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ORIGINAL ARTICLE

Optimum surface roughness evaluation of dies steel H-11 with CNC milling using RSM with desirability function

Mandeep Chahal[1] · Vikram Singh[2] · Rohit Garg[3]

Abstract Machinability aspect is of paramount importance for efficient process planning in manufacturing. Machinability of work materials is an imperative aspect which may affect the different manufacturing phases including product design, process planning and machining operation. Machinability of engineering materials may be evaluated in terms of process output variables like surface roughness (SR), material removal rate, cutting forces etc. CNC milling has become one of the most competent, productive and flexible manufacturing methods, for complicated or sculptured surfaces. With the more precise demands of modern engineering products, the control of surface texture has become more important. This paper reports mathematical model for correlating the milling machining parameters such as spindle speed, table feed rate, depth of cut, step over and coolant pressure, with the response characteristic, SR, while machining hot die steel, H-11 with titanium coated carbide end mill cutter. The response surface methodology in conjunction with face centered central composite rotatable design has been used to develop the empirical model for the response. The significance of the mathematical model developed was ascertained using desirability functions and confirmation experiments. The results obtained depict that the mathematical model is useful not only for predicting optimal process parameters for achieving the desired quality but also for achieving the process optimization.

Keywords RSM · Desirability · CNC milling · Die steel H-11 · SR

1 Introduction

To survive in the global rivalry condition of manufacturing conditions, customer related, fast manufacturing strategies are becoming an unelectable manufacturing philosophy. Especially, inspection and determination of surface roughness in metal processing which has an important place in manufacturing industry has very high importance in the view of economical manufacturing. Surface specification can also be a good reference point in determining the stability of a production process. Quality of manufactured product depends on umpteen numbers of factors which may be interdependent in nature. Among them, machinability of work materials is a crucial factor which may affect the different manufacturing phases including product design, process planning, machining operations, etc. Therefore, machinability aspect of work materials is of substantial importance for efficient process planning (Jangra et al. 2002). Machinability is also function of various input variables such as the inherent properties of work material, machining method, cutting tool material, tool geometry, the nature of tool engagement with the work

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material, cutting conditions, type of cutting, cutting fluid, machine tool rigidity, and its capacity (Rao and Gandhi 2002). Problems crop up because the material may have good "machinability" when assessed in terms of one criterion, but poor in terms of another. Recognizing that work materials machinability is also dependent on the experimental set up and the process details, it is apparent that machinability is not a plain property of material, but rather reflects a mode of behavior of the material during cutting. Assessments of machinability should therefore, specify the conditions of cutting for which they have validity (Trent 1998).

Machinability is one of the important properties of a material. It is about cutting the material with maximum material removal, shortest time, maximum tool life and best surface finish. High quality of surface finish is very vital in order to meet the market requirements (Dweiri et al. 2003).Furthermore, it has been observed that the improvement in the output variables, such as tool life, cutting forces, surface roughness, etc., through the optimization of input parameters, such as feed rate, cutting speed and depth of cut, may result in a significant economical performance of machining operations (Kadirgama et al. 2007).As a basic machining process, milling is one of the most widely used metal removal processes in industry and milled surfaces are principally used to mate with other parts in die, aerospace, automotive, and machinery design as well as in manufacturing industries (Altintas 1994).CNC milling system serve as an alternative to EDM for making dies or moulds from the hardened tool steels. It produces the die faster and is also more accurate, because fewer steps result in reduced error stacking. It can result in significantly lower manufacturing costs and times when compared with existing production processes and its performance is characterized by a lot of the machining factors. Any modifications may lead to significant consequences on the machining performances. Today, the main demands in the machining performances by the mould and die manufacturer are often the dimensional precision and accuracy, the surface roughness, and the tool wear (Tzeng 2007).In order to have an efficient process planning in machining of Fe–C alloys, need of an accurate machinability data is required and CNC milling is the best alternative to machine hard materials into desired shapes by optimizing the surface roughness.

In order to calculate machinability of Fe–C alloy steel, it is important to analyze various factors and sub- factors and their effect on machinability. For this, a mathematical tool is required which is capable of analyzing various factors and their impact on machinability of Fe–C alloy using CNC milling process (Jangra et al. 2002). RSM can be utilized to create an efficient analytical model for surface roughness in terms of cutting parameters: feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerance.

By the application of desirability function the optimum value of surface roughness could be achieved at particular input parameters, which were kept in range so as to achieve a desirability value close to 1. Production industry will be benefitted as the machinist will know the limits of using a tool on a particular work piece on a particular machine and help the machinist in achieving optimum results in terms of production economy. The analyses were conducted using statistical methods, such as factorial design and the Box–Behnken design by the RSM. This study provides guidelines on machinability and machining efficiency for milling.

This paper reveals the utilization of RSM(response surface methodology) in conjunction with desirability to determine the machinability of Fe–C alloy (die steel H-11) in terms of surface roughness (SR) during machining with CNC milling. A detailed literature review has been done to determine the various machine tool factors affecting the machinability. Experimental results and the methodology based on RSM to evaluate the machinability in terms of surface roughness have been discussed in the later sections.

2 Literature review and identification of factors impacting surface roughness

Zhang et al. (2007) suggested that Milling has been one of the most widely used metal removal processes in industry and milled surfaces are largely used to mate with other parts in die, aerospace, automotive and machinery design as well as in manufacturing industries . Lou et al. (1999) carried out experimentation to evaluate that feed rate was the most significant machining parameter used to predict the surface roughness in the multiple regression models. Oktem and Kurtaran (2005) explained how RSM could be utilized to create an efficient analytical model for surface roughness in terms of cutting parameters: feed, cutting speed, axial depth of cut, radial depth of cut and machining tolerance. Gologlu and Sakarya (2008) studied that Milling of machining parts could be accomplished by employing different cutter path strategies (step over), which were one direction, back and forth, and spiral cutter path strategies. Tsai and Chen (1999) stated that as a multi-point machining process, more potential variability makes it even harder to obtain a surface roughness model in milling operations compared with single point machining and the possible factors affecting surface finish were found to be feed rate, cutting speed, depth of cut, cutter geometry, cutter run out, tool wear, and the cutter force and vibration under dynamic cutting conditions.

