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MODELING AND OPTIMIZATION OF SURFACE ROUGHNESS IN TURNING OF EN36 ALLOY STEEL USING RESPONSE SURFACE METHODOLOGY AND GENETIC ALGORITHM

Anshul Kapoor[1], Rajneesh Dwivedi[2], Yogesh Mishra[3]

[1]Research Scholar Master of Technology (APS) Department of Mechanical Engineering, NIIST, Bhopal

[2]Assistant Professor Department of Mechanical Engineering, NIIST, Bhopal

[3]Professor and Head Department of Mechanical Engineering, NIIST, Bhopal

Abstract: Focused on the influence of machining parameter such as spindle speed, feed rate and depth of cut. In the present study, 15 experiments have been conducted as per Box-Behnken design matrix. A mathematically model of the surface roughness was developed using response surface methodology after this model with the help of genetic algorithm to find out the optimum machining parameters. Finally, genetic algorithm has been employed to find out the optimal setting of process parameters that optimize material removal rate. The best response value of surface roughness is obtained from single objective optimization by genetic algorithm was 1.19 µm

Keywords Surface Roughness, CNC turning, Response Surface Methodology, Genetic Algorithm

1. Introduction

CNC (Computer Numerical Control) turning, conventionally an operator decides and adjusts various machines parameters like feed, depth of cut etc., depending on type of job. In a CNC turning machine functions of tools are controlled by motors using computer programs. Turning is one of the most basic machining processes and it is producing the surface quality by various machining process such as spindle speed, feed rate and depth of cut in which a single-point tool remove material from the cylindrical workpiece and its give the smooth surface finish on the surface of workpiece. It is widely used in a variety of manufacturing industries including aerospace and automotive sectors. Surface roughness is an important measure of product quality since it greatly influences the performance of mechanical parts. It is an impact on the mechanical properties like fatigue behaviour, corrosion resistance, creep life, etc. It also affects other functional attributes of parts like friction, wear, light reflection, heat transmission, lubrication, electrical, conductivity, etc.

Reddy NSK et al. [1] this paper presents an experimental investigation of the influence of tool geometry (radial rake angle and nose radius) and cutting conditions (cutting speed and feed rate) on machining performance in dry milling with four fluted solid TiAlN-coated carbide end mill cutters based on Taguchi's experimental design method. The mathematical model, in terms of machining parameters, was developed for surface roughness prediction using response surface methodology. The optimization is then carried out with genetic algorithms using the surface roughness model developed and validated in this work. This methodology helps to determine the best possible tool geometry and cutting conditions for dry milling. Kilickap et al. [3] the present study focused on the influence machining parameters on the surface roughness obtained in drilling of AISI 1045. A mathematical prediction model of the surface roughness was developed using response surface methodology (RSM). The effect of drilling parameters on the surface roughness was evaluated and optimum machining conditions for minimizing the surface roughness were determined using RSM and genetic algorithm. As a result, the predicted and measured value was quite close, which indicates that the developed model can be effectively used to predict the surface roughness. S. Rao et al. [4] the present study is focused on the multi-objective optimization of performance parameters such as specific energy (u), metal removal rate (MRR) and surface roughness (Ra) obtained in grinding of Al-SiC35P composites. In this study non-dominated sorting genetic algorithm (NSGA -II) is used to solve this multi-objective optimization problem. Al-SiC specimens containing 8 vol. %, 10 vol. % and 12 vol. % of silicon carbide particles of mean diameter 35µm, feed and depth of cut were chosen as process variables. A mathematical predictive model for each of the performance parameters was developed using response surface methodology (RSM). Further, an enhanced NSGA-II algorithm is used to optimize the model developed by RSM. Finally, the experiments were carried out to validate the results obtained from RSM and enhanced NSGA-II. The results obtained were in close agreement, which indicates that the developed model can be effectively used for the prediction. Antoni and Mohammad [5] in this study, we need to minimize and to obtain as low as possible the surface roughness by determining the optimum values of the three parameters (radial rake angle, speed, feed rate and cutting condition). In this paper, we present a technique developed using hybridization of kernel principal component analysis (KPCA) based nonlinear regression and

