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# Optimization of Influencing Drilling Parameters in HSS T1 Using Response Surface Methodology

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**Abstract:** In this research, Response Surface Methodology (RSM) is used to investigate the effects of four controllable input variables namely-spindle speed, feed, coolant concentration and flow rate on output parameters of surface roughness (SR) and material removal rate (MRR) in drilling process. In present study the Central Composite Design (CCD) is used to estimate the model adequacy. Four input factors were proposed to find second-order polynomial model for SR and MRR, which alleged to influence the SR and MRR in drilling process. Experiments were conducted on high speed steel (HSS T1 grade) with tungsten carbide drill bit. RSM techniques are utilized to predict the SR and MRR. Correlation coefficients (R2) were observed 97.28 % and 88.89% for MRR and SR respectively. RSM response (MRR and SR) were optimized as 0.0017 g/sec and 1.2718 microns respectively using critical values of variables spindle speed, feed, coolant concentration and flow rate respectively.

**Key words:** Drilling · Surface Roughness · Material Removal Rate · Response Surface Methodology · Central composite design

## INTRODUCTION

Drilling process is frequently used in various industries for the purpose of making different types of hole by rotating a wedge shaped cutting tool called drill bits [1]. Circular whole creations for harder materials are challenging task for the industries using traditional drilling techniques. Drilling is one of the most important machining processes, whose products are rejected 60% approximately due to poor surface quality [2-6]. Non conventional methods have been reported to improve the surface quality, but it reduces the MRR and increases the total cost per unit. Compromise between cost per unit and quality of the drilled products are needed, so its verdict to improve the traditional drilling methodology using critically selected variables and their responses. A rotating drill bit enters into the work piece axially at the rate of hundreds to thousands of revolutions per minutes and cuts a blind hole or a through hole with a diameter equal to the diameter of the tool [7-10]. A drill bit generally consist multiple cutting edges and typically has a pointed end. In industries, twist drill is used very frequently as compared to other drill bits (Masonry bit, Bullet pilot point, step drill bits etc.) [11-17]. in twist drill bit, chips moves out through the flute and chips are formed along the cutting lip angle. A Drill has two cutting edges mainly chisel edge (extrude into the work piece material and contributes substantially to the thrust force) and cutting lips (cut out the material and produced the majority of the drilling torque and thrust) [5]. The input parameters such as cutting speed, drill tool diameter and cutting fluid played most important role to get the better surface finish of the drilling holes. The effect of the machining parameter such as cutting speed , feed rate and cutting environment on the surface roughness in drilling AISI 1045 using response surface methodology and genetic algorithms. It is evident that minimum surface roughness was found at the lower cutting speed and lower feed, also at working with low quality lubricants as compared to compressed air and dry drilling. Wear rate (work piece and tool) and performance of machine are deciding factor in the selection of a material.

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Many attempts have been reported by researchers for modeling and optimization of drilling processes to enhance the surface quality and MRR. Combined responses SR and MRR are still challenging problems, which restrict the expanded application of the technology.

Influencing cutting parameters- spindle speed, feed rate & drill point angle on thrust force and torque in drilling of Glass Fiber Reinforced Composite (GFRC). Experiments were conducted by using HSS twist drill. Mathematical model is being used to correlate the interactions of cutting parameters and their effect on thrust force and torque. Also it was found that the thrust force and torque both depends on the drill point angle, spindle speed and the feed rate and both of them increase with increase in drill point angle and feed rate [18-22].

Surface roughness and material removal rate directly influence on process parameters- spindle speed, feed rate and depth of cut during CNC drilling using high speed steel tool and by applying Taguchi methodology. It was observed that by increasing the spindle speed, MRR increases and the surface roughness initially decreases with increase in spindle speed while after some process there is increase in surface roughness. By increasing the feed rate, MRR and the surface roughness both are decreased. Initially there is decrease in MRR & the surface roughness with increase in depth of cut and after some process, there is increase in MRR and surface roughness with increase depth of cut [22].

This study correlates the interactions of drilling parameters such as speed, feed rate and drill diameter and their effects on axial force and torque acting on the cutting tool through a mathematical model by means of response surface methodology with sheet metal (Aluminium alloy bar) as work piece material. It was found that, drill axial force increases as drill size increases for a given speed and decreases as spindle speed increases for a given diameter. Also drill axial force increases as feed rate increases for a given diameter, while the drill torque varies non-linearly with all the control parameters [7].

Impact of spindle speed, feed rate, type of drill tool, cutting environment were analyzed on performance parameters- material removal rate, surface roughness, Torque, cutting force and power during the drilling of EN8 steel. In the present work, Taguchi method is combined with ANN for effective data representation in wide range with low experimental cost, to predict responses in drilling of EN 8. From ANOVA it was observed that torque and surface roughness is mostly affected by feed and cutting force, material removal rate and power is mostly affected by spindle speed [13].

Neural network model is used to predict the multi-responses and to study the influence of drilling parameters- cutting speeds, feed rates, type of drill tool, cutting fluids on output parameters- Torque, cutting force, surface roughness, material removal rate and power for determining the optimum input parameters combination using Taguchi method. It was found that, Surface finish and torque are mostly affected by types of drill tools. Cutting force is mostly affected by cutting environment. Material removal rate is mostly affected by feed rate, with increase in feed rate there is decrease in MMR and power is mostly affected by cutting speed [14].