Ezugwu (2005) studied that coated carbide and ceramics tools were generally used for high speed machining Inconel

718. For the coated carbide tools, the right selection of the tungsten carbide cobalt alloy for the substrate, the associated coating materials, the coating procedure and the cutting conditions choice were the main problems. Jindal et al. (1999) studied the relative merits of PVD TiN, TiCN and TiAlN coatings on cemented carbide substrate (WC—6wt% Co alloy) in the turning of Inconel 718. The tested cutting speeds were 46 and 76 m/min, the feed rate and the depth-of-cut were maintained constant and respectively equal to 0.15 mm/rev and 1.5 mm. At both speeds, TiAlN and TiCN coated tools performed significantly better than tools with TiN coatings. The end of life for all three coated tools was dictated by maximum flank wear or nose wears. At the lower cutting speed of 46 m/min, the excellent performance of the TiAlN coated tools may be noted. The maximum flank wear was about 0.15 mm after a cutting time of 5 min. In addition the TiAlN tools exhibit lower nose and crater wear than the TiCN and TiN coated tools.

Toh (2006) investigated and evaluated the different cutter path orientations when high-speed finish milling hardened steel, and the results demonstrated that vertical upward orientation has been generally preferred in terms of workpiece surface roughness. Ding et al. (2010) experimentally investigated the effects of cutting parameters on cutting forces and surface roughness in hard milling of AISI H13 steel with coated carbide tools and empirical models for cutting forces and surface roughness were established. The analysis results showed that finish hard milling can be an alternative to grinding process in the die and mold industry.

Siller et al. (2009) studied the impact of a special carbide tool design on the process viability of the face milling of hardened AISI D3 steel in terms of surface quality and tool life. It was found that surface roughness Ra values from 0.1 to 0.3 μm can be obtained in the workpiece with an acceptable level of tool life.

Based on the detailed literature related to the machining of tool steels and other hard materials, various factors like spindle speed, table feed rate, depth of cut, step over and coolant pressure have been identified which affect the SR of tool steels during machining with CNC milling.

3 Response surface methodology

Many researchers (Lee and Kwon 2010; Muhammad et al. 2012; Yang et al. 2012; Saini et al. 2012; Li et al. 2012) have determined optimum cutting conditions for various machining conditions using the response surface methodology (RSM). The influence of various machining parameters on turning and milling has been evaluated using this methodology. Yang et al. (2012) determined the optimum conditions for precise boring processes in CNC machine operations using the RSM. Saini et al. (2012) predicted the influence of cutting parameters on tool wear and surface roughness in hard turning of AISI H11 tool steel using the RSM.

Horng et al. (2008) used the RSM to evaluate the machinability of Hadfield steel in hard turning. The combined effects of four machining parameters, (cutting speed, feed rate, depth of cut and tool corner radius), on the basis of two performance characteristics (flank wear and surface roughness), were investigated; the centered central composite design and the analysis of variance were employed. Results showed that the flank wear was influenced principally by the cutting speed and the interaction effect of feed rate on the nose radius of the tool; the cutting speed and the tool corner radius had a statistical significance on the surface roughness.

Alauddin and Baradie (1997) used response surface method to predict tool life in end milling. The author found that the speed was the dominant factor in both the first and the second order models, followed by the feed and the axial depth of cut. Fnides et al. (2008) developed a mathematical model for cutting forces and surface roughness in turning of hot work steel. The authors pointed that tangential cutting force was very sensitive to the variation of cutting depth what affects the cutting forces, surface roughness was very sensitive to the variation of feed rate and that flank wear has a great influence on the evolution of cutting force components and on the criteria of surface roughness.

The literature showed above exposes that not much work has been stated on prediction and optimization of surface roughness in end milling. In this work, the main objective is to develop a model based on response surface methodology to the surface roughness in terms of machining parameters such as spindle speed, table feed rate, depth of cut, step over and coolant pressure. The mathematical model aided to study the direct and interaction effect of each parameter. Additionally, the statistical model developed was utilized to optimize the machining parameters to obtain minimum surface roughness using desirability.

So, in the next section response surface methodology approach has to be applied on the machining of die steels using titanium coated carbide cutter in CNC milling.

4 Methodology and implementation

Response surface method is the most effective method to study the result obtained from factorial experiments. It is an effective tool for modeling and studying the manufacturing problems. It delivers more information with fewer numbers of investigations. It is an investigation strategy for exploring the limits of the input parameters and emerging

experiential statistical model for the measured response, by approximating the relationship existing between the response and input process parameters. For the development of regression equations related to various quality characteristics of milling process, the second order response surface has been assumed as:

$$Y = b_o + \sum_{i=1}^{k} b_i x_i + \sum_{i=1}^{k} b_{ii} x_i^2 + \sum_{i<j=2}^{2} b_{ij} x_i x_j \pm e_r \tag{1}$$

This assumed surface Y contains linear, squared and cross product terms of parameters x_i's and e represents the residual error.

4.1 Experimental procedure

Using statistical analysis, the results from the prediction equations can be verified through comparison with the experimental results. The object function consists of surface roughness. Design parameters, such as spindle speed, table feed rate, depth of cut, step over and coolant pressure are selected.

The criteria adopted by many researchers, process parameters for CNC milling process based on the quality of the machining are grouped in various categories. The process parameters, their designated symbols and range are given in Table 1. The range of all the process parameters is selected for the present study based on the results obtained from preliminary experiments.