GAs to estimate the optimum values of the three parameters such that the estimated surface roughness is as low as possible. We use KPCA based regression to construct a nonlinear regression and to avoid the effect of multicollinearity in its prediction model. We show that the proposed technique gives more accurate prediction model than the ordinary linear regression's approach. Comparing with the experiment data and RSM, our technique reduces the minimum surface roughness by about 45.3% and 54.2%, respectively. P. S. Sivasakthivel et al. [7] the experiments were conducted on AL6063 by high-speed end mill cutter based on central composite rotatable desings consisting of 32 experiments. The temperature rise was measured using K-type thermocouple. The given model is utilized to analyse direct and interaction effect of the machining parameters with temperature rise. The optimization of machining process parameters to obtain minimum temperature rise was done using genetic algorithm. P. Sivaprakasam et al.[10] this paper investigates the influence of three different input parameters such as voltage, capacitance and feed rate of micro-wire electrical discharge machining (micro-WEDM) performances of material removal rate (MRR), Kerf width (KW) and surface roughness (SR) using response surface methodology with central composite design (CCD). The experiments are carried out on titanium alloy (Tie6Ale4V). Analysis of variance

(ANOVA) was performed to find out the significant influence of each factor. The model developed can use a genetic algorithm (GA) to determine the optimal machining conditions using multi-objective optimization technique. The optimal machining performance of material removal rate, Kerf width and surface roughness are 0.01802 mm3/min, 101.5 mm and 0.789 mm, respectively, using this optimal machining conditions viz. voltage 100 V, capacitance 10 nF and feed rate 15 mm/s. Jayant K et al. [11] models have been developed using central composite design and Box-Behnken design. These two models have been tested for their statistical adequacy and prediction accuracy through analysis of variance (ANOVA) and some practical test cases, respectively. The performance of central composite design is found to be better than Box-Behnken design (BBD) for the response surface roughness and hardness, whereas the latter is found better than the former for the response porosity. The performance is adjudged based on the average absolute percent deviation in predicting the responses. The absolute percent deviation values for the responses surface roughness, hardness, and porosity are found to be equal to 5.95, 1.29, and63.94, respectively, in central composite designs (CCD). On the other hand, corresponding values in BBD are found to be equal to 14.19, 3.04, and 4.94. Further, an attempt is made to minimize the porosity and surface roughness along with maximization of hardness of die cast component. The objective of multi-response optimization was met with a high desirability value of 0.9490. Rudrapati et al. [12] in the present work, experiments and analyses have been made to investigate the influence of machining parameters on vibration and surface roughness in traverse cut cylindrical grinding of stainless-steel material. The experiments have been conducted as per Box-Behnken design matrix with input parameters as infeed, longitudinal feed, and work speed. Mathematical modelling has been done by response surface methodology (RSM) to develop relationships between process parameters and output response(s). The adequacy of the developed models has been tested with analysis of variance. The contour and surface plots for vibration and surface roughness have been made to reveal how output responses vary with change in the machining parameters. Finally, multi-objective genetic algorithm (MOGA) has been applied to optimize vibration and surface roughness simultaneously. And then, predicted parametric condition has been validated by confirmatory experiments. The proposed optimization methodology (RSM cum MOGA) seems to be useful for analyzing and optimizing any manufacturing process where two or more input parameters influence more than one important output responses

2. Experimental Details

EN-36 alloy steel (Bars having diameter 28 mm and length 100 mm) was used as work piece for turning operation and its chemical compositions is shown in Table 2. It is generally used in aeroplane, gears, crane shafts and gear shafts etc. EN-36 steel is a low carbon and high alloy content alloy steel. Characteristics of steel are toughness arising from the use of nickel, generally available in the annealed condition with a maximum brinell hardness of 255, characterized by high core strength, excellent toughness and fatigue resistance in relatively large sections with case hardness upto RC62 when carburized, hardened and tempered

Table 1: Physical properties of EN36 steel

Density (g/cm^3)	Coefficient of thermal expansion	Modulus of Elasticity (KN/mm^2)
15.7	11.6x10^{-6}	669-696

Table 2: Chemical composition of EN36

C	Ni	Cr	Si	Mn	S	P	Mb	Fe
0.700	3.200	1.050	0.250	0.420	0.01	0.012	0.140	94.358

The Coated Tungsten Carbide cutting tool (TNMG160404) is used for turning operation and noise radius of cutting tool is 0.8 shown in Figure 1. Tungsten carbide is an inorganic chemical compound (specifically, a carbide) containing equal parts of tungsten and carbon atoms. Sintered tungsten carbide cutting tools are very abrasion resistant and can also withstand higher temperatures than standard high speed steel tools. Its density is around 15.7 gm/cm3. Hardness is 90 on Rockwell Scale. Its Young's Modulus is 670 GPa. Nose Radius is 0.8 mm. Machining can be performed with six tips.