Responses- surface roughness, material removal rate, torque, cutting force, power of drilling process were predicted using ANN technique while drilling of EN 8 with coated tools. The proposed ANN model can be used in optimization of cutting process for efficient and economic production by forecasting torque, cutting force, MRR, power and surface roughness in drilling operations [15].

Study has been reported on the influence of machining parameters- cutting speed, feed rate and cutting environment on the surface roughness obtained in drilling of AISI 1045. It was found that minimum surface roughness is obtained at lower cutting speeds, while it deteriorates as a feed rate is increased. Surface roughness was much better for the MQL condition than for the compressed air and dry drilling, also it increases under dry drilling [4].

Researcher investigates the drilling of Al/SiC/ Graphite hybrid composite material (Al6061) with spindle speed, feed rate, drill diameter and type of drill as input parameters and surface roughness as performance parameter by using RSM. It was found that minimum surface roughness could be achieved at higher spindle speed, lower feed rate and low or moderate drill diameter [1].

Machining parameters such as spindle speed, feed rate and cone radius ratio were optimized for thermo mechanical form drilling of Aluminium sheet (Al1100) with tungsten carbide tool using desirability function analysis (DFA). The spindle speed (percentage contribution, P = 27.59%) is the more significant machining parameter for affecting the multiple performance characteristics form drilling process [9].

It is verdict that combined optimization of material removal rate (MRR) and surface roughness (SR) of the hard tool and die steel (HSS T1) under drilling processes is need to be done to fulfill the customer demand and economic production. RSM is the robust modeling technique rather than ANN and Taguchi. RSM modeling


Fig. 1: Drilling Setup (BVR 3)

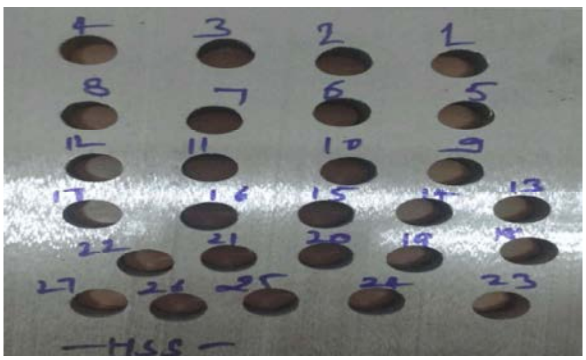


Fig. 2: Work piece material

Fig. 3: Drilling tool

has ability to predict responses using less number of experimental runs. In this radial drilling machine operation spindle speed, feed rate, fluid concentration and fluid flow rate were selected as critical influencing parameters which affects directly to the MRR and SR. The combined effect of the parameters will be critically analyzed on responses. Experiments were carried out on HSS T1 tool steels as work piece using tungsten carbide drilling tool. The experimental setup is being shown as Fig. 1.

**Experimental Set-Up:** A number of experiments were conducted to study the effects of various machining parameters on drilling process. These studies were undertaken to investigate the effects of spindle speed, feed, coolant concentration and flow rate on surface roughness (SR) and material removal rate (MRR). The selected work piece material for this research work was high speed steel (HSS T1 grade). HSS was selected due to its emergent range of applications in the field of machine tools in various industries. Experiments were conducted on radial drilling machine (BVR 3). A tungsten carbide drill bit with a diameter of 10 mm was used as a tool and work piece materials used as HSS plates of dimensions100mm X 75mm X 80mm, its composition and properties are shown in Table 1 and Table 2 respectively. Tungsten carbide twist drill bit tool is also selected appropriately as per the industrial scope and work piece material. Drill bit hardness must be higher than the work piece hardness, also the drill bit must have proper lip angle and lip clearance for the job cutting. Work piece material and tool are given in Fig. 2 and Fig. 3 respectively. The experimental design conditions are depicted in Table 3.

**Surface Roughness Measurements and MRR Calculation:** Surface Roughness measurement was carried out using a portable stylus type profile-meter, Mitutoyo Surface Tester SJ-201. The profile-meter was set to a cut-off length of 0.8 mm, filter 2CR and traverse speed 1mm/second and 4 mm evaluation length. Centre line average (CLA) values of surface roughness (SR) were measured in the transverse direction of work piece. The values of SR measurement were repeated three times for each reading and average value was recorded. The parameters that affect MRR and surface roughness are spindle speed, feed, coolant concentration and flow rate. Optimal parametric combination may deals the technological quality of a product, which mostly influence the manufacturing cost of the product. SR is defined as the arithmetic value of the profile from the centerline along the length. This can be express as;

Table 1: Chemical Composition of AISI T-1

| Element | C | Si | Mn | Cr | V | W |
|---|---|---|---|---|---|---|
| % | 0.65-0.75 | 0.20-0.40 | 0.200.40 | 3.754.50 | 0.90-1.30 | 17.25-18.75 |

Table 2: Properties of HSS T1

| Mechanical Properties | Matrix | Imperial |
|---|---|---|
| Hardness Rockwell C | 63.0-65.0 | 63.0-65.0 |
| Poisson's ratio | 0.27-0.30 | 0.27-0.30 |
| Elastic modulus | 190-210 GPa | 27557-30457 ksi |
| Density | 8.67 g/cm3 | 0.313 lb/in3 |