Hot die steel H11 in the plate form was employed to carry out the experimentation. The H-11 die steel plate blank has been heated to a temperature of 1025°C with half an hour soak time followed by quenching in a 500°C hot salt bath. It was then tempered in three cycles with maximum temperature of 550°C and 2 h of soak time to obtain a final hardness of 55 HRC. The chemical composition of this material as obtained by Electro Dispersive X-ray

Spectroscopy (EDAX) test as in Table 2 and Scanning electron microscope (SEM) analysis is a type of electron microscope that produces images of a sample by scanning it with a focused beam of electrons. The electrons interact with atoms in the sample, producing various signals that can be detected and that contain information about the sample's surface topography and composition and has been used to study the microstructure of the work-piece as in Fig. 1. Solid Carbide 4-flute end mill cutter of 10 mm diameter was the tool used in the experiments.

The experimental studies were performed on SURYA VF30 CNC VS machine (Fig. 2).Two work piece materials, H-11 hot die steel with dimension of 180 mm × 100 mm × 24 mm size was used, and the cuts were made lengthwise. During the experiments, cuts were made of 30 mm length and 11.25 mm width, whereas the cutter diameter was 10 mm, the cutting of this extra width has been done by to and fro movement of the cutter and this was where the step over parameter has its application. Back and forth milling has been employed in this work. Surface roughness measurements in (μm) were repeated three times on respective cuts using a Surfcom 130A as shown in Fig. 3 and the average value was considered for the analysis purpose.

4.2 Fractional factorial experiments and ANOVA

To perform an experiment using a design of experiments, major factors must be selected to analyze their influence on the object functions. In this study, a five-level fractional factorial design method has been implemented. Each parameter consists of five levels. The experimental conditions are provided above. The surface roughness was used as an object function. The effects of the parameters on the object functions were analyzed using the statistical analysis package MINITAB. A statistical analysis was conducted for the experimental results and the main effects and interaction effect were estimated. Montgomery (2005; Montgomery and Peck 2005) proposed the central composite rotatable design for fitting a second order response surface based on the criterion of rotability. The 32 experiments were conducted according to the central composite second order rotatable design for investigating surface roughness. Five levels of each parameter have been taken. The experimental data along with the experimental design matrix are given in Table 3.

The residual analysis as a primary diagnostic tool has been done and then the Normal probability plot has been

Table 1 Process parameters, symbols and their ranges

Process parameters	Symbol	Units	Range
Spindle speed	SS	Rpm	1500–3900
Table feed rate	FR	mm/min	400–960
Depth of cut	DOC	Mm	0.4–1.2
Step over	SO	Mm	0.25–1.25
Coolant pressure	CP	lb/inch^2	0.4–2.0

Table 2 Chemical composition of work piece

Constituent	C	Si	Mn	P	S	Cr	Mo	V
Composition (In %)	0.38	0.93	0.4	0.012	0.027	5.25	1.35	1.0

Fig. 1 Structure of work-piece before machining

Fig. 2 Vertical CNC machine tool

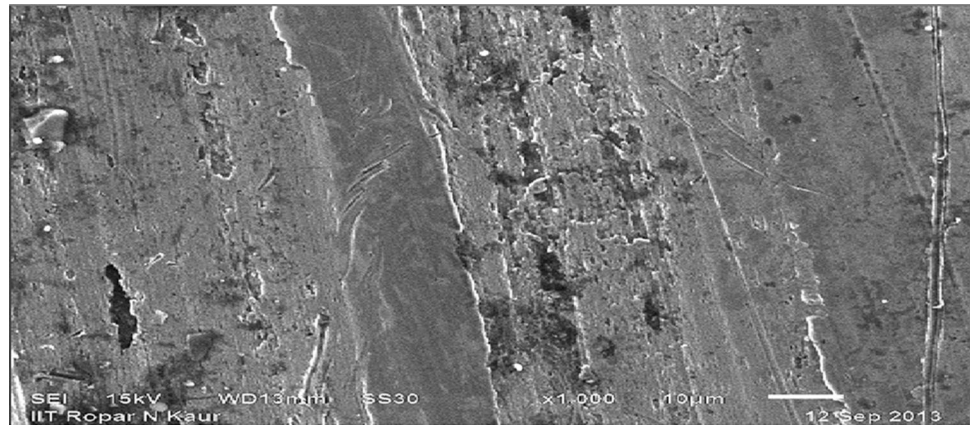

Fig. 3 Surfcom 130A

drawn for residuals in Fig. 4. Linearity of this normal plot confirms the normal distribution of the data. It can be seen from Fig. 5 that all the actual values are following the predicted values.

For, the selection of adequate model for surface roughness, Sequential model sum of squares, lack of fit test and model summary statistics have been used and the source should be quadratic, model should be significant and the lack of fit should be not significant. It can be observed that for all the responses, the quadratic model is appropriate. The 'lack of fit' test compares the residual error to the pure error from the replicated design points. Another test 'model summary statistics' further confirms that the quadratic model is the best to fit as it exhibits low standard deviation and high "R-Squared" values. In order to statistically analyze the results, ANOVA was performed. Process variables having p value <0.05 are considered significant terms for the requisite response characteristic. The insignificant parameters were pooled using backward

elimination method. The pooled version of ANOVA for surface roughness (Table 4) indicates that the spindle speed (A), table feed rate(B), depth of cut(C), step over(D) and coolant pressure(E), the interaction terms (AE,BC, CD) and the quadratic terms (A^2, B^2, C^2, D^2) are significant parameters affecting surface roughness.

Statistical relationships between independent and dependent parameters are referred to as effects. There are main effect and interaction effect. The main effect is the effect of the parameters on the object functions, which is the effect according to level variation of the parameters. In other words, it is the average differences among the levels of each parameter. The interaction effect is the effect that the effect of one independent parameter depends on the level of the other.

