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Design optimization in hard turning of E19 alloy steel by analysing surface roughness, tool vibration and productivity

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Abstract. In the present work, the optimization of machining parameters to achieve the desired technological parameters such as surface roughness, tool radial vibration and material removal rate have been carried out using response surface methodology (RSM). The hard turning of EN19 alloy steel with coated carbide (GC3015) cutting tools was studied. The main problem faced in manufacturer of hard and high precision components is the selection of optimum combination of cutting parameters for achieving required quality of surface finish with maximum production rate. This problem can be solved by development of mathematical model and execution of experiments by RSM. A face centred central composite design (FCCD), which comes under the RSM approach, with cutting parameters (cutting speed, feed rate and depth of cut) was used for statistical analysis. A second-order regression model were developed to correlate the cutting parameters with surface roughness, tool vibration and material removal rate. Consequently, numerical and graphical optimization were performed to obtain the most appropriate cutting parameters to produce the lowest surface roughness with minimal tool vibration and maximum material removal rate using desirability function approach. Finally, confirmation experiments were performed to verify the pertinence of the developed mathematical models.

Keywords: hard turning; optimization; mathematical model; surface roughness; tool vibration

1. Introduction

In turning of hardened steel, the main challenge emerging is the achievement of high product quality, in terms of dimensional accuracy, surface finish, and high production rate and cost effectiveness. The mechanism of surface roughness formation depends on various uncontrollable factors. The cutting conditions of machining operation, including the cutting speed, feed rate, depth of cut, tool geometry, and the material properties of both the tool and workpiece, have been reported to be fairly strongly correlated with the surface finish quality of machined workpiece (Chae *et al.* 2006). During the machining process, the relative vibration condition, occurring among the instrument, cutting tool, chuck, and workpiece, is an inextricable part and it has detrimental effects on the quality of machined surface (Tounsi *et al.* 2000). Especially, the relative vibrations of cutting tool and workpiece cause the poor machined surface finish, poor dimensional accuracy of the workpiece and tool breakage, which lowers down the productivity and increases the cost of production. The appearance of vibrations on the cutting tools is mainly subjected to the cutting dynamics process under various cutting conditions. The dynamic phenomena of cutting tool induced by the interaction of elastic system in the cutting process causes the relative displacement between tool and workpiece, which generates the vibration of the cutting tool (Marinescu *et al.* 2002). Moreover, the major detrimental effect of vibration for the workpiece further worsens the quality of the machined surface. Surface roughness has been widely used in the index of the machined surface quality since a reasonably good surface finish was good for improving the tribological properties, fatigue strength, corrosion resistance, and esthetic appeal of the machined product (Dimla, 2004, Thomas *et al.* 1996). The surface roughness sensitivity according to cutting parameters such as cutting speed, feed rate and depth of cut while keeping constant tool edge geometry in hard turning will be presented in this paper. Due to inadequate knowledge of the complexity machining technology, numerous mathematical models have been proposed and extensively developed by a growing numbers of papers for the analysis of the machinability (Yıldırım *et al.* 2019, Çiçek *et al.* 2015, Junaid Mir *et al.* 2018, Umamaheswarrao *et al.* 2018, Azizi *et al.* 2012 and Keblouti *et al.* 2017). The machining parameters such as cutting speed, feed rate, depth of cut and tool vibration will highly affect surface roughness. When hard turning process is applied in metal cutting industry, high dimensional accuracy and better surface finish is urgently demanded. A lot of factors can affect the quality of the surface finish and one of the most affecting is the cutting tool vibration. It is necessary to select the most appropriate machining settings in order to improve cutting efficiency, process at low cost, and produce high-quality products. The optimization techniques of machining

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parameters through experimental methods and mathematical as well as statistical models have grown substantially in order to achieve a common goal of improving higher machining process efficiency.

To achieve the desired surface finish, a good predictive model is required for stable machining. The number of surface roughness prediction models available in the literature is very limited (Suresh *et al.* 2002). Most surface roughness prediction models are empirical and are generally based on experimental investigation. In addition, it is very difficult in practice to keep all factors under control as required to obtain reproducible results (Van Luttervelt *et al.* 1998).

Several researchers have made attempts to predict and understand the effect of various machining parameters during turning of hardened steel for optimization different performance parameters such as surface roughness, cutting tool vibration, material removal rate, tool wear, cutting force and power consumption, etc.

Neseli *et al.* (2011) applied response surface methodology to optimize the effect of tool geometry parameters on surface roughness in hard turning of AISI 1040 steel with P25 cutting tool. Asiltürk and Akkus (2011) selected the optimum cutting conditions to get the lowest surface roughness in hard turning of AISI 4140 steel. The study used a coated carbide cutting tool with the L_9 orthogonal array. Optimal cutting parameters were determined using Taguchi method. Keblouti *et al.* (2017) established the correlation among cutting and response parameters in turning of AISI 52100 bearing steel using RSM. They optimized the process parameters in order to maximize productivity. Hessainia *et al.* (2013) proposed an optimum range of cutting parameters for surface roughness, cutting tool vibration and force by establishing a mathematical model using RSM. Bhardwaj *et al.* (2014) developed first-order and quadratic models for prediction of surface roughness and determined optimum cutting parameters using RSM in turning of EN 353 steel. Bouziane *et al.* (2018) determined the best machining conditions to reduce surface roughness by desirability function approach. They also used RSM to establish required correlation among the experimental and predicted values. Recently, keblouti *et al.* (2019) established the RSM approach in turning of hardened 4140 steel. They reported good surface quality and minimum flank wear with optimum machining parameters. Meddour *et al.* (2015) conducted the experiments on hard turning of AISI 52100 steel to predict mathematical models for surface roughness and cutting forces using RSM and concluded that these models provided good results. Finally, optimization and verification of surface roughness were carried out. Upadhyay *et al.* (2013) focussed on developing an empirical model for the prediction of surface roughness using different cutting parameters and tool vibrations. Kirby *et al.* (2004) used multiple linear regression analysis and analysis of variance (ANOVA) for showing a good relationship between feed rate and tool vibrations for estimation of surface roughness. It is found that only vibration is unable to predict surface roughness correctly.

Literature related to multiobjective optimization of surface roughness, cutting tool vibration and material removal rate during turning of hardened E19 steels under dry cutting conditions with coated carbide cutting tools are limited. Face centred central composite design (FCCD) of RMS was used to study the interaction effects of cutting speed, feed rate and depth of cut. This paper is devoted to the development of a mathematical model and carry out experimental study in order to obtain the most appropriate cutting parameters to produce the lowest surface roughness with minimal tool vibration and maximum material removal rate during hard turning of E19 steel with coated carbide tools.

2. Experimental details

2.1 Workpiece material and tool inserts

EN19 alloy steel of 80 mm in diameter and a length of 300 mm were chosen as workpiece materials for the present experimentation. The nominal chemical composition of EN19 steel is shown in Table 1. This workpiece material was selected found on its applications in automotive, crankshafts, spindles, connecting rods, pump, gear shafts, tie rods and bolts requiring high resistance. The microstructures of raw materials are shown in Fig. 1. The ferrite-pearlite microstructure is characterized by its lamellar pearlite structure with embedded pure ferrite.