Table 3: Different variables used in the experiment and their levels

| | | Levels | | |
|---|---|---|---|---|
| Code | Factors | 1 | 0 | -1 |
| A | Spindle speed (rpm) | 1800 | 1120 | 710 |
| B | Feed (mm/rev) | 0.315 | 0.20 | 0.08 |
| C | Coolant (solu.oil) in 1000ml (ml/Lit.) | 15 | 10 | 5 |
| D | Flow rate of coolant (ml/min) | 60 | 50 | 40 |

Fig. 4: Surface roughness measuring instrument (SJ 201)

$$Ra = 1/L \int y(x)\,dx \tag{1a}$$

where L is the sampling length, y is the profile curve and x is the profile direction. The average 'Ra' is measured within stylus travelling length of 0.8 mm. Centre-line average 'CLA' value of SR measurements were taken to provide quantitative evaluation of the effect of drilling parameters on surface finish. The average value of three reading up to two decimal place of microns will be obtained the least count 1nm (nanometer) as Fig. 4.

The amount of material removal was obtained by finding the weight difference before and after machining using a precision electronic digital weight balance with 0.1mg resolution. The MRR is calculated using the following formula in equation 1b:

$$\text{MRR (gram/sec)} = (W_i - W_f)\,/t \tag{1b}$$

were $Wi$ is initial weight of work piece in gram (before machining); $Wf$ is final weight of work piece in gram (after machining); $t$ is machining time in seconds.

**Response Surface Methodology:** RSM is a collection of mathematical and statistical techniques that are useful for modeling and analysis of problems in which output or response is influenced by several input variables and the objective is to find the correlation between the response and the variables investigated [10]. It is one of the Design of Experiments (DOE) methods used to approximate, an unknown function for which only a few values are computed. These relations are then modeled by using least square error fitting of the response surface. A Central Composite Design (CCD) is used since it gives a comparatively accurate prediction of all response variable averages related to quantities measured during experimentation [12]. CCD offers the advantage that certain level adjustments are acceptable and can be applied in the two-step chronological RSM. In these methods, there is a possibility that the experiments will stop with few runs and decide whether the prediction model is satisfactory or not.

In CCD, the limits of the experimental domain to be explored are defined and are made as wide as possible to obtain a clear response from the model. The spindle speed, feed, coolant concentration and flow rate are the machining variables selected for this investigation. The different levels taken for this study are depicted in Table 3. An experiment in series of test called runs.

Table 4: L27 Orthogonal array and Experimental data

| Sl.No | Spindle Speed (rpm) | Feed (mm/m) | Fluid con. (g/l) | Flow rate (ml/min) | MRR (gm/sec) | Ra (micron) |
|---|---|---|---|---|---|---|
| 1 | 1120 | 0.20 | 10 | 50 | 0.001179 | 2.11 |
| 2 | 1800 | 0.20 | 10 | 60 | 0.001886 | 1.92 |
| 3 | 1800 | 0.20 | 10 | 40 | 0.001587 | 2.15 |
| 4 | 1120 | 0.315 | 5 | 50 | 0.001796 | 1.95 |
| 5 | 1120 | 0.20 | 10 | 50 | 0.001207 | 2.07 |
| 6 | 1800 | 0.20 | 15 | 40 | 0.001788 | 2.05 |
| 7 | 1120 | 0.20 | 5 | 50 | 0.001064 | 2.58 |
| 8 | 710 | 0.20 | 10 | 60 | 0.000892 | 2.75 |
| 9 | 710 | 0.20 | 10 | 40 | 0.000945 | 2.82 |
| 10 | 1120 | 0.20 | 5 | 60 | 0.001100 | 2.10 |
| 11 | 1120 | 0.08 | 10 | 60 | 0.000877 | 1.98 |
| 12 | 710 | 0.20 | 15 | 50 | 0.000865 | 2.71 |
| 13 | 1800 | 0.08 | 10 | 50 | 0.001222 | 2.27 |
| 14 | 710 | 0.315 | 10 | 50 | 0.001501 | 2.50 |
| 15 | 1120 | 0.20 | 10 | 50 | 0.001390 | 2.13 |
| 16 | 1800 | 0.20 | 5 | 50 | 0.001520 | 1.66 |
| 17 | 1800 | 0.315 | 10 | 50 | 0.002465 | 1.19 |
| 18 | 1120 | 0.08 | 5 | 50 | 0.001169 | 2.21 |
| 19 | 1120 | 0.315 | 10 | 60 | 0.002033 | 1.88 |
| 20 | 1120 | 0.08 | 15 | 50 | 0.000618 | 1.84 |
| 21 | 710 | 0.20 | 5 | 50 | 0.000843 | 2.80 |
| 22 | 1120 | 0.20 | 15 | 40 | 0.001281 | 2.15 |
| 23 | 1120 | 0.08 | 10 | 40 | 0.000795 | 2.14 |
| 24 | 1120 | 0.315 | 10 | 40 | 0.001825 | 1.96 |
| 25 | 710 | 0.08 | 10 | 50 | 0.000573 | 2.61 |
| 26 | 1120 | 0.20 | 15 | 60 | 0.001333 | 1.32 |
| 27 | 1120 | 0.315 | 15 | 50 | 0.001929 | 1.80 |

L27 runs DOE at three levels were selected critically as per the feasibility and scope of setup. Material removal rate and surface roughness values are given in Table 4 for 27 tests according to different control levels.