This establishes the fact that surface roughness increases with the increase of table feed rate, depth of cut and step over and decreases with increase in spindle speed and coolant pressure. It has been observed from Fig. 6 that the combined effect of spindle speed and coolant pressure is to

Table 3 Observed values for performance characteristic

Std. order	Factor 1 spindle speed	Factor 2 table feed rate	Factor 3 depth of cut	Factor 4 step over	Factor 5 coolant pressure	Response SR
1	2100	540	0.6	0.5	1.6	1.031
2	3300	540	0.6	0.5	0.8	0.942
3	2100	820	0.6	0.5	0.8	1.373
4	3300	820	0.6	0.5	1.6	1.294
5	2100	540	1.0	0.5	0.8	0.978
6	3300	540	1.0	0.5	1.6	0.897
7	2100	820	1.0	0.5	1.6	1.212
8	3300	820	1.0	0.5	0.8	1.189
9	2100	540	0.6	1.0	0.8	0.875
10	3300	540	0.6	1.0	1.6	0.799
11	2100	820	0.6	1.0	1.6	1.312
12	3300	820	0.6	1.0	0.8	1.275
13	2100	540	1.0	1.0	1.6	1.286
14	3300	540	1.0	1.0	0.8	1.199
15	2100	820	1.0	1.0	0.8	1.489
16	3300	820	1.0	1.0	1.6	1.423
17	1500	680	0.8	0.75	1.2	1.125
18	3900	680	0.8	0.75	1.2	1.075
19	2700	400	0.8	0.75	1.2	0.899
20	2700	960	0.8	0.75	1.2	1.55
21	2700	680	0.4	0.75	1.2	1.125
22	2700	680	1.2	0.75	1.2	1.285
23	2700	680	0.8	0.25	1.2	1.1
24	2700	680	0.8	1.25	1.2	1.265
25	2700	680	0.8	0.75	0.4	0.96
26	2700	680	0.8	0.75	2.0	0.933
27	2700	680	0.8	0.75	1.2	0.951
28	2700	680	0.8	0.75	1.2	0.956
29	2700	680	0.8	0.75	1.2	0.952
30	2700	680	0.8	0.75	1.2	0.960
31	2700	680	0.8	0.75	1.2	0.975
32	2700	680	0.8	0.75	1.2	0.978

decrease the surface roughness with their decrement and from Figs. 7 and 8 that the combined effect of feed rate and depth of cut, and depth of cut and step over is to increase the surface roughness with their increment respectively.

To propose the prediction equations, a fitted model was designed in full quadratic polynomial equation form, which considers the response surfaces of all factors. The adequacy of the prediction model was verified using the lack-of-fit, residual analysis and the coefficient of determination of the fitted model. The lack-of-fit should exceed 0.05. If the selected prediction model is inadequate, a new model can be reconstructed through reduction of the response surface model by pooling insignificant terms from the analysis of variance (ANOVA).

The surface roughness prediction equation can be obtained using the least square method, which is presented in Eq. 2.

$$
\begin{aligned}
SR = {} & +3.64287 - 4.34149E - 004 \times \text{Spindle Speed} \\
& - 2.10548E - 003 \times \text{Feed Rate} - 2.54065 \\
& \times \text{DOC} - 2.59908 \times \text{Step Over} + 0.21109 \\
& \times \text{Coolant Pressure} - 8.28125E - 005 \\
& \times \text{Spindle Speed} \times \text{Coolant Pressure} - 1.45982E \\
& - 003 \times \text{Feed Rate} \times \text{DOC} + 1.87500 \\
& \times \text{DOC} \times \text{Step Over} + 9.05961E - 008 \\
& \times \text{Spindle Speed2} + 3.25202E - 006 \times \text{Feed Rate2} \\
& + 1.47161 * \text{DOC2} + 0.85183 \times \text{Step Over2}
\end{aligned}
\tag{2}
$$

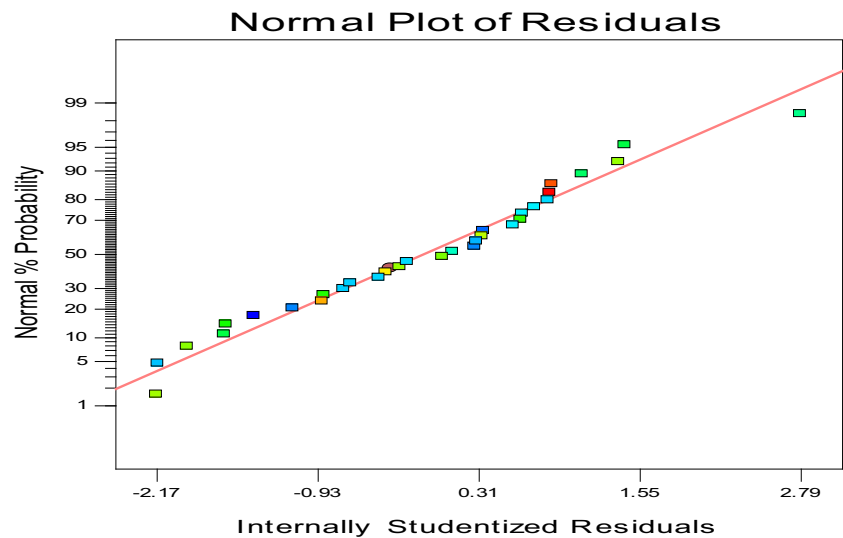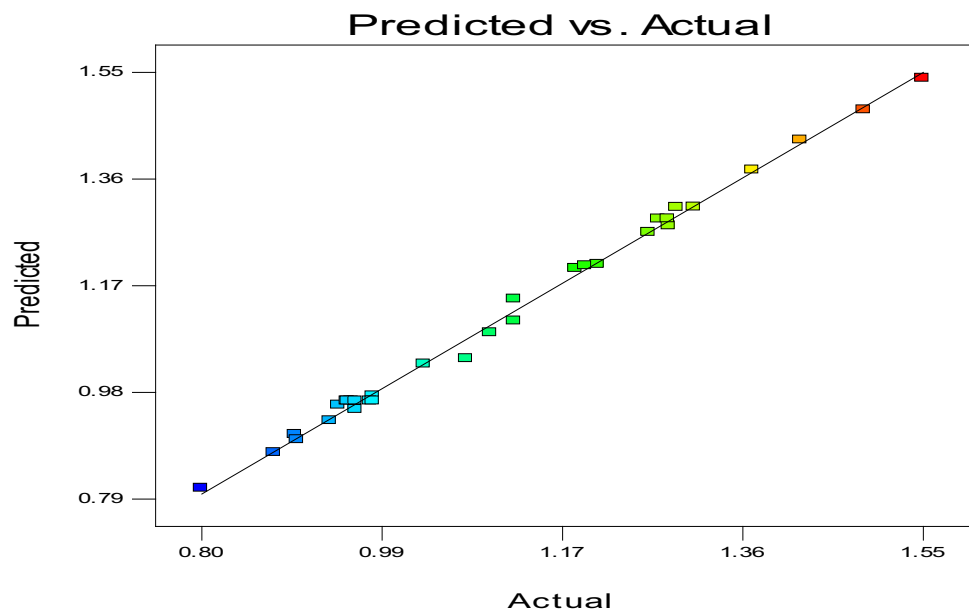**Fig. 4** Normal plot of residuals for surface roughness