Table1 Nominal chemical composition of EN19 steel (wt %)

Chemical composition	Fe	C	Si	Mn	Ni	Cr	Mo
Measured values	96.86	0.38	0.21	0.91	0.23	1.04	0.23

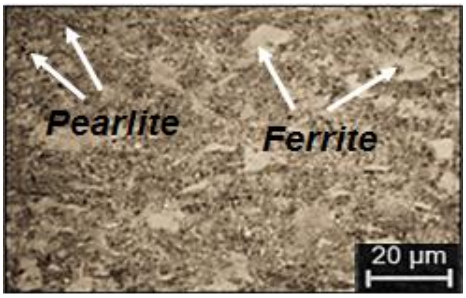


Fig. 1 Microstructure of the EN19 steel (Etching: Nital 0.2%)

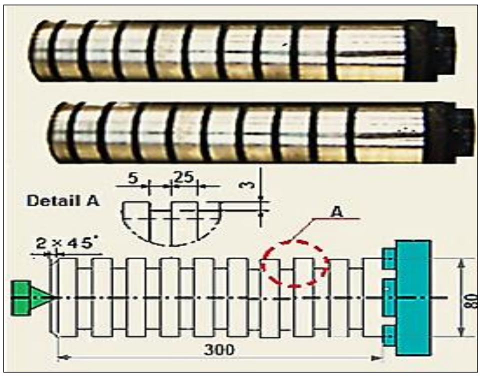


Fig. 2 The workpieces used

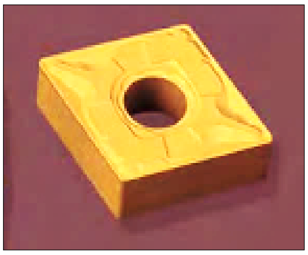


Fig. 3 Coated carbide insert (GC3015)

Initially, the workpiece materials were applied to heat treatment at 850°C (austenisation temperature) for 1 hour and oil quenched. Thereafter, tempering was done at 330°C for 1.5 hours followed by air cooling. A standard workpiece hardness of 50 HRC was obtained after heat treatment. The workpieces used in the experiment are shown in the Fig. 2.

The cutting tool used was coated carbide inserts (Sandvik's Grade GC3015) in accordance with ISO designation of SNGA 120408T01520. The inserts were clamped onto a tool holder with a designation of PSBNR2525M12. The cutting tool used is shown in Fig 3. Combination of the insert and the tool holder resulted in negative rake angle $\gamma = -6°$, clearance angle $\alpha = 6°$, negative cutting edge inclination angle $\lambda = -6°$ and cutting edge angle $\chi_r = 45°$.

2.2 Experimental procedure

The experiment was conducted on universal lathe TOS TRENCIN model SN40C, with cutting tool inserts of SNGA 120408 having nose radii of 0.8 mm. The workpiece material is an EN19 alloy steel bars is used in this experiment. These bars are nominally of 80 mm diameter and were cut to 300 mm length. The measurements of arithmetic surface roughness (*Ra*) for each cutting condition were obtained from a Surftest 201 Mitutoyo roughnessmeter. The length examined is 24 mm with a basic span of 3 mm. The measurements were repeated at three equally spaced locations around the circumference of the workpieces and the result is an average of these values for a given machining pass.Vibration Digital Meter (VM-6360), with measuring ranges: 0-199 mm/s velocity, 0-20g acceleration and 1-1999 µm displacement has been set to record vibration signals in cutting tool.

Radial vibrations have been recorded by mounting a uni-axial accelerometer sensor the tool holder in the radial direction. Fig. 4 depicts the overview of the experimental setup, measurement process and analysis procedure that was followed during the present study.

2.3 Experimental design

In the present work, experiments were designed by using a face central composite design (*FCCD*) and regression technique in response surface methodology (*RSM*) for three parameters with three levels of each parameter. The design expert 7.0 software was utilized for analysis and optimization using RSM. Experiments were carried out and the influence of these machining parameters

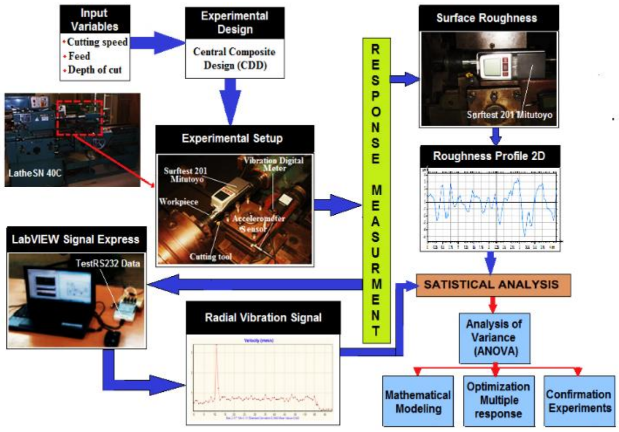


Fig. 4 Experimental design diagram

Table 2 Levels of cutting parameters

Symbol	Factors	Unit	Level		
			-1	0	1
Vc	Cutting speed	m/min	40	80	120
f	Feed rate	mm/rev	0.08	0.16	0.24
ap	Depth of cut	mm	0.4	0.8	1.2

on surface roughness (*Ra*), radial cutting tool vibration (*Vy*) and material removal rate (*MRR*) was investigated. The experimental parameters and their levels are listed in Table 2.

FCCD is used to determine the optimum values of parameters (*Vc*, *f* and *ap*). The numbers of experiments in this method (FCCD) are $2^k + 2k + n$. Note that k and n are the numbers of factors and center points, respectively. FCCD design is required to 19 experiments (2^3 (factorial points) + 2×3 (axial points) + 5 (central points)) with cutting speed (*Vc*), feed rate (*f*) and depth of cut (*ap*). Fig. 5 shows the generation of a central composite design for three factors. In this figure, we assumed a zero central point for each factor. Also, the design is symmetric around this point. A series of experiments according to the experimental plan and FCCD design for surface roughness (*Ra*), radial cutting tool vibration (*Vy*) and material removal rate (*MRR*) are presented in Table 3. The statistical analysis was carried out in three phases. In the first phase, analysis of variance (ANOVA) was used to analyze the effect of parameters and their interactions with the response variables. The second phase is concerned with quadratic regression for the building of analytical models showing the variation of outputs. The last one is used for the optimization of results. The second phase is concerned with quadratic regression for the building of analytical models showing the variation of outputs. Finally, confirmation experiments were carried out to examine the robustness of the developed model.

2.3.1 Response surface methodology

RSM is an optimization technique that applies mathematical and statistical methods for building an empirical model. This technique optimizes a response as the output variable. Note that the output variables are influenced by several independent variables as the input variables. In this method, changes are made in the input

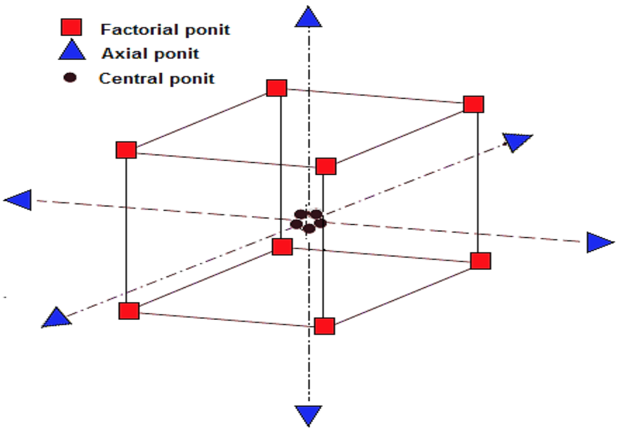


Fig. 5 Generation of a FCCD design for three factors

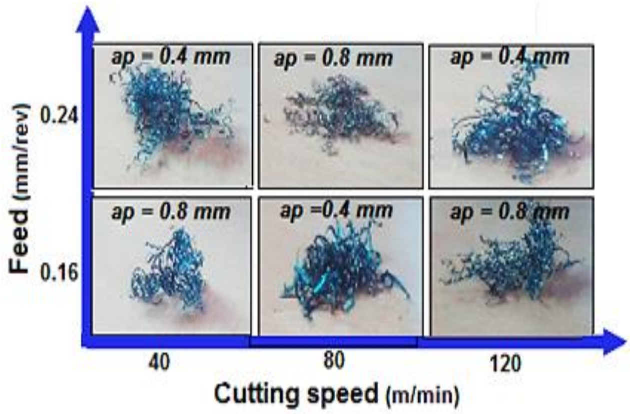


Fig. 6 Chips produced while hard turning of EN19 steel

variables in order to identify the reasons for changes in the output response. The experimental data were analyzed by the response surface regression procedure using the following second-order polynomial equation:

$$y = b_0 + \sum_{i=1}^{3} b_i x_i + \sum_{i=1}^{3} b_{ii} x_i^2 + \sum_{i<j}^{3} b_{ij} x_i x_j \qquad (1)$$

Where y is the response, x_i and x_j are the coded independent variables. When normalized centred representations (coded levels) are used to represent factor levels, b_0, b_i, b_{ii} and b_{ij} are the mean values of responses, linear, quadratic and interaction constant coefficients, respectively. Each coefficient (except interactions) allowed estimation of the change in the mean response per unit increase in x when all other factors were held constant.