The second-order model is normally used when the response function is not known or nonlinear. In the present study, a second order model has been utilized. The experimental values are analyzed and the mathematical model is then developed that illustrate the relationship between the process variable and response. The second-order model in equation 2 explains the behavior of the system.

$$Y = \beta_o + \sum_{i=1}^{k} \beta_i X_i + \sum_{i=1}^{k} \beta_i i X_i^2 + \sum_{i,j=1, i\neq j}^{k} \beta_{ij} X_i X_j + \in \tag{2}$$

where Y is the corresponding response, Xi is the input variables, Xi2 and Xi, Xj are the squares and interaction terms, respectively, of these input variables. The unknown regression coefficients are βo, βi, βij and βii and the error in the models.

**Regression Models:** Based on the experimental data, statistical regression analysis enabled to study the correlation of process parameters with the MRR and SR. Both linear and non-linear regression models were examined, acceptance was based on high to very high coefficients of correlation (R2) calculated. In this study, four variables are under consideration to obtain the polynomial regression modeling. For simplicity, a quadratic model of MRR and SR are proposed. The coefficients of regression model can be estimated from the experimental results. The effects of these variables and the interaction between them were included in this analysis's. The unknown coefficients are determined from the experimental data as presented in Table 5 & 6. The standard errors on estimation of the coefficients are tabulated in the column 'MRR coefficient' and 'SR coefficient'. The P & T values are calculated for 95% level of confidence and the factors having p-value more than 0.05 are considered strictly insignificant (shown with ** in p-column) whereas * is less significant. The model made to represent MRR and SR depicts that speed, feed, feed2 and interaction of feed and fluid cons. and speed, feed and interaction of feed2 are most influencing parameters in order of significance. The final response equation for MRR and SR are non-linear in nature, a linear polynomial will not be able to predict the response accurately. Therefore the second-order model (quadratic model) is found to be adequately model for the drilling process. The equations to calculate SR and MRR are being given as;

Table 5: Estimated Regression Coefficients for SR (micron)

| Term | Mean Square Coef. | Sum of Esquires Coef | T (term coef.) | 'P' value |
|---|---|---|---|---|
| Constant | 2.09246 | 0.14620 | 14.313 | 0.000 |
| Speed (rpm) | -0.43250 | 0.06261 | -6.907 | 0.000 |
| Feed (mm/m) | -0.19188 | 0.06314 | -3.039 | 0.011 * |
| Fluid con. (g/L) | -0.11532 | 0.06927 | -1.665 | 0.124** |
| Flow rate (m L/min) | -0.11129 | 0.06721 | -1.656 | 0.126** |
| Speed (rpm)*Speed (rpm) | 0.30038 | 0.10295 | 2.918 | 0.014 * |
| Feed (mm/m)*Feed (mm/m) | -0.18113 | 0.09847 | -1.839 | 0.093* |
| Fluid con. (g/L)*Fluid con. (g/L) | -0.13180 | 0.10273 | -1.283 | 0.226** |
| Flow rate (m L/min)* Flow rate (mL/min) | -0.07121 | 0.10348 | -0.688 | 0.506** |
| Speed (rpm)*Feed (mm/m) | -0.26872 | 0.10320 | -2.604 | 0.025 * |
| Speed (rpm)*Fluid con. (g/L) | 0.07772 | 0.11480 | 0.677 | 0.512** |
| Speed (rpm)*Flow rate (m L/min) | -0.02550 | 0.09844 | -0.259 | 0.800** |
| Feed (mm/m)*Fluid con. (g/L) | 0.05490 | 0.10529 | 0.521 | 0.612** |
| Feed (mm/m)*Flow rate (m L/min) | 0.01904 | 0.10529 | 0.181 | 0.860** |
| Fluid con. (g/L)* Flow rate (m L/min) | -0.22059 | 0.12692 | -1.738 | 0.110* |
| S = 0.210612 | PRESS = 3.02164 | | | |
| R-Sq = 88.89% | R-Sq(adj) = 86.68%. | | | |

