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MULTI OBJECTIVE OPTIMIZATION OF BTA DEEP HOLE DRILLING PROCESS PARAMETERS USING RESPONSE SURFACE METHODOLOGY

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ABSTRACT

In this work an attempt has been made to drill Aluminium casting using BTA (Boring Trepanning Association) deep hole drilling tool and optimize the deep hole drilling process parameters using 'Response Surface Methodology (RSM)'. BTA machining is capable of drilling holes having large length to diameter ratio in a single pass. The present work deals with optimization of surface roughness (Ra) and Metal Removal Rate (MRR) of BTA machined Aluminium components using RSM. Experiments were carried out over a wide range of cutting conditions and the effect of various process parameters like spindle speed, feed rate and depth of cut using Box-Behnken design of experimental design technique. Results are analyzed using Analysis of Variance (ANOVA) and response surface considering individually output parameters such as Metal Removal Rate (MRR) and surface roughness (Ra). ANOVA and response surface analyses indicated that combinations of BTA deep hole drilling process parameters such as high speed, high feed and high depth of cut resulted in higher Metal Removal Rate (MRR), whereas low speed, low feed and low depth of cut resulted in lower Ra in Aluminium casting material. The output of this work will be useful for manufacturing engineers in deep hole drilling of Aluminium casting material which finds its application in various mechanical fields like automobile, aerospace, defense, etc.,

KEYWORDS: BTA Deep Hole Drilling, Aluminium L9 Casting Material, Box-behnken Method, Response Surface Methodology.

INTRODUCTION

Deep hole drilling methods are used for drilling holes with a high length- to- diameter ratio, good surface finish and straightness. For drilling holes with a diameter of 20 mm and above, the BTA (Boring and Trepanning Association) deep hole machining principle is usually employed. The literatures related to the deep hole drilling and RSM are shortly presented here. Biermann et al. (2012) studied that the deep hole drilling with solid carbide twist drills yields higher feed rates and the consequently higher productivity[1]. Xavier et al (2013) studied about the conventional deep hole drilling process to produce small deep holes. They found many factors that increase the tool wear that affects dimensional accuracy and surface finish, which can be rectified by tool geometry, chip disposal etc [2]. Jathkar et al. (2012) made attempt on analysis of BTA machining using RSM. They worked with surface roughness (Ra) and hole size of BTA machined stress proof steel components using back propagation neural network [3]. Weinert et al. investigated about difficulties in the deep hole drilling methods and found that the slender tool-boring bar combination needed for producing holes with a high length-to-diameter ratio leads to dynamic disturbance. [4] D.Biermann et al. (2009) have studied an optimization process, to develop the BTA drill head. [5]. Sarafi Amir et al. (2013) have discussed the application of Response Surface Methodology (RSM) and Central Composite Rotatable Design (CCRD) for modeling and optimization of the influence of some operating variables on the performance of a lab scale thickener for dewatering of tailing in the notifications circuit. [6] Thiagarajan Rajmohan et al. (2012) have studied the application of Response Surface Methodology (RSM) and Central Composite Design (CCD) for modeling, optimization, and an analysis of the influences of dominant machining parameters on thrust force, surface roughness and burr height in the drilling of hybrid metal matrix composites produced [7].

METHODOLOGY

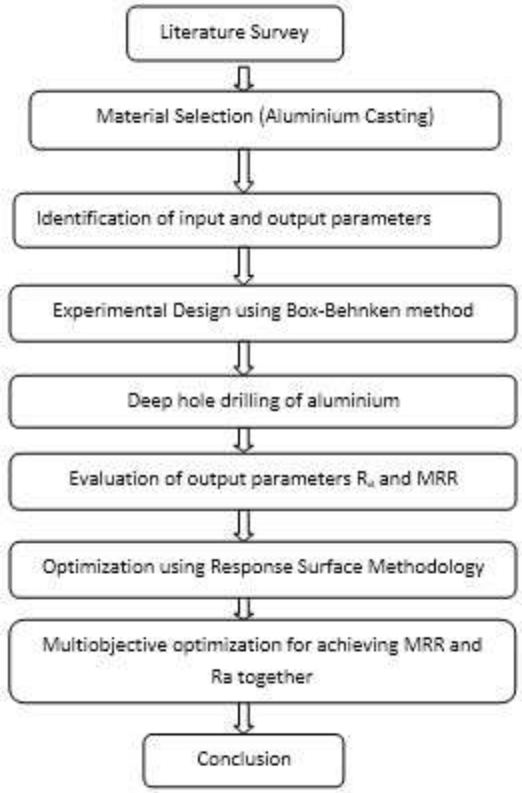

Fig.1 methodology of the work

Workpiece Material: Aluminium casting material (LM9).

a. Silicon (Si)- **11.5 %**
b. Magnesium (Mg)- **0.4 %**
c. Magnese (Mn)- **0.5 %**

Experimental Design using RSM Box- Behnken Design using RSM technique for multi-objective optimization considering Metal Removal Rate (MRR) and Surface Roughness (R_a) together.