Fig. 5 Predicted versus actual for surface roughness

5 Optimization of cutting conditions using desirability function

Desirability is an objective function that ranges from zero outside of the limits to one at the goal. The numerical optimization finds a point that maximizes the desirability function. The characteristics of a goal may be altered by adjusting the weight or importance. For several responses and factors, all goals get combined into one desirability function. So, desirability function has been used to determine the optimum parameters for CNC milling for optimization of surface roughness.

The constraints for the optimization of individual response characteristics viz. surface roughness is provided

in Table 5. Goals and limits were (initially) established for the response in order to accurately determine their impact on its desirability. A maximum or minimum level is provided for surface roughness, which (and this level) has to be optimized. The goal of optimization is to find a good set of conditions that will meet all the goals. A set of 47 optimal solutions is derived for the specified design space constraints for surface roughness using Design Expert statistical software. The set of conditions possessing highest desirability value is selected as optimum condition for the desired response.

The ramp function graph and bar graph (Figs. 9, 10) have been drawn using Design Expert solver to show the desirability for each factor and response. The dot on each

Table 4 Pooled ANOVA-surface roughness

Source	Sum of source	Df	Mean square	F value	p value Prob > F	Model
Model	1.19	12	0.099	227.66	0.0001	Significant
A-spindle speed	0.017	1	0.017	38.97	0.0001	
B-feed rate	0.62	1	0.62	1427.92	0.0001	
C-depth of cut	0.050	1	0.050	114.16	0.0001	
D-step over	0.048	1	0.048	110.02	0.0001	
E-coolant pressure	6.00e−004	1	6.00e−004	1.38	0.2548	
AE	6.32e−003	1	6.32e−003	14.52	0.0012	
BC	0.027	1	0.027	61.42	0.0001	
CD	0.14	1	0.14	323.11	0.0001	
A^2	0.031	1	0.031	72.19	0.0001	
B^2	0.12	1	0.12	275.74	0.0001	
C^2	0.10	1	0.10	235.17	0.0001	
D^2	0.084	1	0.084	192.37	0.0001	
Residual	8.269e−003	19	4.352e−004			
Lack of Fit	7.583e−003	14	5.417e−004	3.95	0.0689	Not significant
Pure error	6.860e−004	5	1.372e−004			
Cor total	1.20	31				

R-squared = 0.9931 Adj R-squared = 0.9887

Pred R-squared = 0.9732 Adeq precision = 53.859

Fig. 6 Combined effect of SS and CP on surface roughness
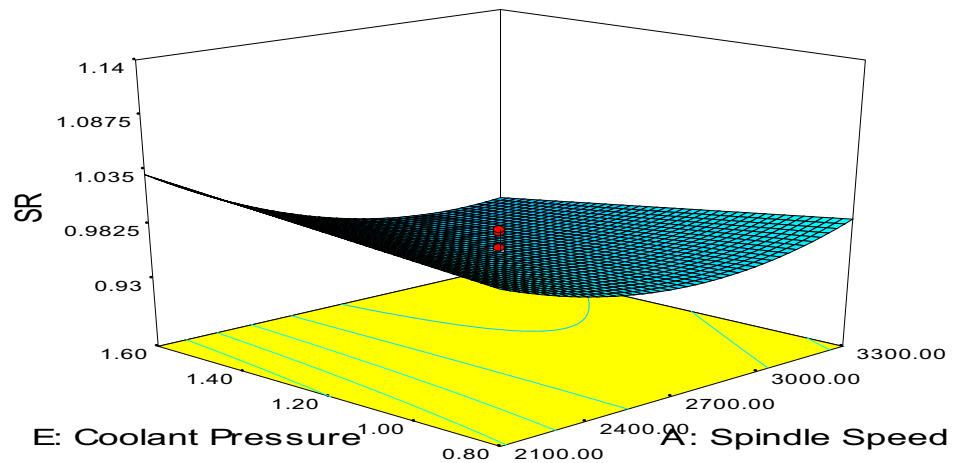
ramp reflects the factor setting or response prediction for that response characteristic. The height of the dot shows how desirable it is (signifies the status/level of desirability). A linear ramp function is created between the low value and the goal or the high value and the goal as the weight for each parameter was set equal to one. Bar graph show(that) the individual/ partial desirability functions (d_i) of surface roughness varies from 0 to 1 depending upon the closeness of the response towards target (Aggarwal et al. 2009).The bar graph shows how well each variable satisfies the criterion: values close to one are considered good. Table 6

reports the final set of optimum levels of various process parameters and the predicted value of surface roughness.