Table 6: Estimated Regression Coefficients for MRR

| Term | Mean Square Coef. | Sum of Esquires Coef | T (term coef.) | 'P' value |
|---|---|---|---|---|
| Constant | 0.001334 | 0.000083 | 16.023 | 0.000 |
| Speed (rpm) | 0.000413 | 0.000036 | 11.594 | 0.000 |
| Feed (mm/m) | 0.000538 | 0.000036 | 14.958 | 0.000 |
| Fluid con. (g/L) | 0.000052 | 0.000039 | 1.311 | 0.216** |
| Flow rate (m L/min) | 0.000048 | 0.000038 | 1.265 | 0.232** |
| Speed (rpm)*Speed (rpm) | -0.000037 | 0.000059 | -0.634 | 0.539** |
| Feed (mm/m)*Feed (mm/m) | 0.000153 | 0.000056 | 2.726 | 0.020* |
| Fluid con. (g/L)*Fluid con. (g/L) | -0.000029 | 0.000058 | -0.500 | 0.627** |
| Flow rate (m L/min)* Flow rate (m L/min) | 0.000016 | 0.000059 | 0.274 | 0.789** |
| Speed (rpm)*Feed (mm/m) | 0.000080 | 0.000059 | 1.365 | 0.199** |
| Speed (rpm)*Fluid con. (g/L) | 0.000105 | 0.000065 | 1.604 | 0.137** |
| Speed (rpm)*Flow rate (m L/min) | 0.000073 | 0.000056 | 1.296 | 0.221** |
| Feed (mm/m)*Fluid con. (g/L) | 0.000174 | 0.000060 | 2.898 | 0.014* |
| Feed (mm/m)*Flow rate (m L/min) | 0.000031 | 0.000060 | 0.510 | 0.620** |
| Fluid con. (g/L)* Flow rate (m L/min) | 0.000020 | 0.000072 | 0.275 | 0.788** |
| S = 0.000119931 | PRESS = 8.517204E-07 | | | |
| R-Sq = 97.28% | R-Sq(adj) = 93.81% | | | |

*SR* = Constant + Speed (rpm) + Feed (mm/m) + Fluid con. (g/L)- Flow rate (m L/min)+ Speed (rpm)*Speed (rpm) - Feed (mm/m)*Feed (mm/m)+ Fluid con. (g/L)*Fluid con. (g/L)- Flow rate (m L/min)* Flow rate (mL/min)+ Speed (rpm)*Feed (mm/m)- Speed (rpm)*Fluid con. (g/L)+ Speed (rpm)*Flow rate (m L/min)+ Feed (mm/m)*Fluid con. (g/L)- Feed (mm/m)*Flow rate (m L/min)- Fluid con. (g/L)* Flow rate (m L/min).

*MRR* = Constant + Speed (rpm)- Feed (mm/m)- Fluid con. (g/L)+ Flow rate (m L/min)+ Speed (rpm)*Speed (rpm)+ Feed (mm/m)*Feed (mm/m) - Fluid con. (g/L)*Fluid con. (g/L)+ Flow rate (m L/min)* Flow rate (m L/min)+ Speed (rpm)*Feed (mm/m)+ Speed (rpm)*Fluid con. (g/L)+ Speed (rpm)*Flow rate (m L/min)+ Feed (mm/m)*Fluid con. (g/L)- Feed (mm/m)*Flow rate (m L/min)- Fluid con. (g/L)* Flow rate (m L/min).

The ANOVA for the curtailed quadratic model depicts the value of coefficient of determination of MRR and SR are R2 as 97.28% and 88.89%, which signifies that how much variation in the response is explained by the model. The higher of R2, indicates the better fitting of the model with the data. However, R2adj is 93.31% and 86.68%, which accounts for the number of predictors in the model describes the significant coefficient relationship. It is important to check the adequacy of the fitted model, because an incorrect or under-specified model can lead to misleading conclusions. By checking the fit of the model one can check whether the model is underspecified. The model adequacy checking includes the test for significance of the regression model, model coefficients and lack of fit, which is carried out subsequently using ANOVA on the curtailed model.

The total error on regression is sum of errors on linear, square and interactions terms (26.7139 = 19.8984 + 2.6913 + 4.1241). The residual error is the sum of pure and lack-of-fit errors. The fit summary recommended that the quadratic model is statistically significant for analysis of SR. In the table, p-value for the lack-of-fit is 0.318, which is insignificant, so the model is certainly adequate. Moreover, the mean square error of pure error is less than that of lack-of-fit.

## RESULT AND DISCUSSION

It is very clear that one response is optimum at certain input parametric combinations. Similarly others responses are also optimum at others input parametric combinations. It is very difficult to obtain such influencing parametric combinations which applicable to achieve the optimal responses as surface roughness and material removal rate. Lot of modeling and optimization techniques are frequently used in the drilling processes for different materials, but the response surface methodology (RSM) was the most important modeling and optimization tool which applicable for the multi objective response optimization. Multi objective response optimization (MORO) technique is being incorporated as Fig. 5. In the present investigation, intelligence approach (MORO) is being used to combine optimization of SR and MRR at a time using optimal values of influencing parametric combinations like speed, feed, fluid concentrations and flow rate as given in Fig. 5.

The effect of the machining parameters (spindle speed, feed, coolant concentration and flow rate) on the response variables MRR have been evaluated by relation to the process parameters of spindle speed and feed while coolant concentration and flow rate constant at their maximum value. It can be seen from the Fig. 5, the MRR tends to increase significantly with the increase in feed for any value of spindle speed. However, the MRR tends to decrease with increase in spindle speed, especially at higher feed. The effect of the machining parameters (spindle speed, feed, coolant concentration and flow rate) on the response variables SR have been evaluated by relation to the process parameters of spindle speed and feed while coolant concentration and flow rate constant at their maximum value. It can be seen from the figure, the SR tends to increase significantly with the increase in feed for any value of spindle speed. However, the SR tends to increase with increase in spindle speed, especially at higher feed. The details of other parameters are describe below;

The effect of feed and speed on SR is shown in Fig. 6. Here it is observed that SR decreases with increase in feed and speed in drilling of hard material with conventional drilling, but such circumstances always lead to the tool breakage.