Design of experiments

An important aspect of RSM is the design of experiments (Box and Draper, 1987), usually abbreviated as DoE. These strategies were originally developed for the model fitting of physical experiments, but can also be applied to numerical experiments. The objective of DoE is the selection of the points where the response should be evaluated. Most of the criteria for optimal design of experiments are associated with the mathematical model of the process. The choice of the design of experiments can have a large influence on the accuracy of the approximation and the cost of constructing the response surface. Its purpose is to identify the design variables that have large effects for further investigation. A detailed description of the design of experiments theory can be found in Box and Draper (1987) [8]. Myers and Montgomery (1995) and Montgomery (1997), among many others. Schoofs (1987) has reviewed the application of experimental design to structural optimization [9]. Unal et al. (1998) discussed the use of several designs for response surface methodology and multidisciplinary design optimization [10]. Simpson et al. (1997) presented a complete review of the use of statistics in design. As introduced, a particular combination of runs defines an experimental design. Where, represents the noise or error observed in the response. The surface represented by $f(x_1, x_2)$ is called a response surface [11].

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In this response surface methodology there are three methods of design experiments. They are as follows:

1. Box-Behnken method
2. full-factorial design method
3. Central composite method

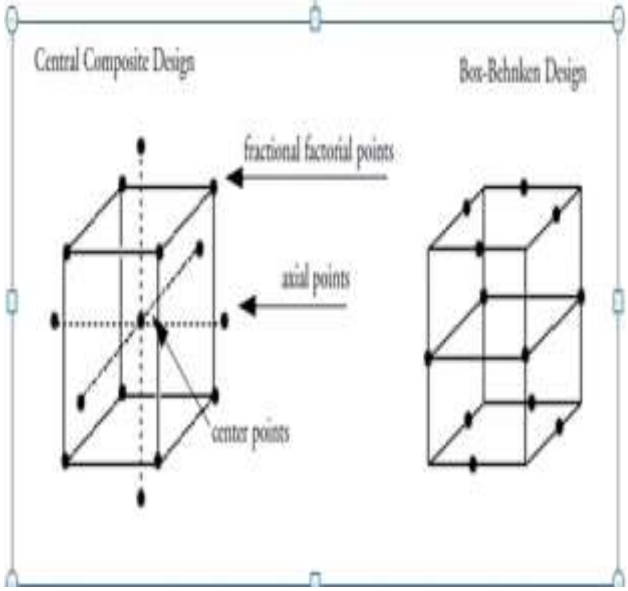

Fig.2 CentralCompositeandBox-BehnkenMethods

EXPERIMENTAL PROCEDURE

Experiments are carried out based on Response Surface Methodology (RSM) using Box-Behnken design method in order to establish relationship between the controllable BTA deep hole drilling input process parameters and output parameters (MRR and Ra). RSM helps to optimize the response that is influenced by the various input process parameters.

The important BTA deep hole drilling process parameters such as Speed (N), Feed (F) and Depth Of Cut (DOC) are varied at three levels (low, medium and high) while machining aluminium casting material as shown in Table 1. The experiments are conducted in random order and the typical machined component of Aluminium casting material is shown in Fig. 3. The non-variable BTA Deep Hole Drilling process parameters while machining are shown in Table 2.

Table 1. BTA deep hole drilling Input Process parameters and their levels

PARAMETERS	LOW	MEDIUM	HIGH
	-1	0	+1
SPEED (rpm)	1000	2000	3000
FEED (mm/rev)	0.07	0.16	0.25
DOC (mm)	180	190	200

Table 2. Non Variable Factors and their Levels

FACTOR LEVELS	**FACTOR**
Capacity of cooling unit (Kcal/hr)	9000
Operating pressure (Kgf/cm^2)	4-5
Solenoid coil voltage (v)	24 v DC
Coolant tank capacity(ltrs)	1200

Lubrication tank capacity (ltrs)	5
No. Of fixtures (nos)	1
Tool diameter (mm)	26
Hole diameter (mm)	26

Fig 3. Photograph of Aluminium workpiece

RESULTS AND DISCUSSION

The following sections deals with the analysis of MRR and R_a individually using ANOVA and response surface considering the output parameters MRR and R_a together.