2.3.2 Analysis of variance

In this investigation, the analysis of variance (ANOVA) is performed to determine which machining parameter significantly affects the technological parameters of hard turning process and also to find the relative contribution of machining parameters in controlling the response parameters. To proceed with the ANOVA, the method of least squares is used. The results of this experiment in the form of ANOVA are presented. An ANOVA summary table is commonly used to summarize the test of the regression model as well as the test of the significance factors. A "Model F-Value" is calculated from a model mean square divided by a residual mean square. It is a test of comparing a model variance with a residual variance. If the variances are close to the same value, the ratio will be close to one and it is less likely that any of the factors have a significant effect on the response. In addition, if the "Model P-Value" is very small (less than 0.05) then the terms in the model have a significant effect on the response.

3. Results and discussion

The combined effects of cutting parameters (Vc, f, and ap) on the generated surface obtained when hard turning EN19 alloy steel on responses of Ra, Vy and MRR were investigated. These responses are reported in Table 3. Tables 3 reports the values of the best surface roughness (Ra) which is achieved with the combination of lowest feed rate, 0.08 mm/rev, in the medium value of cutting speed, 80 m/min and in the medium value of depth of cut, 0.8 mm. This is explained by the slow elimination of small chip thickness, resulting in a continuous removal of the material that contributes to the improvement of surface quality. However, the highest values of surface roughness is observed for high feed rate of 0.24 mm/rev. This is explained by the rapid removal of matter, the change of the chip morphology and the distance between the scratches that degrade the machined surface. The material removal rate (MRR) is calculated by Eq. (2) (Saidi *et al.* 2019):

$$MRR = Vc \times f \times ap \quad \left[cm^3/\text{min}\right] \qquad (2)$$

Where, MRR is the material removal rate (cm^3/min). The highest MRR was 34.6 cm^3/min obtained at the highest levels of inputs due to more volume of material removed. Fig.6 presents the chips were collected during the experiment numbers of 3, 4, 9, 11, 14, and 17 respectively.

Rubbing between tool and chip interface was one of the major factors affecting the chip morphology. Significant changes in the form, the colour and the curvature of the chips were also observed due to the cutting temperature and friction at the tool-chips interface during hard turning of dual phase EN19 steel under dry conditions with coated carbide (GC3015) inserts.

In Table 3 the surface roughness (Ra), tool radial vibration (Vy) and material removal rate (MRR) were obtained in the range of 0.92−2.64 µm, 0.48−1.59 mm/s and −34.6 cm^3/min, respectively. All three technological parameters (Ra, Vy and MRR) are influenced mainly by the feed rate.

3.1 Statistical analysis

The results of ANOVA for machinability models using coated carbide (GC3015) cutting tools are summarized in Tables 4, 5 and 6. A data variance analysis of surface roughness (Ra), radial cutting tool vibration (Vy) and material removal rate (MRR) was carried out. The main purpose was to analyze the influence of the cutting speed (Vc), the feed rate (f), and the depth of cut (ap) on the total variance of the results.

Table 3 Experimental results for *Ra*, *Vy* and *MRR* 1.28

N°	Cutting conditions			Response parameters		
	Vc (m/min)	*f* (mm/rev)	*ap* (mm)	*Ra* (μm)	*Vy* (mm/s)	*MRR* (cm^3/min)
1	80	0.16	0.8	1.16	0.88	10.2
2	40	0.08	0.4	1.35	0.58	1.28
3	80	0.24	0.8	2.18	1.59	15.4
4	120	0.16	0.8	1.76	1.17	15.4
5	40	0.24	1.2	2.44	1.35	11.5
6	80	0.16	0.8	1.21	0.75	10.2
7	120	0.08	1.2	1.14	0.63	11.5
8	120	0.24	1.2	2.54	1.42	34.6
9	80	0.16	0.4	1.29	0.55	5.12
10	80	0.16	1.2	1.16	0.52	15.4
11	120	0.24	0.4	2.64	1.12	11.5
12	120	0.08	0.4	0.96	0.48	3.84
13	80	0.16	0.8	1.19	0.77	10.2
14	40	0.24	0.4	2.44	1.25	3.84
15	80	0.16	0.8	1.23	0.98	10.2
16	80	0.16	0.8	1.18	0.96	10.2
17	40	0.16	0.8	1.92	0.86	5.12
18	40	0.08	1.2	1.11	0.59	3.84
19	80	0.08	0.8	0.92	0.73	5.12

Table 4 ANOVA results of surface roughness (*Ra*)

Source	Sum of squares	df	Mean square	F-Value	Prob> F	Cont. %	Remark
Model	6.21	9	0.69	51.9	< 0.0001	–	Signif.
Vc	0.0048	1	0.0048	0.365	0.561	0.076	No Signif.
f	4.57	1	4.57	344.36	< 0.0001	72.19	Signif.
ap	0.0084	1	0.0084	0.634	0.447	0.133	No Signif.
Vc x f	0.0545	1	0.0545	4.10	0.0735	0.86	No Signif.
Vc x ap	0.0128	1	0.0128	0.964	0.352	0.20	No Signif.
f x ap	0.0002	1	0.0002	0.0151	0.905	0.003	No Signif.
Vc^2	0.677	1	0.677	51.03	< 0.0001	10.69	Signif.
f^2	0.118	1	0.118	8.88	0.0154	1.86	Signif.
ap^2	0.0376	1	0.0376	2.83	0.127	0.59	No Signif.
Residual	0.119	9	0.0133	–	–	–	–
Cor Total	6.33	18	–	–	–	–	–

The ANOVA is performed to establish the statistical significance of the regression models, model terms. It is done by comparing "*Prob>F*" to 0.05 or in other words at 95% of confidence level. Tables 4, 5 and 6 show that surface roughness (*Ra*), radial cutting tool vibration (*Vy*) and material removal rate (*MRR*) models are significant with *Prob > F values* less than 0.0001. The proportion of contribution of each model term was calculated.