Fig. 7. Show the effect of feed and fluid cons. on SR, it indicates that the SR decreases with increased in feed and fluid concentration in drilling. Therefore high fluid concentration is needed to achieve the good surface finish of HSS T1 tool material.

The effect of flow rate and speed on SR is shown in Fig. 8. It indicates that SR decreases with decrease of speed and by moderate flow rate, because the lower circumferential speed of the drill bit indicates the good surface finish, whereas flow rate is required to be moderate to achieve better surface finish in drilling.

The effect of feed and speed on MRR is shown in Fig. 9. It represents that moderate feed rate lead to MRR whereas high speed is improving the material removal rate in drilling of hard die/tool steel (HSS T1) using tungsten carbide drill, but other hand the tendency to wear the tool and chances to breakage of tool improves.

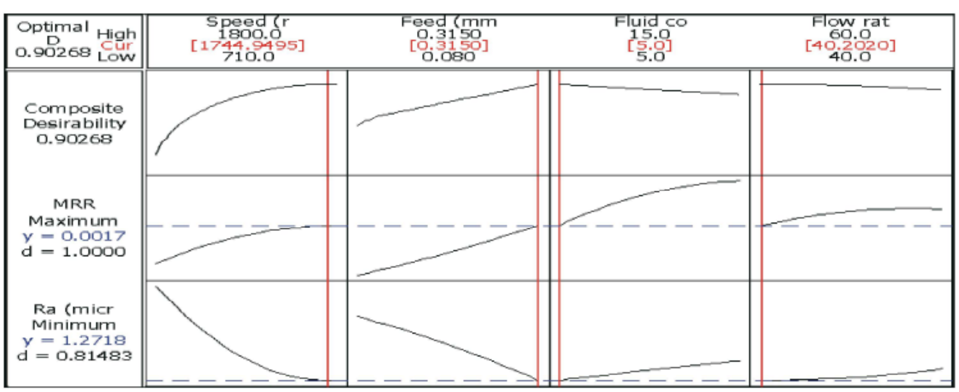


Fig. 5: Response optimization plot (SR and MRR)