Desirability 3D-plots were first drawn keeping input parameters in range and surface roughness at minimum. Figure 11 shows a plot of desirability function distribution of surface roughness for H-11 steel according to spindle speed and coolant pressure. It can be visualized that high level of spindle speed and high value of coolant pressure favor minimum surface roughness. Likewise plots were drawn between table feed rate and depth of cut, plots revealed that low value of feed rate and lower value of

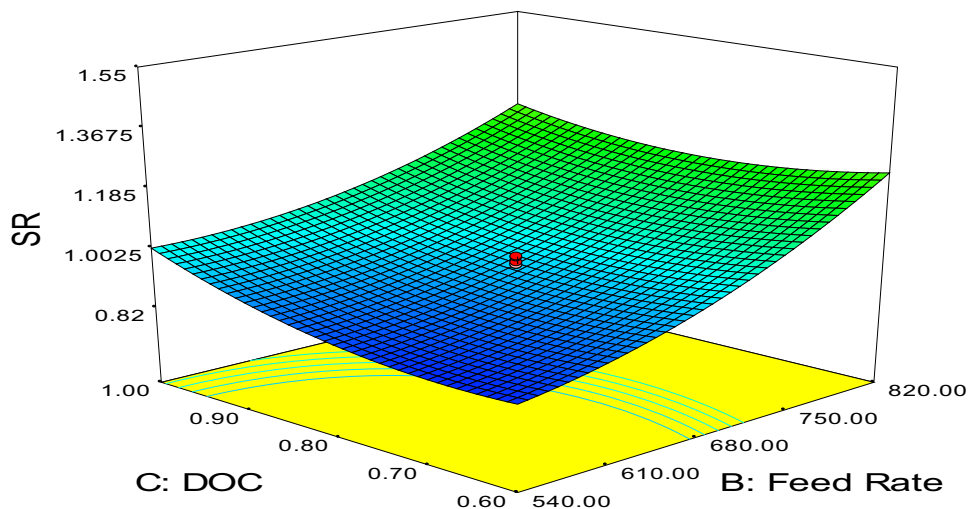**Fig. 7** Combined effect of FR and DOC on SURFACE ROUGHNESS
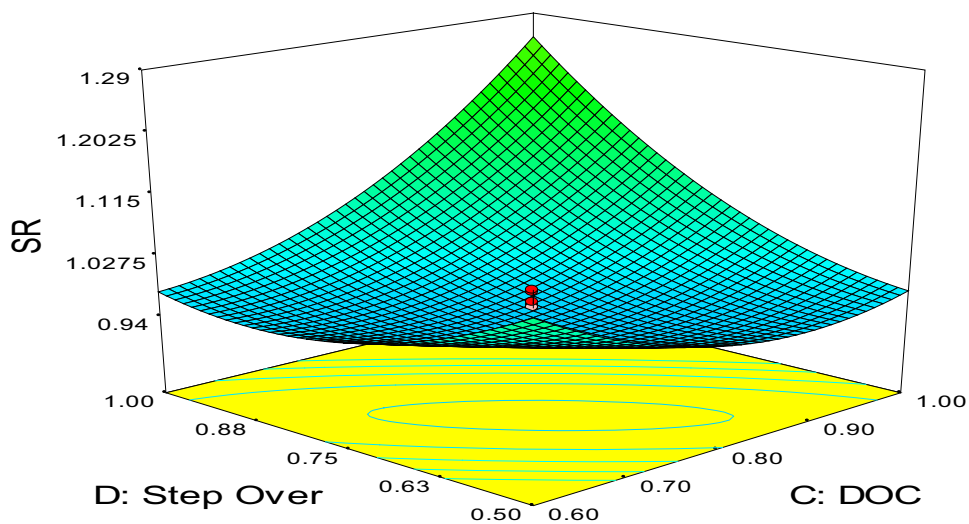

Fig. 8 Combined effect of DOC and SO on surface roughness

Table 5 Range of input parameters and surface roughness for desirability

Process parameter	Goal	Lower limit	Upper limit	Lower weight	Upper weight	Importance
Spindle speed	Is in range	2100	3300	1	1	3
Table feed rate	Is in range	540	820	1	1	3
Depth of cut	Is in range	0.6	1	1	1	3
Step over	Is in range	0.5	1	1	1	3
Coolant pressure	Is in range	0.8	1.6	1	1	3
Surface roughness	Minimize	.799	1.55	1	1	3

depth of cut favor minimum surface roughness Fig. 12. From Fig. 13 it can be seen that the high values of step over favor higher values of surface roughness.