Table 5 ANOVA results of radial vibration (*Vy*)

Source	Sum of squares	df	Mean square	F-Value	Prob> F	Cont. %	Remark
Model	1.87	9	0.208	16.2	< 0.0001	–	Signif.
Vc	0.0036	1	0.0036	0.280	0.609	0.18	No Signif
f	1.38	1	1.38	107.42	< 0.0001	69.34	Signif.
ap	0.0281	1	0.0281	2.18	0.174	1.422	No Signif
Vc x f	0.0001	1	0.0001	0.0006	1.0001	0.005	No Signif
Vc x ap	0.0145	1	0.0145	1.12	0.317	0.728	No Signif
f x ap	0.0072	1	0.0072	0.559	0.474	0.361	No Signif
Vc^2	0.0453	1	0.0453	3.51	0.0936	2.276	No Signif
f^2	0.205	1	0.205	15.9	0.00318	10.30	Signif.
ap^2	0.337	1	0.337	26.2	0.00063	16.93	Signif.
Residual	0.116	9	0.0129	–	–	–	–
Cor Total	1.99	18	–	–	–	–	–

The ANOVA for average surface roughness parameter is presented in Table 4. The *F*-value for the model is 51.9 and there is less than 0.0001% chance that this large *F*-value is due to noise only. The significant model terms are *f*, Vc^2 and f^2, which have *Prob>F* value less than 0.05. Percentage contribution of each factor and their interaction terms have been calculated. From the ANOVA results it is clearthat the effect of depth of cut on surface roughness (*Ra*) is not statistically significant and the variation of surface roughness with depth of cut is minimal as reported in previous investigators; however, the effect of feed rate on surface roughness is of statistical importance. The percent contribution gives a better understanding for the interpretation of the results, which shows that the contribution due to the feed rate is 72.19%. This can be explained by the feed rate increase generates helicoid furrows which are deeper and broader, resulting from tool shape and movement combination between the tool and workpiece. On the other hand, this phenomenon is explained by the reduce of feed caused low cutting forces, which results less vibration, providing a better surface finish (keblouti *et al.* 2019). It can also be seen from Table 4 that the quadratic effect Vc^2 was found to be the second most significant factor with a contribution of 10.69% followed by quadratic effect f^2 with a contribution of 1.86 %. Dilbag and Venkateswara (2007) reported that the surface roughness are most sensitive to the interaction of feed rate and nose radius followed by the quadratic effect f^2 with a contribution of 6.45 %.

From the analysis of Table 5, *P-values* greater than 0.05 indicate model terms are not significant. In this case cutting speed, depth of cut and all interaction between these terms are not significant model. The Model *F-value* of 16.21 implies the model is significant. There is only a 0.02% chance that an *F-value* this large could occur due to noise. Based on obtaining results, feed is the most significant factor on the cutting tool radial vibration (*Vy*) evolution. This is consistent with the surface roughness results analysis subsection in this study.

Besides, it can be noted that a strong effect of cutting tool radial vibration on the surface roughness evolution. In

Table 6 ANOVA results of material removal rate (*MRR*)

Source	Sum of squares	df	Mean square	F-Value	Prob> F	Cont. %	Remark
Model	944	9	105	72	< 0.0001	–	Signif.
Vc	262	1	262	180	< 0.0001	27.37	Signif.
f	262	1	262	180	< 0.0001	27.37	Signif.
ap	262	1	262	180	< 0.0001	27.37	Signif.
Vc x f	52.4	1	52.4	36	0.0002	5.47	Signif.
Vc x ap	52.4	1	52.4	36	0.0002	5.47	Signif.
f x ap	52.4	1	52.4	36	0.0002	5.47	Signif.
Vc^2	0	1	0	0	1	0	No Signif
f^2	0	1	0	0	1	0	No Signif
ap^2	0	1	0	0	1	0	No Signif
Residual	13.12	9	1.46	–	–	–	–
Cor Total	957	18	–	–	–	–	–

the same manner, the main effect of feed rate factor (*f*) and the quadratic effects f^2 as well as ap^2 are significant model terms. It can be seen that the feed rate (*f*) is the most important factor affecting the cutting tool radial vibration (*Vy*). Its contribution is 69.34% followed by the quadratic effect ap^2 with a contribution of 16.93 % whereas the the quadratic effect f^2 contribute only 10.30%. Sahoo *et al.* (2007) reported that feed rate and the quadratic effect of spindle speed are most influencing parameters for tool vibration. Recently, keblouti *et al.* (2019) indicated that feed rate (*f*) and squared term of feed rate f^2 only the both factors have statistical and physical significance on the cutting tool radial vibration (*Vy*) during hard turning.

Finality from analysis of the influence of Table 6, it can be apparently seen that all cutting parameters (*Vc*, *f*, and *ap*) have statistically significant on *MRR* with the same contribution (27.37%). The interactions ($Vc{\times}f$, $Vc{\times}ap$ and $f{\times}ap$) were found to be less significant rate with the same contribution (5.47 %), while all quadratic effects (Vc^2, f^2 and ap^2) does not statistically significant on *MRR*. Kaladhar *et al.* (2012) reported that the depth of cut is found to be the most significant factor affecting the material removal rate (*MRR*) with a contribution of 61.31%, and that the cutting speed was found to be the second most significant factor with a contribution of 20.40% followed by feed rate with a contribution of 5.38 %.

The normal probability plots of the residuals (i.e. error = predicted value from model−actual value) surface roughness (*Ra*), radial cutting tool vibration (*Vy*) and material removal rate (*MRR*) are shown in Figs.7 (a), (b) and (c), respectively. Figs.7 (a), (b) and (c) reveal that the residuals lie reasonably close to a straight line, giving support that the terms mentioned in the model are significant (Montgomery 2001).

The perturbation plot helps us to compare the effect of all the factors at a particular point in the design space. The response is plotted by changing only one factor over its range while holding of the other factors constant. A steep slope or curvature in a factor shows that the response is sensitive to that factor. A relatively flat line shows insensitivity to change in that particular factor. If there are

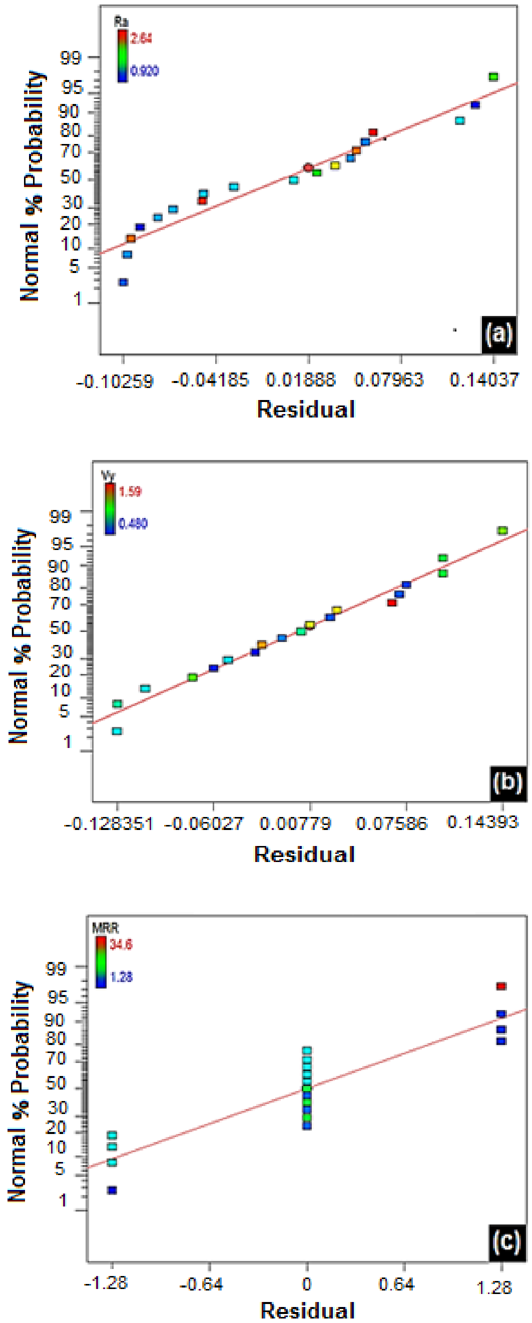


Fig. 7 Normal probability plot of residuals for *Ra* (a), *Vy* (b) and *MRR* (c)

more than two factors, the perturbation plot could be used to find those factors that most affect the response. These influential factors are good choices for the axes on the contour plots. The perturbation plot shows the effect ofcutting parameters (*Vc*, *f*, and *ap*) on All three technological parameters (*Ra*, *Vy* and *MRR*) are shown in Figs.8 (a), (b) and (c). The figures depict that optimization point of this system occurs at the maximum level for all machining parameters. The degree of curvature for each curve shows the level of decrement, which occurs in a log or linear pattern. It is observed from the perturbation plot that the feed rate (*f*) has large effect on the surface roughness (*Ra*), tool radial vibration (*Vy*) and material