Measure the surface roughness (Ra) of workpiece was done using a portable stylus-type profilometer, Mursurf ld 130 shown in Fig. 2. The profilometer was set to a cut-off length is 0.33 mm. The average roughness (Ra) parameter was measured only one time along the tool path and measured value of surface roughness are shown in Table 4.

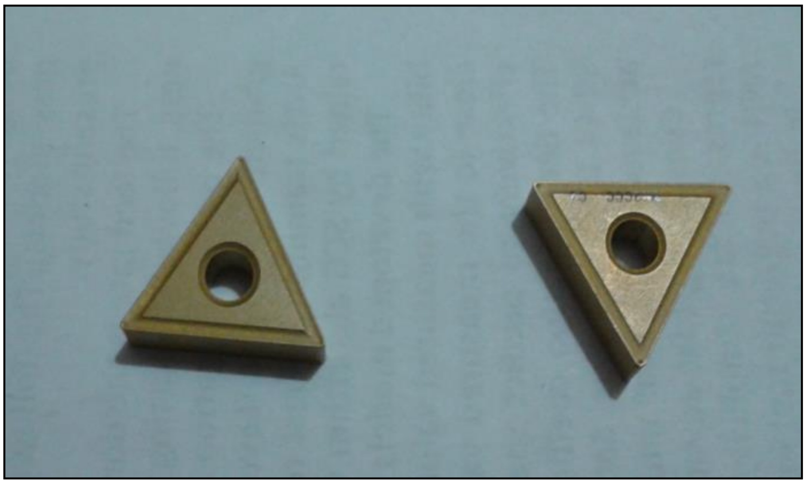

Figure 1 Tungsten carbide cutting tool

3. Experimental methodology

In this optimization of control factor two methodologies are used. One is Response Surface Methodology for analysis and second is Genetic Algorithm for optimization. These two methodologies are explained below.

3.1 Response surface methodology

Response surface methodology (RSM) is a collection of mathematical and statistical techniques for empirical model building. It is useful for modeling and analysis of problem in which output or response is influenced by several variables and the objective is to optimize a response function (output variable). It provides more information with less number of experimental.
In this study, RSM's Box-Behnken experimental design with three factors, three levels, and 15 runs are selected. The machining parameters used and their levels of CNC turning machine are depicted in table 3 and using the Minitab software for develop the Box Behnken design matrix is shown in table 4. In the RSM, the true relationship between y and the independent variables is generally approximated by the lower-order polynomial model such as:

$$y = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \ldots\ldots\ldots. + \beta_n x_n + \varepsilon \quad (1)$$

If there is curvature in the system, then polynomial of higher degree must be used, such as the second order model.

$$y = \beta_0 + \sum_{i=1}^{n} \beta_i \, x_i + \sum_{i=1}^{n} \beta_{ii} \, x_i^2 + \sum_{i<j}^{n} \beta_{ij} \, x_i \, x_j + \varepsilon \quad (2)$$

Where, y is the response surface, ε represent the statistical error term, x_i and x_j are the input variables, x_i^2 *and* x_i *and* x_j are quadratic and interaction terms of input variables, respectively. The $a_i,\ a_{ii}$ *and* a_{ij} are unknown regression coefficients.

Table 3: Input parameters and their levels of CNC turning machine

Symbol	Parameter	Levels		
		-1	**0**	**1**
X_1	Spindle speed (rpm)	750	1000	1250
X_2	feed rate (mm/rev)	10	20	30
X_3	depth off cut (mm)	0.1	0.2	0.3

Table 4: Experimental Design-Box Behnken design matrix

Specimen no.	Spindle speed X1	Feed rate X2	Depth of cut X3	Surface roughness (Ra)
1	1250	30	0.2	6.50
2	750	10	0.2	1.64
3	1250	10	0.2	5.06
4	1000	20	0.2	2.96
5	1000	30	0.1	5.13
6	1250	20	0.1	6.78
7	750	20	0.1	2.66
8	1000	20	0.2	2.96
9	1250	20	0.3	5.60
10	1000	10	0.1	2.62
11	1000	30	0.3	550
12	1000	20	0.2	2.96
13	750	30	0.2	2.10
14	1000	10	0.3	2.11
15	1250	20	0.3	2.68