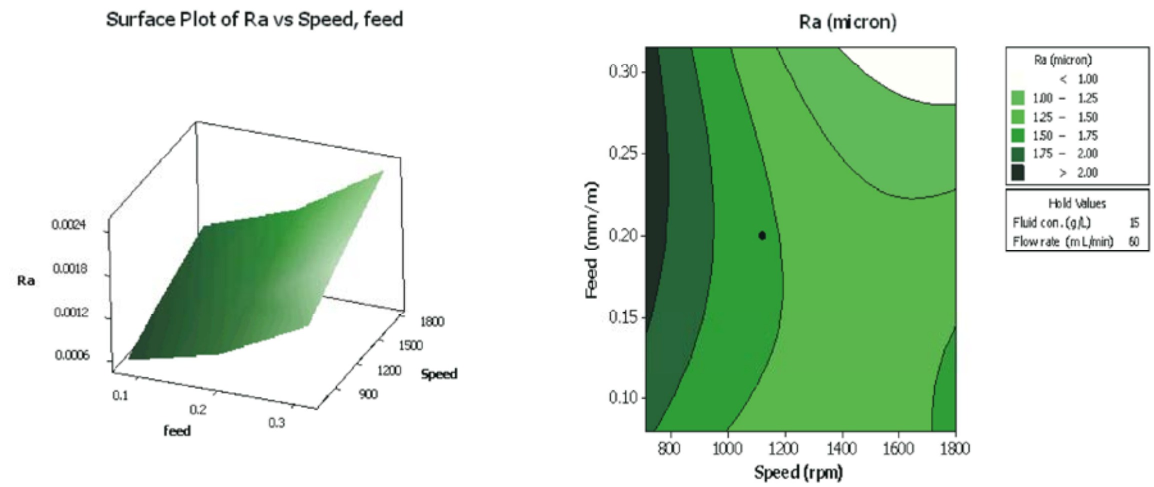


Fig. 6: Surface and Contour plots of SR vs. feed and speed

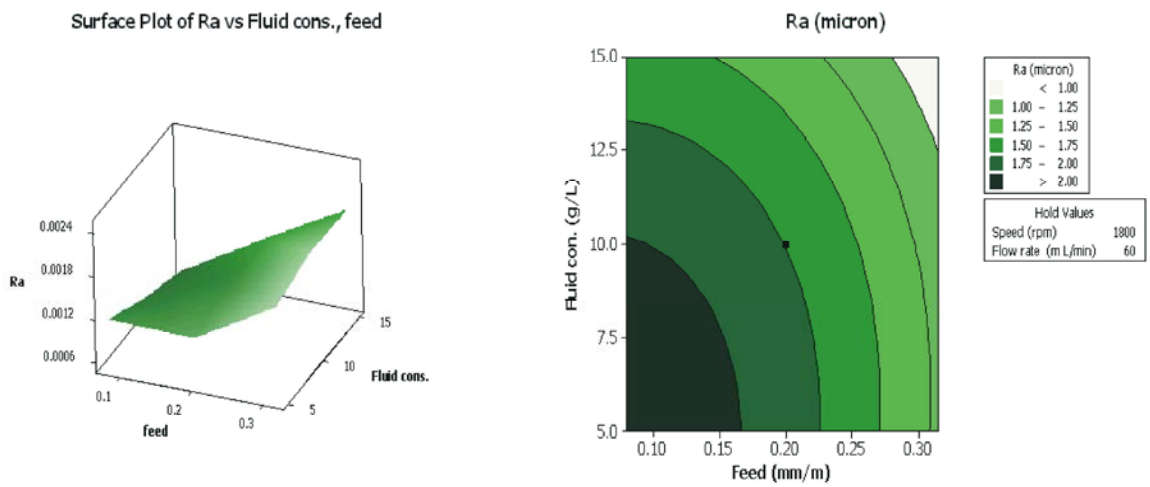


Fig. 7: Surface and Contour plots of SR vs. feed rate and fluid cons

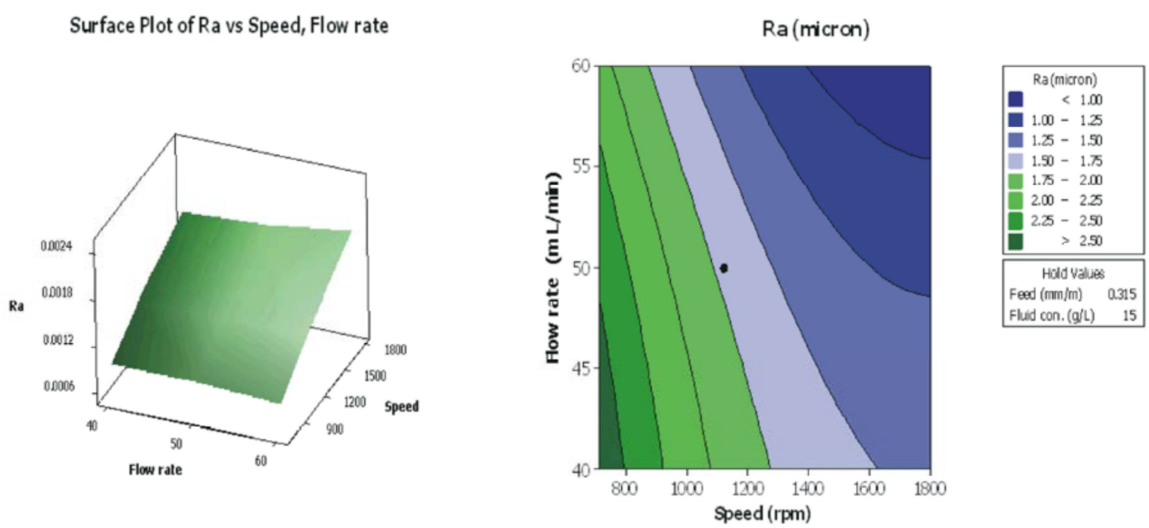


Fig. 8: Surface and Contour plots of SR vs. flow rate and speed

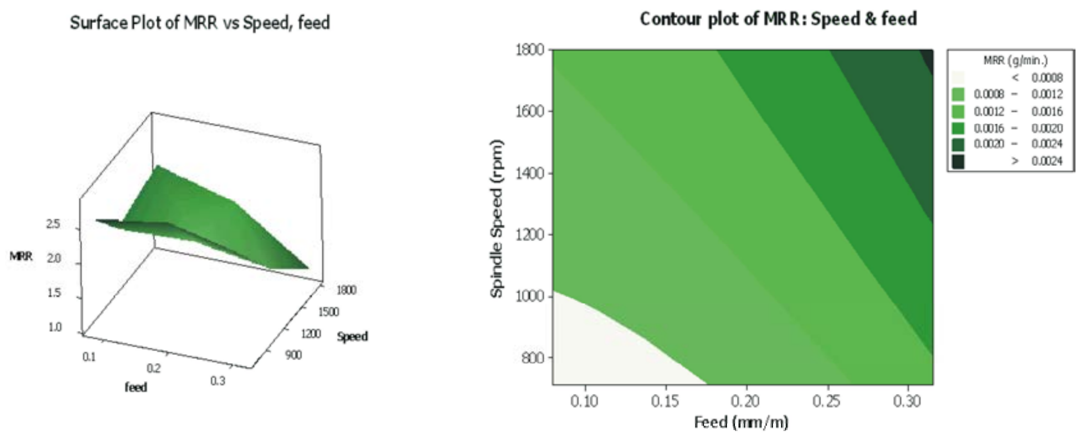


Fig. 9: Surface and Contour plots of MRR vs. speed and feed rate

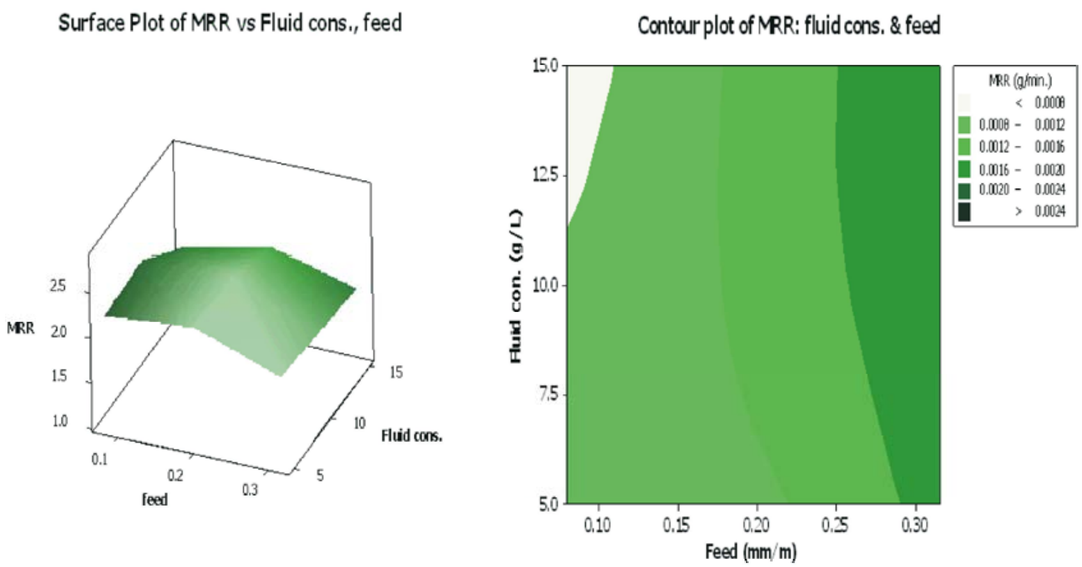


Fig. 10: Surface and Contour plots of MRR vs. feed rate and fluid cons

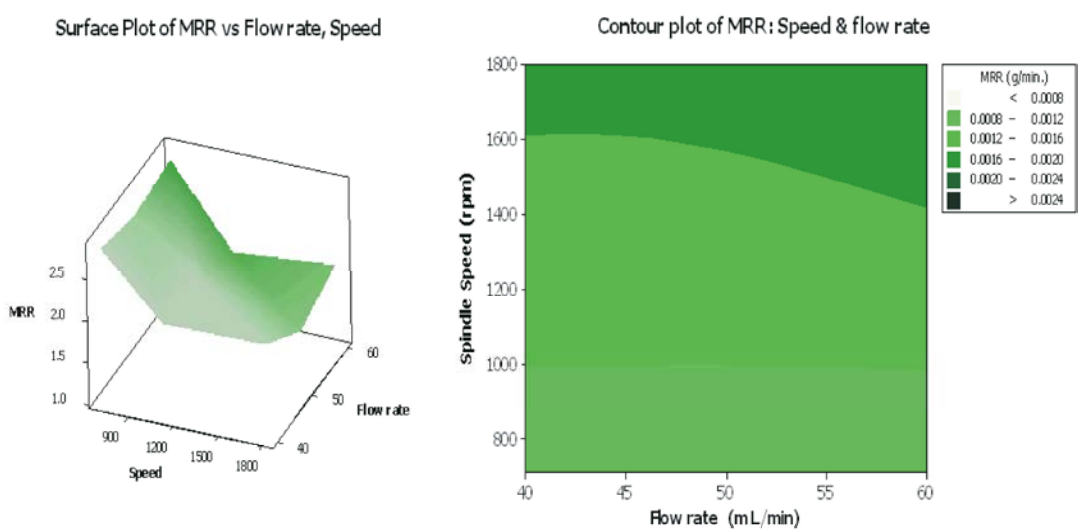


Fig. 11: Surface and Contour plots of MRR vs. speed and flow rate

The effect of feed and fluid cons. on MRR is shown in Fig. 10. It is observed that within the range of feed and fluid cons. Investigated, moderate feed rate lead to MRR whereas high fluid concentration is improving the material removal rate in drilling of hard die/tool steel (HSS T1) using tungsten carbide drill.

The effect of speed and flow rate on MRR is shown in Fig. 11. The graph represents the higher speed is required to improving the material removal rate in drilling of very hard work material. Also the high flow rate is essential to improve the MRR, therefore machined debris has to be remove adequatly with the influence of high flow rate of cutting fluid.

## CONCLUSION

In the present study, the process parameters are significantly influencing on SR and MRR. A second order response model of these parameters are developed and found that spindle speed, feed and interaction term of spindle speed and feed, feed and fluid cons. with other parameters significantly affect the SR and MRR. Drilling experiment conducted on radial drilling machine having different slurry concentration on HSS work piece. RSM techniques were also implemented to predict the surface roughness and MRR. Correlation coefficient (R2) values were observed 97.28 % and 88.89% for MRR and SR respectively. Responses (MRR and SR) were also optimized as 0.0017 g/sec and 1.2718 micron respectively using critical values of variables spindle speed, feed, coolant concentration and flow rate as 1744.9495 rpm, 0.3150 mm/min, 5.0 g/l and 40.2020 l/min respectively with influence of RSM technique. The research findings of the present study based on RSM models can be used effectively in machining of HSS in order to obtain best possible drilling efficiency. This research can also help researches and industries for developing a robust, reliable knowledge base and early prediction of SR and MRR without experiment with drilling process for HSS.

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