Using the desirability function, the optimum values of the various process parameters have been derived and also the optimum value of surface roughness. Finally, the cut of optimal conditions have been made and SEM analysis test has been performed and it has been observed that the asperities have been removed after the machining and the surface roughness has been significantly improved (Fig. 14).
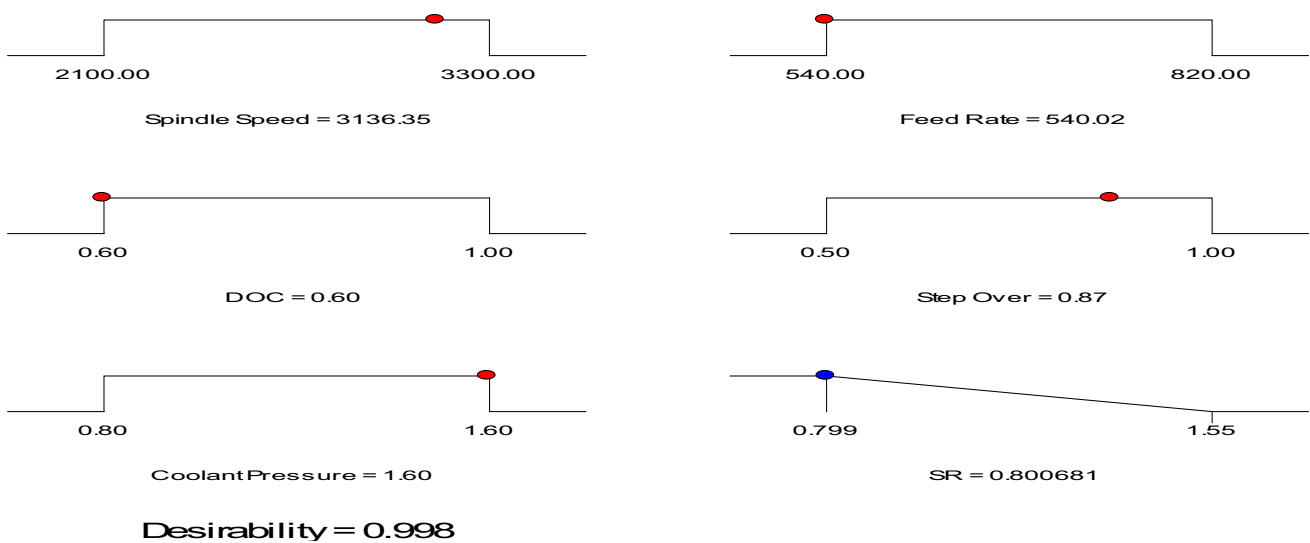
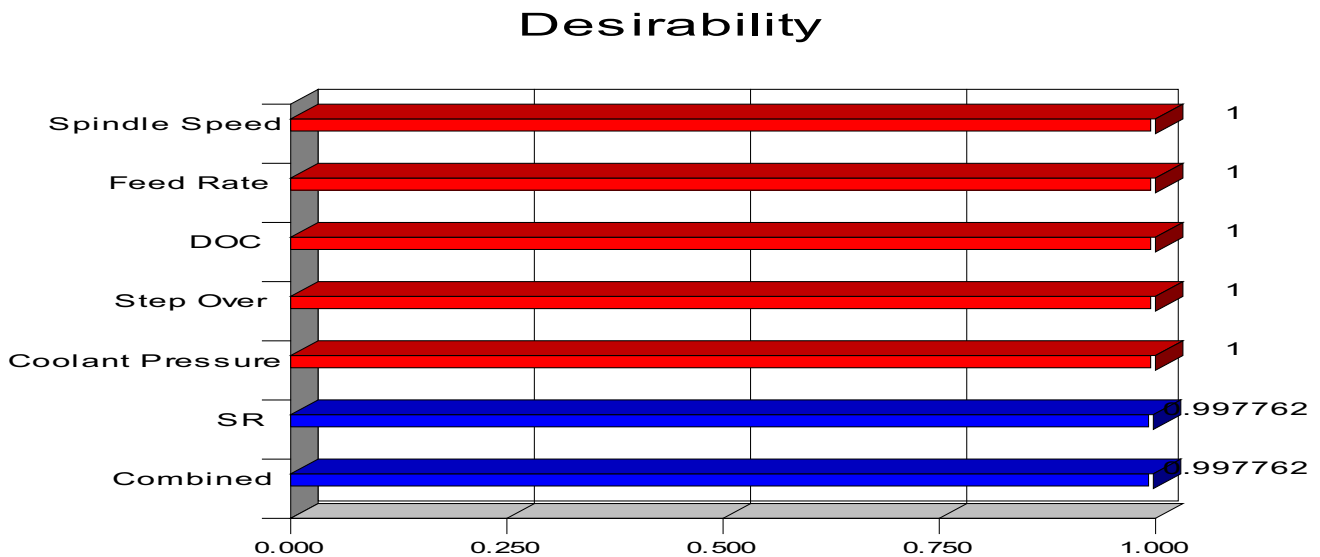**Fig. 9** Ramp function graph of desirability for surface roughness

Fig. 10 Bar graph of desirability for surface roughness

	S. no	SS	FR	DOC	SO	CP	SR	Desirability	
Table 6 Optimal set of conditions with highest desirability function	1	3136.14	540.05	0.6	0.87	1.6	0.800615	0.998	Selected

6 Result and discussion

The Model F-value of 227.66 implies the model is significant. There is only a 0.01 % chance that a "Model F-Value" of this much magnitude could occur due to noise. The "Lack of Fit F-value" of 3.95 implies the Lack of Fit is not significant relative to the pure error. There is a 6.89 % chance that a "Lack of Fit F-value" of this order could occur due to noise. Non-significant lack of fit is good. The "Pred R-Squared" of 0.9732 is in reasonable agreement with the "Adj R-Squared" of 0.9887. "Adeq Precision" measures the signal to noise ratio. Values of "Prob > F" less than 0.0500 indicate model terms are significant. In this case A, B, C, D,E, AE, BC, CD, A^2, B^2, C^2,D^2 are significant model terms. Spindle speed, feed rate, depth of cut, step over and coolant pressure are all significant parameters effecting surface roughness, but combined effects of feed rate,

Fig. 11 3D surface graph of desirability for surface roughness (SS, CP)
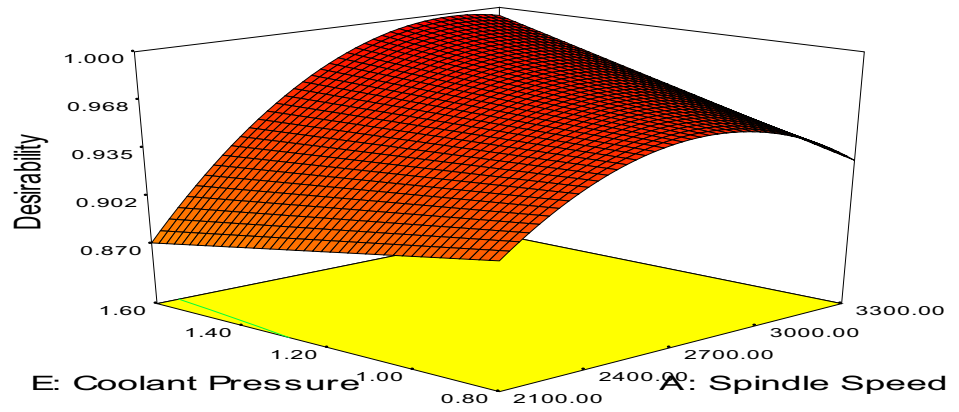