4. Results and analysis

4.1 Modelling of surface roughness

The complete result from the 15 machining trials for EN36 performed as per the experiments plan are shown in Table 5 along with the run order selected at random. The second-order response surface equations have been using Minitab software for one response variables (R_a). The equations can be given in terms of the un-coded value of the dependence variables as the following:

The regression equation is:
Ra = 0.12 - 0.0000 X1 - 0.076 X2 - 6.6 X3 + 0.000005 x1*x1 + 0.00239 x2*x2 + 49.4 x3*x3 + 0.000021 x1*x2 - 0.0137 x1*x3 + 0.044 x2*x3 (3)

4.2 Analysis of variance for surface roughness (R_a)

ANOVA has been carried out, with the use of MINITAB 14 software. The results of this analysis are shown in Table. It is known that if p value (significance probability value) is less 0.05, the corresponding parameter or variable is considered to be "significance" in influence the output response, at 95% confidence level. The coefficient of determination (R^2) and Adj. R^2 are found to be 96.6% and 90.5%, respectively. As a further check, the normality test of residuals is carried out. It is evidence from Figure 5.1 that residuals are distributed as per normal distribution.

Table 5: ANOVA for surface roughness (R_a)

Source	DF	Seq SS	Adj SS	Adj MS	F	P
Regression	9	47.2200	47.22003	5.24667	15.89	0.004
Linear	3	41.3337	1.60721	0.53574	1.62	0.296
Square	3	5.3326	5.33263	1.77754	5.38	0.050
Interaction	3	0.5537	0.55370	0.18457	0.56	0.665
Residual Error	5	1.6511	1.65110	0.33022		

Lack-of-Fit	3	1.6511	1.65110	0.55037		
Pure Error	2	0.0000	0.00000	0.0000		
total	14	48.8711				