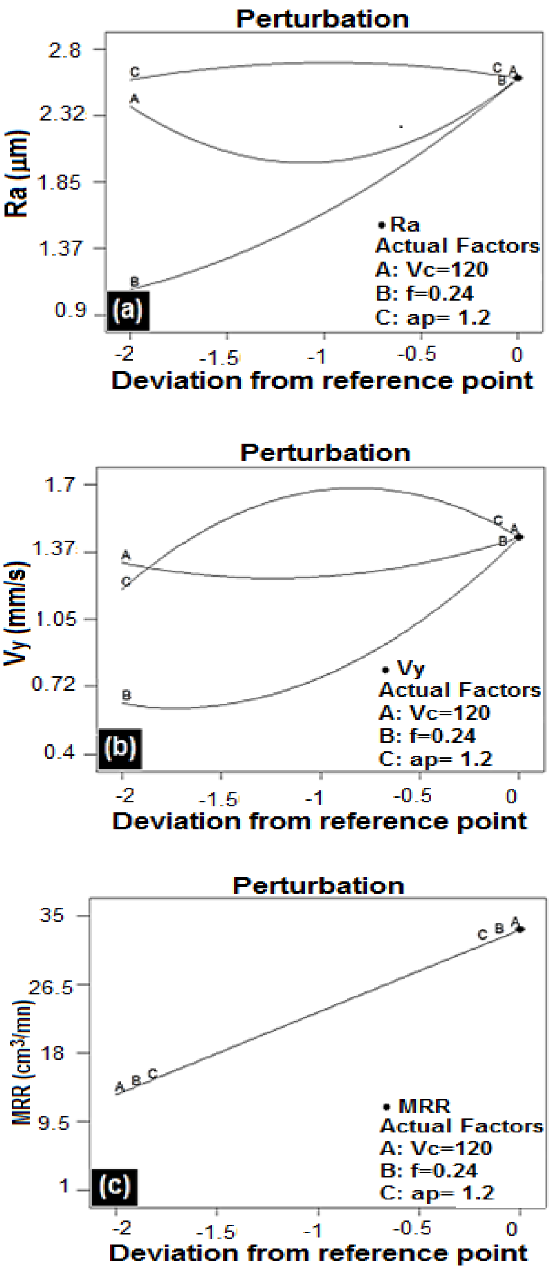


Fig. 8 Perturbation plot for various responses (a) *Ra*, (b) *Vy* and (c) *MRR*

removal rate (*MRR*) as the curvature of it is steep slope. The perturbation plot is presented in Fig. 8(a) which reveals that the surface roughness increases significantly with increase in the feed rate. This is anticipated as it is well known that for a given tool nose radius, the theoretical surface roughness is proportional to the square of the feed rate. It is seen that cutting speed (*Vc*) and feed rate (*f*) contribute to the highest increment of surface roughness compared to depth of cut (*ap*). However, the increment in surface roughness by cutting speed (*Vc*) is a negative quadratic model where it increases until a certain level is achieved and then, decreases. Fig. 8(b) shows the perturbation graph which gives the deviation of each machining parameter with tool radial vibration (*Vy*). It is seen that feed rate (*f*) is most sensitive to tool radial vibration (*Vy*), the cutting speed (*Vc*) and the depth of cut (*ap*) are less sensitive to tool radial vibration (*Vy*). It also can be noted that the effect of all factors on the tool radial vibration is non-linear. For *MRR* in Fig. 8(c), all factors show with same linear perturbation where all factors increase the *MRR* as its level increases from minimum to maximum level. This direct proportional relationship occurs due to the higher chip tool interface area.

3.2 Regression equations

The relationship between the machining parameters and the performance measures was modeled by quadratic regression. The insignificant terms were excluded, except the main effects. Thus, reduced and improved *Ra*, *Vy* and *MRR* prediction models was generated. The regression equations obtained were as follows.

The surface roughness (*Ra*) model is given below in Eq. (3). Its coefficient of determination (R^2) is 98%.

$$Ra = 2.83 - 0.0564\, Vc - 3.87\, f + 0.925\, ap\ 3.11\text{E}{-}04\, Vc^2 + 32.5\, f^2 \quad (3)$$

The tool radial vibration (*Vy*) model is given below in Eq. (4). Its coefficient of determination (R^2) is 94%.

$$V_y = 0.485 - 0.0145\, Vc - 9.79\, f + 3.28\, ap + 42.8\, f^2 - 2.20\, ap^2 \quad (4)$$

The material removal rate (*MRR*) model is given below in Eq. (5). Its coefficient of determination (R^2) is 98%.

$$MRR = 10.2 - 0.128\, Vc - 64.02\, f - 12.8\, ap + 0.8\, Vc\cdot f + 0.16\, Vc\cdot ap + 80.01\ f\cdot ap \quad (5)$$

The relationship between the predicted and the actual values are shown in Figs. 9(a), (b) and (c). There is a small percentage error between the predicted and actual results. The experiment values are clearly in agreement with the predicted values.

3.3 3D Response surface plots

A graphical analysis was carried out using design expert. The surface plots obtained for the most influential factors related to the surface roughness (*R*a), tool radial vibration (V_y) and material removal rate (*MRR*) in hard turning with respect to the machining parameters is presented. Figs. 10–13 show the variation of surface roughness, tool radial vibration and material removal rate with the machining parameters namely cutting speed, feed rate and depth of cut. Fig.10 shows the variation of surface roughness with feed rate and cutting speed. It is seen that feed rate has significant effect on surface roughness and its variation is very high when compared to other parameters. With the increasing feed rate, the raised chip load leaded to aggravated friction at the interface of rake face–chip while the cutting temperature raised to melt material in the cutting zone. The influence of cutting speed at low feed rate (0.08–0.12 mm/rev) on surface roughness can be nearly neglected, indicating a steady cutting process. In addition, with the increasing cutting speed, the surface roughness becomes more sensitive to the changes in feed rate. It is confirmed that cutting speed increasing in the range of 40–100 m/min,

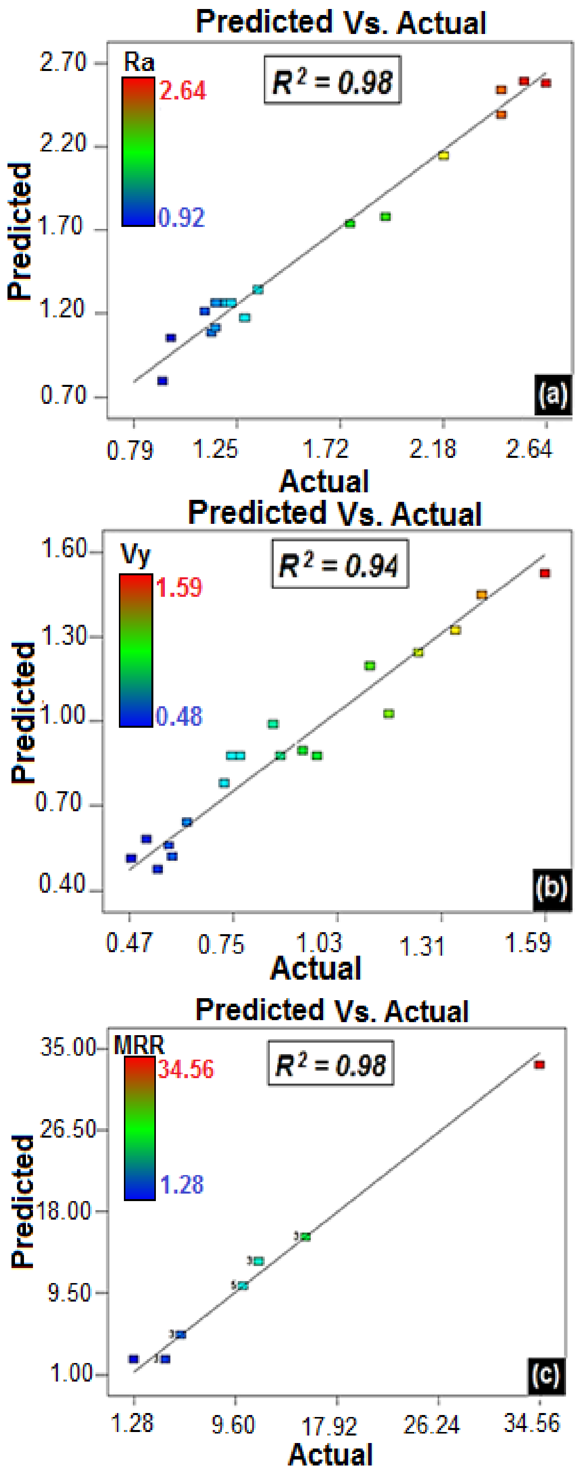


Fig. 9 Actual vs. predicted **value** for Ra (a), Vy (b) and MRR (c)

