadratic and cubical models with the interaction of two or all studied cutting conditions using polynomial regression. To evaluate these models and quantify the effects of cutting parameters on surface roughness, statistical analysis and surface response were used respectively. The study shows that:

The third order polynomial model (cubical model) developed with three variables, despite its complexity, was the best appropriate model that gives the best fit to experimental results, whereas the predicted surface roughness from this model is very close to the values measured experimentally with a determination coefficient R^2=0.9480.

Whatever the number of variables considered the cubic model offered the best performance.

The statistical analysis ANOVA indicate that most model terms are significant and only few terms are less significant to the generation of surface roughness. The most significant factor on the parameter Ra is cutting speed Vc in the first position with a contribution at 46.19% of the total variation. The next largest contribution on Ra comes from the feed f and interaction of depth of cut with cutting speed Ap.*Vc.^2 with a 15.62% and 13.92% contribution respectively. The depth of cut Ap present also a statistical significance on surface roughness parameters but with a value less than 0.10%.

The value of surface roughness is directly related to the feed and inversely related to cutting speed.

The optimum combination of machining parameters input values have given the optimal surface roughness and metal-removal rate when using response surface optimisation and composite desirability.

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References

[1] BOOTHROYD, G.W.A. (2006). *Knight, fundamentals of machining and machine tools*, third ed., CRC press, Taylor & Francis Group. ISBN 1-57447-659-2.

[2] WHITEHOUSE, D.J. (1994). *Handbook of Surface Metrology*, Institute of Physics Publishing, Bristol, UK. ISBN 0-7503-0039-6.

[3] FANG, X. D.; SAFI-JAHANSHAHI, H. (1997). A new algorithm for developing a reference-based model for predicting surface roughness in finish machining of steels, *International Journal of Production Research*, 1997, Vol. 35: Nr.1, pp. 179-199.

[4] CHOUDHURY, I.A., EL-BARADIE, M.A. (1997). Surface roughness in the turning of high-strength steel by factorial design of experiments. *Journal of Material Processing Technology*, 1997, Vol. 67, pp. 55– 61.

[5] DURMUS, K. (2009). Prediction and control of surface roughness in CNC lathe using artificial neural network, J*ournal of materials processing technology*, 2 00 9, pp. 3125–3137.

[6] ESCALONA, P.M., CASSIER, Z. (1998). Influence of critical cutting speed on the surface finish of turned steel, *Wear*, 1998, Vol. 218, pp. 103–109.

[7] DAVIM, J.P. (2001). A note on the determination of optimal cutting conditions for surface finish obtained in turning using design of experiments, *J. Mater. Process. Technol.*, 2001, Vol. 116, pp. 305–308.

[8] MAKADIA A.J., NANAVATI, J.I. (2013). Optimisation of machining parameters for turning operations based on response surface methodology, *Measurement*, 2013, Vol. 46, pp. 1521–1529.

[9] OZEL, T., KARPAT, Y. (2005). Predictive modeling of surface roughness and tool wear in hard turning using regression and neural networks, *International Journal of Machine Tools & Manufacture*, 2005, Vol. 45, pp. 467–479.

[10] HAMDI, A., MOHAMED A.Y., KAMEL C., TAREK M., JEAN-FRANÇOIS R. (2012). Analysis of surface roughness and cutting force components in hard turning with CBN tool: Prediction model and cutting conditions optimization, *Measurement*, 2012, Vol. 45, pp. 344–353.

[11] KOPAC, J., BAHOR, M., SOKOVIC, M. (2002). Optimal machining parameters for achieving the desired surface roughness in fine turning of cold preformed steel work pieces, *Int. J. Mach. Tools Manuf.*, 2002, Vol. 42, pp. 707–716.

[12] ILHAN, A., HARUN, A. (2011). Determining the effect of cutting parameters on surface roughness in hard turning using the Taguchi method, *Measurement*, 2011, Vol. 44, pp.1697–1704

[13] FUAT, K., (2017). Taguchi optimization of surface roughness and flank wear during the turning of DIN 1.2344 tool steel", *Material Testing*, 2017, Vol. 59, Nr.10, pp. 903-908.

[14] ABDUL-LATEEF, A., HAMID, A., CHEE, P.L., WISAM A.Y. (2018). Force and temperature modelling of bone milling using artificial neural networks, *Measurement*, 2018, Vol. 116, pp. 25-37.

[15] BÍLEK, O., PATA, V., KUBIŠOVÁ, M.,„ŘEZNÍČEK, M. (2018). Mathematical methods of surface roughness evaluation of areas with a distinctive inclination, *Manufacturing Technology*, Vol.18, No. 3, pp. 363-368.

[16] Mohamed, T., Hamid, H., Salah, A., Salim, B.(2017). Effect of Roller Burnishing Parameters on Roughness Surface and Hardness of

Unalloyed S 355 J0 Steel by Using Response Surface Methodology. *Manufacturing Technology*, vol. 17, pp. 602-610.

[17] BLOUL, B., BOURDIM, A., AOUR, B., HARHOUT, R. (2017). Measurement default diagnostics of a oughness meter with TS100 head using a rectified specimen and solved by fuzzy logic estimator, *Int J Adv Manuf Technol*, 2017, Vol. 92, pp. 673–684.

[18] BOJANOV, B., XU, Y. (2003). On polynomial interpolation of two variables, *J. Approximation Theory*, 2003, Vol. 120, pp. 267–282.

[19] DUREJA, J.S., GUPTA, V.K., DOGRA, M. (2009). Design optimization of cutting conditions and analysis of their effect on tool wear and surface roughness during hard turning of AISI-H11 steel with a coated mixed ceramic tool, *J. Eng. Manuf.*, 2009, Vol. 223, pp. 1441–1453.

[20] BENLAHMIDI, S., AOUICI, H., BOUTAGHANE, F., KHELLAF, A., FNIDES, B., YALLESE M.A. (2017). Design optimization of cutting parameters when turning hardened AISI H11 steel (50 HRC) with CBN7020 tools, *Int J Adv Manuf Technol*, 2017, Vol. 89, pp. 803–820.

[21] PHILIP, S. D., CHANDRAMOHAN, P., MOHANRAJ, M. (2014). Optimization of surface roughness, cutting force and tool wear of nitrogen alloyed duplex stainless steel in a dry turning process using Taguchi method, *Measurement*, 2014, Vol. 49, Nr. 1, pp. 49205–215.