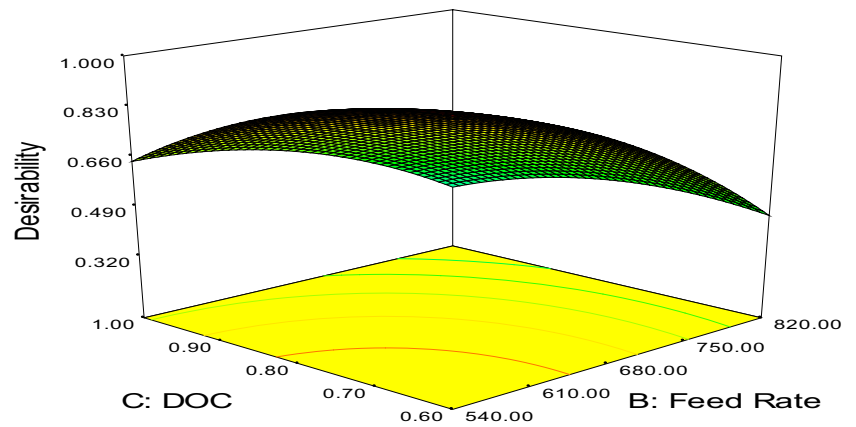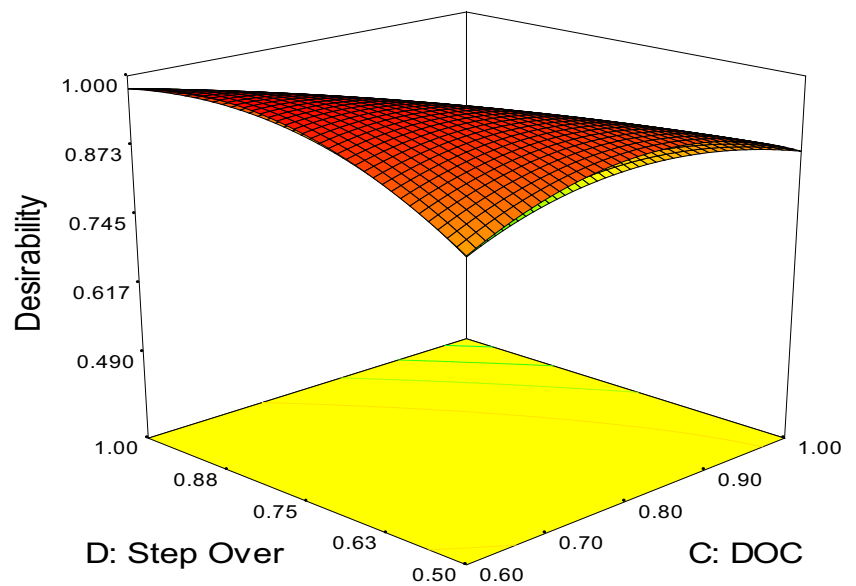Fig. 12 3D surface graph of desirability for surface roughness (FR, DOC)

Fig. 13 3D surface graph of desirability for surface roughness (SO, DOC)

depth of cut and step over are significant. It has been observed that coolant pressure itself is not a significant parameter, but its interaction with spindle speed make it a significant parameter.

Desirability function has been used to determine the optimum parameters for CNC milling while machining die steels with carbide cutter and a set of 47 optimal solutions is derived for the specified design space constraints for
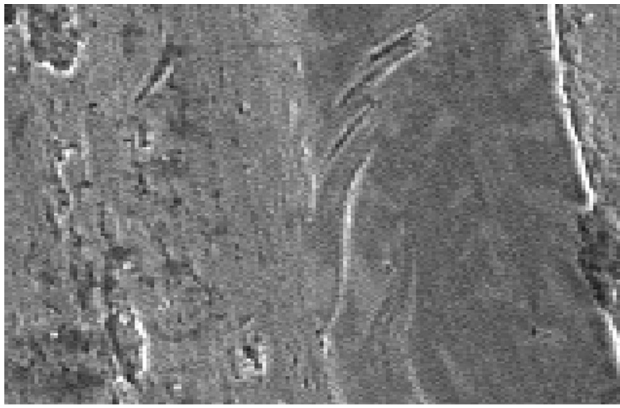
Fig. 14 Structure of work-piece after machining at optimum conditions

Table 7 shows the results of confirmation run

Sample	SR (μm)
1	0.798
2	0.809
3	0.791
4	0.794
5	0.806
6	0.811
7	0.814
8	0.790
9	0.789
10	0.805
Mean	0.8007

surface roughness using Design Expert statistical software. The set of conditions possessing highest desirability value is selected as optimum condition for the desired response. The ramp function graph and bar graph have been drawn using Design Expert solver to show the desirability for each factor and response. Desirability 3D-plots were first drawn keeping input parameters in range and surface roughness at minimum. Then using the desirability function, the optimum values of the various process parameters have been derived and also the optimum value of surface roughness. It was concluded that the optimal values for minimizing surface roughness (0.8006 μm) were spindle speed of 3136.14 rpm, table feed rate of 540.05 mm/min, depth of cut of 0.6 mm, step over of 0.87 mm and coolant pressure of 1.6 lb/inch^2 with a high desirability value of 0.998.

In nutshell, machining at knowing values improve the micro-structure of the work piece, which could benefit a lot to the machinist. Also by knowing the parameter range for machining a particular work-piece with a particular tool on a particular machine the surface roughness can be significantly improved and the production industry will be definitely benefitted.

7 Confirmation run

After the optimal level of all the process parameters were identified, the next step is to conduct the confirmation run. The combination of the optimal level of all the parameters should produce the optimal magnitude of surface roughness (SR).This conclusion must be supported through the confirmation runs. Ten samples were cut for the purpose of confirmation run. The optimal levels for the process parameters were spindle speed of 3136.14 rpm, table feed

rate of 540.05 mm/min, depth of cut of 0.6 mm, step over of 0.87 mm and coolant pressure of 1.6 lb/inch^2 (Table 7).

The confirmation run indicated that the selection of optimal levels for all the parameters produced the best surface roughness.

8 Conclusions

In this study, the optimal cutting conditions for the end milling were selected by varying the cutting parameters through the RSM central composite design. With the use of half fraction and single block of the numbers of experiments were reduced to 32. ANOVA analysis predicts the significant terms and interactions and with the implementation of desirability function, the optimal values have been predicted and the surface micro-structure has been studied by SEM analysis. So, it can be deduced/concluded that RSM in conjunction to desirability is an efficient and effective method for optimizing surface roughness in an end milling operation.

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