the probable reason for the decreased surface quality is that the mass chips gathered at the tool rake face unable to exhaust resulting in high cutting force. When the cutting speed increases from 100 to 120 m/min, the cutting temperature reaches to a certain threshold that caused the material softening, thereby inducing the surface quality deterioration. Fig.11 shows the variation of surface roughness with feed rate and depth of cut. It is established that feed rate has the highest impact on surface roughness. The surface roughness does not vary much with depth of cut at higher feed rate ranges, but tends to decrease almost with increasing depth of cut at lower values of feed rate. This can be explained by the improvement in surface roughness with increase in depth of cut can be related to increase in the temperature of chip leading to its softening and lowering frictional forces, thereby improving the surface finish. Similar results were reported by Thomas *et al.* (1996), particularly when machining within the built-up range. Fig. 12 depicts the 3D response surface and contour plot behavior of tool radial vibration with cutting speed and feed rate. For higher values of feed rate and cutting speed, the tool radial vibration is considerably high. It is seen that feed rate has the highest impact on tool radial vibration. As feed rate increases, that results increase in undeformed chip thickness, and undeformed chip thickness is directly proportional to cutting force. Therefore, if cutting force increases it will affects the stability and damping characteristics, which cause tool radial vibration. The variation of material removal rate (*MRR*) with cutting speed and feed rate is shown in Fig.13. It also can be noted that the effect cutting speed and feed rate on the material removal rate is linear. It is confirmed that the both factors increase the material removal rate (*MRR*) as its level increases from minimum to maximum level with the same degree of influence. This direct proportional relationship occurs due to the higher chip tool interface area.

3.4 Validation of the regression models

In order to verify the accuracy of the mathematical models of the surface roughness (*Ra*), tool radial vibration (*Vy*) and material removal rate (*MRR*), three groups of experiment data are randomly selected within the range of the levels defined in experiment and tested to compare with the results predicted by the mathematical models. The process parameters and validation results of the mathematical models are presented in Table 7. The predicted values and the actual experimental values were compared and the percentage error was calculated. The percentage error range between the actual and predicted value for response factors (*R*a, *Vy* and *MRR*) are as follows: *Ra* = −3.75 to 6.61%, *Vy* = −9.61 to 9.52% and *MRR* = −4.34 to 5.07%. It can be said that the empirical models developed were reasonably fairly well.

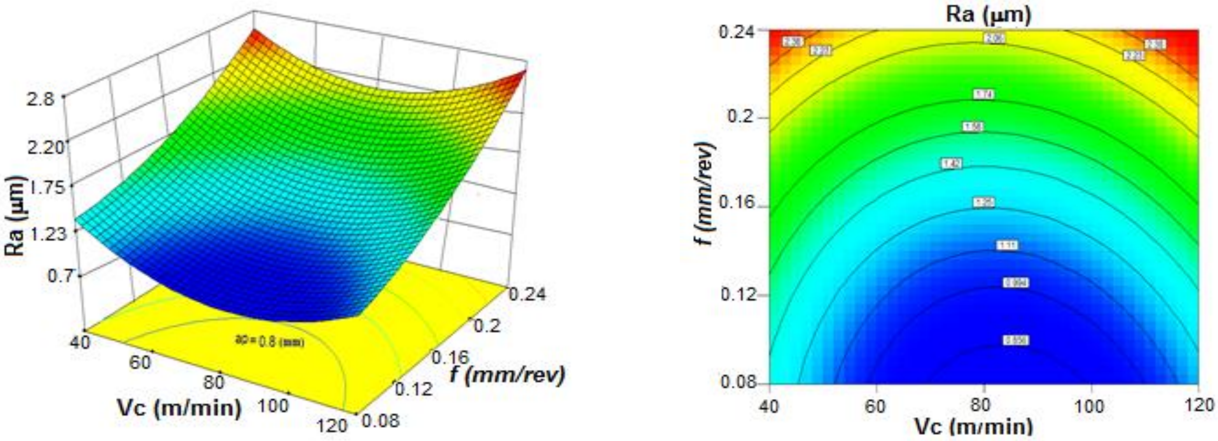
4. Optimization multiple response

The desirability function approach is one of the most widely used methods for optimization of multiple response processes in diverse field of applied science and engineering (Akhnazarova and Kafarov, 1982). This approach involves first, specification of the individual desirability function (d_i) for each response (Y_i) by assigning to the predicted values a score ranging from 0 (very undesirable) to 1 (very desirable). This transformation can be represented as:

$$d_i = \exp[-\exp(-(c_{i1} + c_{i2} Y_i))] \quad \forall i = 1{,}2 \tag{6}$$

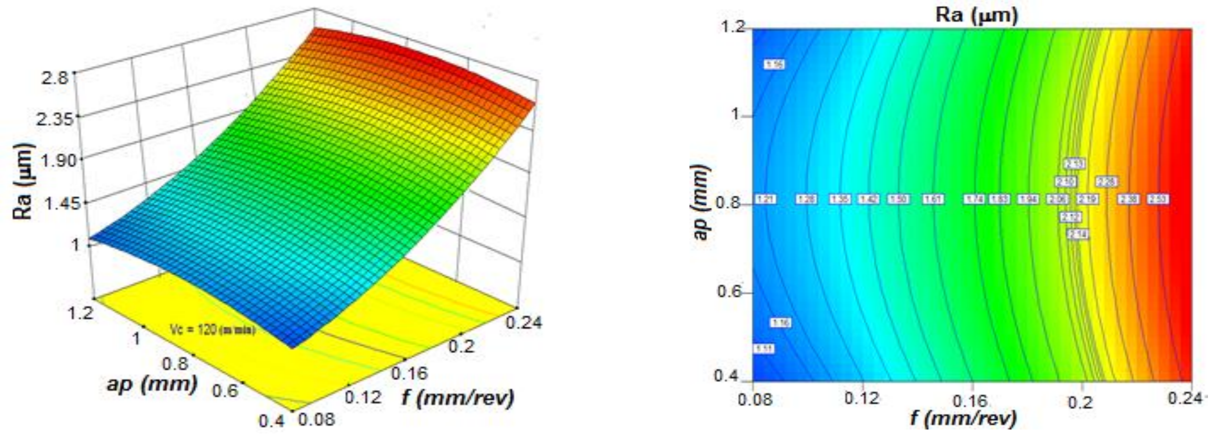
Table 7 Validation results of the mathematical model

N°	Cutting conditions			*Ra* (μm)			*Vy* (mm/s)			*MRR* (cm^3/min)		
	Vc (m/min)	*f* (mm/rev)	*ap* (mm)	Pred	Actual	Error (%)	Pred.	Actual	Error (%)	Pred.	Actual	Error (%)
1	60	0.12	1	1.078	1.12	-3.75	0.69	0.63	9.52	6.99	7.2	-2.91
2	120	0.22	0.5	2.355	2.23	5.60	1.14	1.11	2.70	13.87	13.2	5.07
3	90	0.16	0.4	1.354	1.27	6.61	0.47	0.52	-9.61	5.51	5.76	-4.34