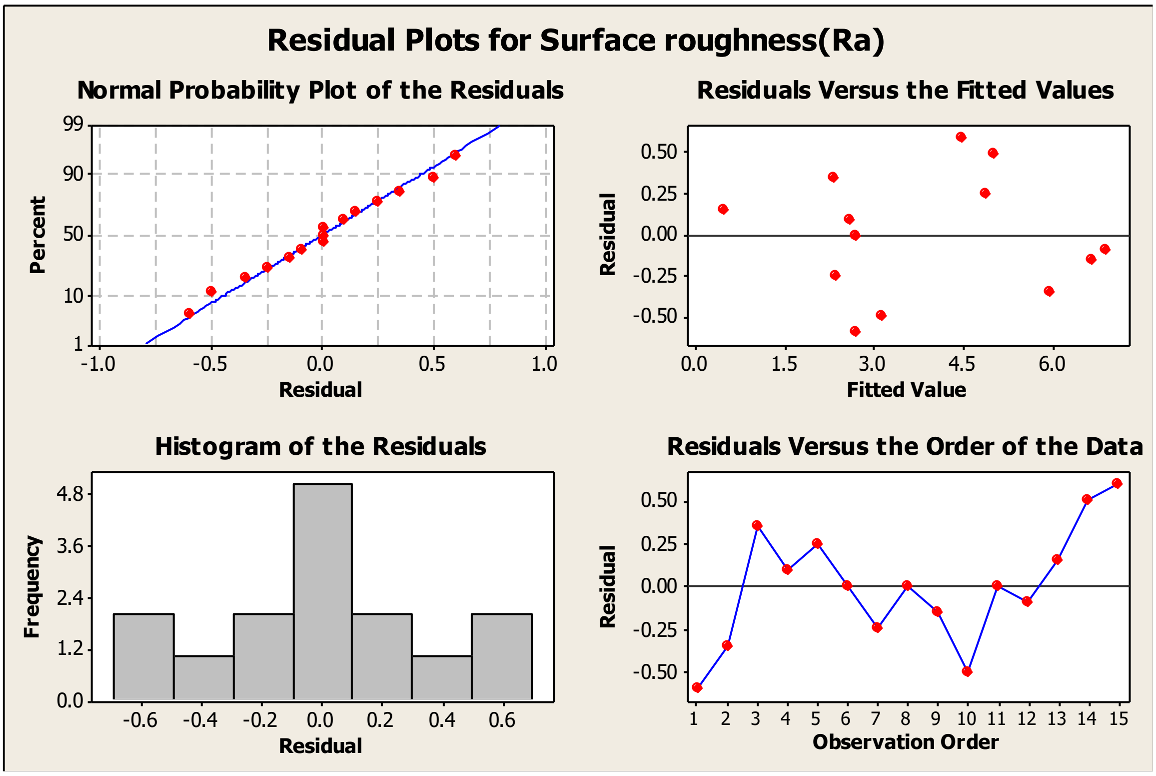

Figure 2 Residual plots for surface roughness

The normality of the data was assessed by means of the normal probability plot. The normal probability plot of the residuals for, Ra is shown in Figure 2. The normal probability plot for the responses reveals that the residuals fall in a straight line. This means the errors are distributed normally. The Independence of the data was tested, by plotting a graph between the residuals, and the run order for the responses confirms that there was no predictable pattern observed, because all the run residues lay on or between the levels.

4.3 SURFACE PLOT OF SURFACE ROUGHNESS

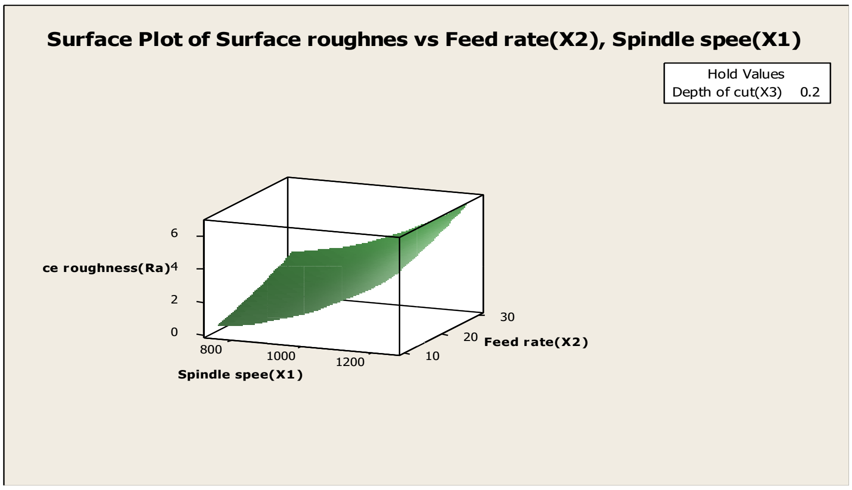

Figure 3 Surface plot of surface roughness vs Feed rate(X2), Spindle speed(X1)

As show in Figure 3, the 3D surface graph for the surface roughness, as the spindle speed and the feed rate vary and depth of cut kept at 0.2 mm. From Figure 3, the surface roughness increasing for all the three feed rates as the spindle speed is increased from 750 to 1250 rpm. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level feed rate gives optimum surface roughness

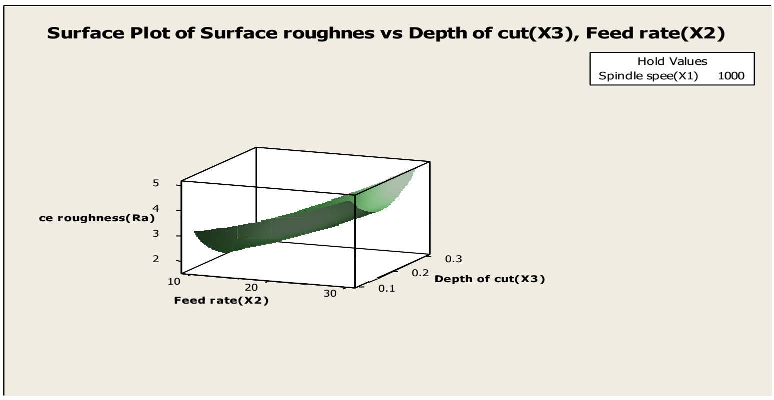

Figure 4 Surface plot of surface roughness vs Feed rate(X2), Depth of cut(X3)

As show in Figure 4, the 3D surface graph for the surface roughness, as the feed rate and the depth of cut and spindle speed kept at 1000 rpm. From Figure 4, the surface roughness increasing for all three depth of cut as the feed rate is increased from 10 to 30 m/min. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level depth of cut gives optimum surface roughness.