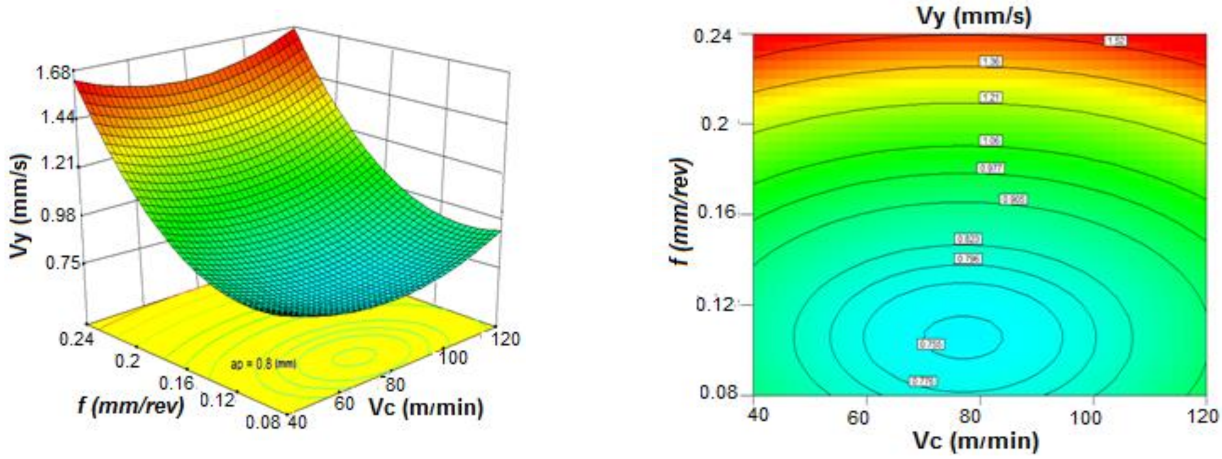
(a) Response surface (b) Contour plots

Fig. 10 Effect of feed rate and cutting speed on surface roughness



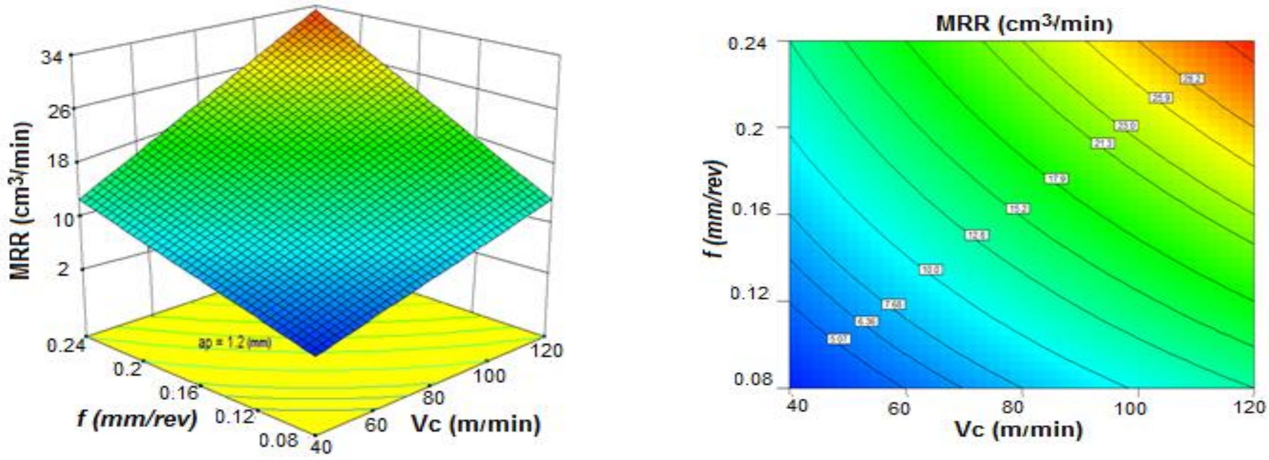
(a) Response surface (b) Contour plots

Fig. 11 Effect of feed rate and depth of cut on surface roughness



(a) Response surface (b) Contour plots

Fig. 12 Effect of feed rate and cutting speed on tool radial vibration



(a) Response surface (b) Contour plots

Fig. 13 Effect of feed rate and cutting speed on material removal rate

For a one-sided transformation, d_i will increase as Y_i increases and d_i will have a role in the maximisation of Yi (note that the minimisation of Y_i implies the maximisation of $-Y_i$). Individual desirability of all of the responses can be combined to get a single value of desirability.

Where the coefficients c_{i1} and c_{i2} are determined by assigning for two values of Y_i the corresponding values of d_i, preferably in the range $0.2 < d_i < 0.8$ (Akhnazarova and Kafarov, 1982). Subsequently, the individual desirability scores for the predicted values for each response are combined by computing their geometric mean that represents the overall desirability function (D) (Chakraborty and Bordoloi, 2006, Akhnazarova and Kafarov, 1982):

$$D = (d_1 \times d_2 \times \cdots \times d_n)^{1/n} = \left(\prod_{i=1}^{n} d_i\right)^{1/n} \quad (7)$$

$$F(x) = -DF \quad (8)$$

Where d_i is the desirability defined for the i th targeted output and n is the number of responses in the measure. For simultaneous optimization, each response must have a low and high value assigned to each goal.

Desirability function approach has been used for multiple response factors (*Ra, Vy*, and *MRR*) optimization using design expert software. The optimization module searches for a combination of factor levels that simultaneously satisfies the requirements placed on each of the responses and factors in an attempt to establish the appropriate model. During the optimization process the aim was to find the optimal values of machining parameters in order to produce the lowest surface roughness (*Ra*) with minimal tool radial vibration and maximum material removal rate during the hard turning. The constraints used during the optimization process are summarized in Table 8. The optimal solutions are reported in Table 9 in order of decreasing desirability level. The desirability value of 0.773 corresponds to the lowest value of surface roughness with minimal tool radial vibration and maximum material removal rate in the given range of parameters. Ramp function graph of most desirable solution are shown in

Table 8 Constraints for optimization of cutting parameters

Conditions	Objective	Lower limit	Upper limit	Importance
Vc (m/min)	in range	40	120	3
f (mm/rev)	in range	0.08	0.24	3
ap (mm)	in range	0.4	1.2	3
Ra (µm)	Target = 0.92	0.92	2.64	5
Vy (mm/s)	Minimized	0.48	1.59	3
MRR (cm^3/min)	Maximized	1.28	34.6	3

Table 9 Optimal solutions

N°	*Vc* (m/min)	*f* (mm/rev)	*ap* (mm)	*Ra* (µm)	Vy (mm/s)	MRR (cm^3/min)	Desirability
1	95.2	0.125	1.2	0.925	0.499	14.5	0.773
2	95.2	0.126	1.2	0.932	0.501	14.6	0.773
3	95.2	0.13	1.2	0.958	0.512	15	0.772
4	90.6	0.13	1.2	0.928	0.492	14.2	0.771
5	74	0.158	1.2	1.110	0.563	14	0.715

Fig. 14. Ramp graph show what shall be the value of machining parameters (*Vc*, *f* and *ap*) to obtain optimal solution. For clear assessment, desirability value of each individual factor and responses associated with the modeling are shown in Fig. 15.

The surface roughness was found with more desirability (0.9972) than the tool radial vibration (0.9833) and the material removal rate (0.3970) due to imposed higher importance on surface roughness.

The optimal solutions are reported in Table 9 in order of decreasing desirability level. The desirability value of 0.773 corresponds to the lowest value of surface roughness with minimal tool radial vibration and maximum material removal rate in the given range of parameters. Ramp function graph of most desirable solution are shown in

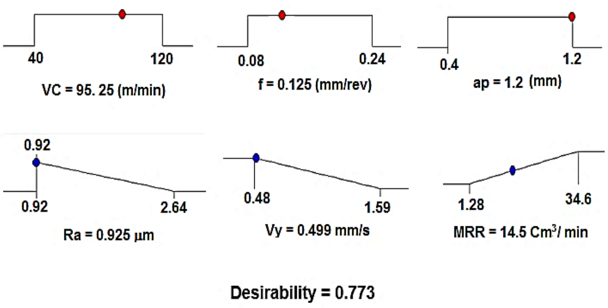


Fig. 14 Ramp function graph of most desirable solution

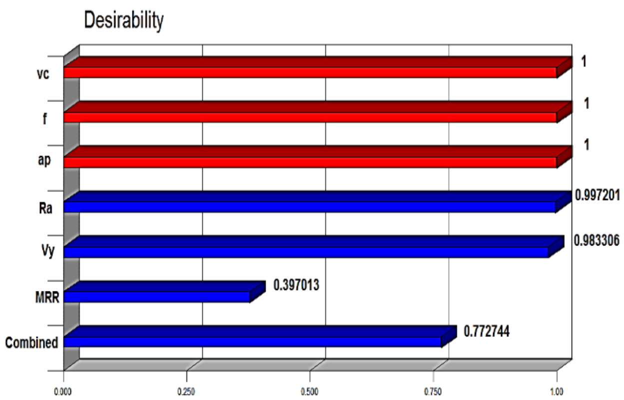


Fig. 15 Bar chart of the optimization

Fig.14. Ramp graph show what shall be the value of machining parameters (*Vc*, *f* and *ap*) to obtain optimal solution. For clear assessment, desirability value of each individual factor and responses associated with the modeling are shown in Fig. 15. The surface roughness was found with more desirability (0.9972) than the tool radial vibration (0.9833) and the material removal rate (0.3970) due to imposed higher importance on surface roughness.

The result of graphical optimization is illustrated in Fig. 16. The graphical optimization plot also known as an overlay plot is a convenient tool where by superimposing or overlaying critical response contours on a contour graph, the models can be visually searched for the best compromise or optimum factor settings. The overlay plot highlights the "sweet spot" with multiple responses regions where response criteria can be met or requirements simultaneously meet the critical properties.

The contours are plotted at the limits specified by the criteria ($0.92 \leq Ra \leq 2.64$, $0.48 \leq Vy \leq 1.59$ and $1.28 \leq MRR \leq 34.6$). Furthermore, the graphical optimization displays the area of feasible response values in the factor space shaded yellow. From this analysis it is found that the cutting speed, 95.2 m/min; feed rate, 0.125 mm/rev and depth of cut, 1.2 mm are the optimum values of machining parameters while the optimum value of surface roughness, tool radial vibration and material removal rate are 0.925 µm, 0.499 mm/s and 14.5 cm^3/min, respectively.

Fig.17 shows a 2D contour plot of the overall desirability function $D(x)$ for the (Vc, f) plane when *ap* is fixed at 1.2 mm. The maximum value of function $D(x)$ =0.773 located in the factor space shaded blue approximately the optimal solution, indicating that small

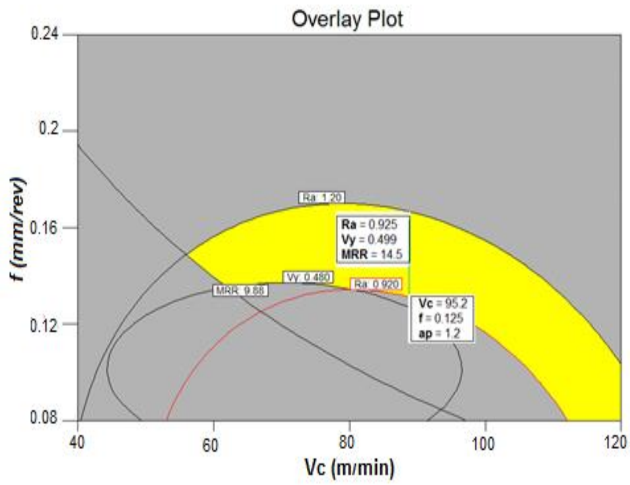


Fig. 16 Overlay plot of most desirable solution

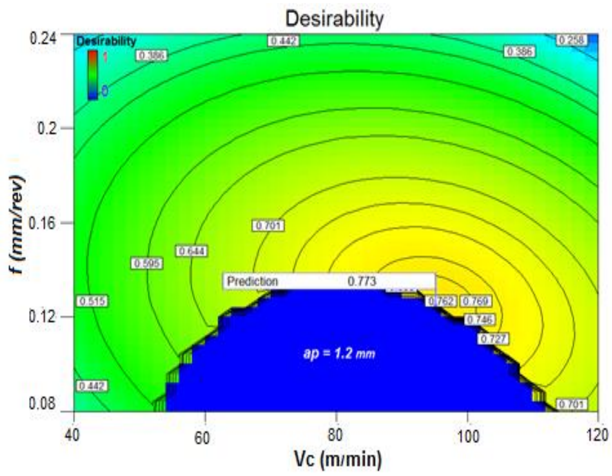


Fig. 17 Contour plots of desirability function

variations in the region of: cutting speed, 95.2 m/min; feed rate, 0.125 mm/rev and depth of cut, 1.2 mm are predicted to not change the overall desirability drastically. However, the importance of performing confirmatory runs at the estimated optimal operating conditions should be emphasized.

5. Conclusions

In this study, the application of statistical analysis on the hard turning of EN19 alloy steel under dry conditions with coated carbide (GC3015) inserts had carried out the mathematical models of the surface roughness, tool radial vibration and material removal rate to investigate the influences of machining parameters. In order to find the optimum value of machining conditions to produce the lowest surface roughness with minimal tool radial vibration and maximum material removal rate, the second-order regression model associated with desirability function optimization was used. The following conclusions can be drawn from this study:

- The surface roughness is most prominently influenced by the feed rate (72.19 %), followed by quadratic effect of cutting speed (10.69 %) and lastly by quadratic effect of feed rate (1.86 %). The surface roughness increases with the increase of feed rate and almost decreases at medium cutting speeds.

- The tool radial vibration was found to be influencing the surface roughness during hard turning process. Variation in surface roughness was noted to be directly proportional to the tool radial vibration. Machining parameters such as feed rate, wall deflection were found to be influencing the surface roughness through the cutting forces. As the feed rate increases, the thickness of the undeformed chip increase. This results in increase in cutting force variation, which cause tool vibration and ultimately affects the quality of machined surface.
- Generally speaking, the cutting speed, feed rate and depth of cut are the three factors increase the material removal rate as its level increases from minimum to maximum level with same linear perturbation. This direct proportional relationship occurs due to the higher chip tool interface area.
- Normality tests on the residuals of the second-order regression models ensure that the models have extracted all applicable information from the experimental data, and these tests also validate the adequacy of the models.
- The average percentage error obtained by confirmation experiments was determined to be 5.32%, 7.27% and 4.10% for surface roughness (*Ra*), tool radial vibration (*Vy*) and material removal rate (*MRR*), respectively; which proves the reliability of the mathematical models established. Thus the mathematical models are recommended to be employed in practice.
- Desirability based multi-response optimization asserted that the optimum value of machining conditions to produce the lowest surface roughness with minimal tool radial vibration and maximum material removal rate are in the region of: cutting speed, 95.2 m/min; feed rate, 0.125 mm/rev and depth of cut, 1.2 mm; with estimated surface roughness of 0.925 μm, tool radial vibration of 0.499 mm/s and material removal rate of 14.5 cm^3/min.

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