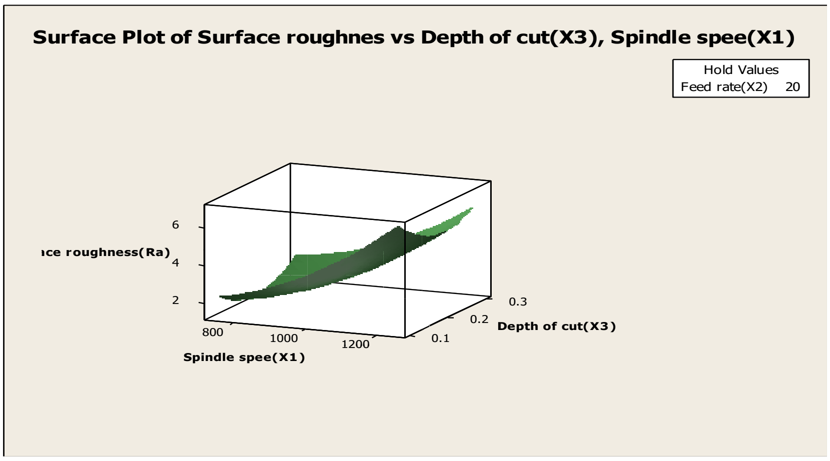

Figure 5 Surface plot of surface roughness vs Depth of cut(X3), Spindle speed(X1)

As show in Figure 5, the 3D surface graph for the surface roughness, as the spindle speed and depth of cut varies and feed rate kept at 20 m/min. From Figure 5, the surface roughness increasing for all the three feed rates as the spindle speed is increased from 750 to 1250 rpm. Hence the interaction effect of spindle speed and feed rate is most significant. Low level spindle speed combined with low level feed rate gives optimum surface roughness.

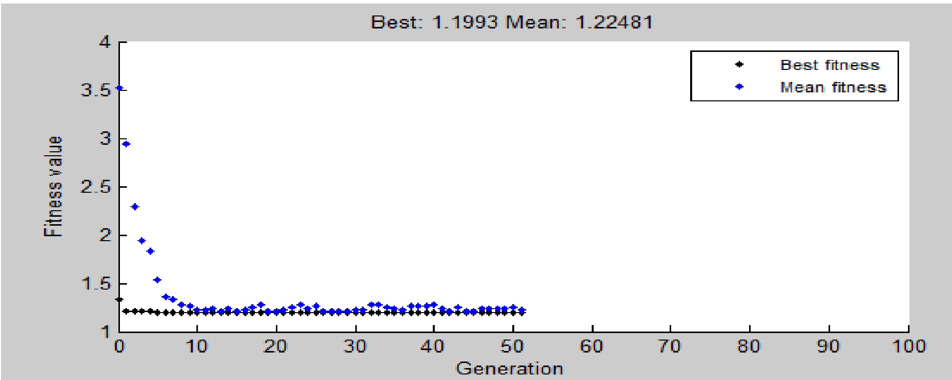

Figure 6 Typical GA Plot for Surface Roughness

Table 6 Best individuals for minimum Surface Roughness (Ra)

Process parameter	Value
Spindle speed (X_1)	751 rpm
Feed rate (X_2)	11 m/min
Depth of cut (X_3)	0.1 mm

5. Conclusion

Experiments were conducted on CNC turning machine using tungsten coated carbide tool, the data surface roughness was collected under different turning conditions for various combination of cutting speed, feed rate and depth of cut.

In this study is to the minimum surface roughness and to find out optimum cutting condition using an integration of RSM and GA. RSM and GA approach provide a systematic and effective methodology for the modelling and the optimization.

RSM provides a large amount of information with a small amount of experimentation. The RSM based surface roughness model in terms of cutting speed, feed rate, and cutting environment was developed by means of the experimental database as per Box-Behnken design of experiments. The quadratic modes developed using RSM were reasonable accurate and can be used for prediction within the limits of the factors investigated. Genetic algorithms have been very useful in optimisation of the response variable and also in multi-response cases. The RSM based surface roughness model can be optimized using a genetic algorithm in order to find the optimum values of independent variables.

For the surface roughness, the feed rate and spindle speed are the main influencing factor. Depths of cut have no significant effect on the surface roughness.

Optimal parametric condition obtained by GA for minimization of surface roughness is spindle speed 751 rpm, feed rate 11 m/min, depth of cut 0.1 mm. The best response value for surface roughness (Ra) obtained from GA was 1.193 at 51 iterations.

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