ALLOCATION OF INPUT PARAMETERS

The allocation of input process parameters and the results obtained are shown in table 3. The responses for various combinations of input process parameters are summarized as shown in the table 4. The significant combinations of BTA Deep Hole Drilling process parameters and their levels are obtained using ANOVA and response surface graphs (Fig. 2 to Fig. 7). The response surface graphs are obtained using experimental data (as given in Table 3) with Design-Expert software based on the regression equations. During each trail, among the three input process parameters studied in this work, any two input parameters are varied from low to high levels. For example in the case of S. No. 1 (Table 4), Depth Of Cut (DOC) is kept statistically constant, while Speed (N) is varied form 1000-3000 rpm and Feed(F) also varied from the range 0.07-0.25 mm/rev. The MRR and R_a obtained for the above combination is found to be 397×10^3 (mm^3/min) and 0.015 µm respectively (Table 4, S. No.1).

Table 3. Allocation of input process parameters and experimental results

Ex No	INPUT PROCESS PARAMETERS			OUTPUT PROCESS PARAMETERS				
	Speed (rpm)	Feed (mm/min)	Depth Of Cut(mm)	R_a1 (µm)	R_a2 (µm)	R_a3 (µm)	MEAN(R_a) (µm)	MRR $\times 10^3$ mm^3/min
1	1000	0.07	190	0.032	0.036	0.040	0.036	37.165
2	3000	0.07	190	0.135	0.127	0.131	0.131	111.495
3	1000	0.25	190	0.149	0.151	0.153	0.151	132.732
4	3000	0.25	190	0.080	0.082	0.078	0.080	398.196
5	1000	0.16	180	0.052	0.046	0.049	0.049	84.948
6	3000	0.16	180	0.062	0.059	0.065	0.062	254.845
7	1000	0.16	200	0.051	0.053	0.052	0.052	84.948
8	3000	0.16	200	0.093	0.092	0.094	0.093	254.845
9	2000	0.07	180	0.049	0.041	0.045	0.045	74.330
10	2000	0.25	180	0.058	0.062	0.054	0.058	265.464
11	2000	0.07	200	0.105	0.107	0.103	0.105	74.330
12	2000	0.25	200	0.090	0.092	0.094	0.092	265.464
13	2000	0.16	190	0.059	0.062	0.065	0.062	169.897
14	2000	0.16	190	0.067	0.070	0.073	0.070	169.897
15	2000	0.16	190	0.073	0.072	0.071	0.072	169.897

Table 4. Responses for various combinations of input process parameters

SL. NO	Speed (rpm)	Feed (mm /rev)	DOC (mm)	MRR $\times 10^3$ (mm^3 /min)	R_a (µm)
1	1000-3000	0.07 - 0.25	180	397	0.015
2	1000-3000	0.07 - 0.25	190	397	0.040
3	1000-3000	0.07 - 0.25	200	398	0.045
4	1000-3000	0.07	180-200	110	0.013
5	1000-3000	0.16	180-200	260	0.035
6	1000-3000	0.25	180-200	398	0.045
7	1000	0.07 - 0.25	180-200	135	0.012
8	2000	0.07 - 0.25	180-200	260	0.045
9	3000	0.07 - 0.25	180-200	398	0.040

ANALYSIS OF MRR

Table 5 shows the ANOVA results for the Metal Removal Rate. It indicates that among the input process parameters studied in this work the effect of Speed, Feed and Depth Of Cut are found to be significant, while there is no

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insignificant for Metal Removal Rate. The relationship between input process parameters and the response Metal Removal Rate is expressed in the form of regression equation which is given below

MRR = -1.33333E-004 +5.55556E-008 *N +0.000000 *F +0.000000 *DOC +0.53093 *N*F +0.000000 *N*DOC +0.000000 *F*DOC (1)

The model F-value o model 63660000.00 implies the model is significant. There is only a 0.01% chance that a "Model F- Value" this large could occur due to noise. The values of "Prob> F" less than 0.05 indicates model terms are significant. Value greater than 0.1 indicates model terms are not significant.

Table 5. ANOVA for Metal Removal Rate (MRR)

Source	**Sum of squares**	**df**	**Mean square**	**F value**	**p- value Prob> f**
Model	139900	9	15547.49	63660000	<0.0001
*A-Speed	57729.8	1	57729.98	63660000	<0.0001
*B-Feed	73064.41	1	73064.41	63660000	<0.0001
*C-DOC	0.000	1	0.000	-	-
*AB	9133.05	1	9133.05	63660000	<0.0001
*AC	0.000	1	0.000	-	-
*BC	0.000	1	0.000	-	-
*A^2	0.000	1	0.000	-	-
*B^2	0.000	1	0.000	-	-
*C^2	0.000	1	0.000	-	-
Residual	0.000	5	0.000	-	-
Lack of fit	0.000	3	0.000	-	-
Pure error	0.000	2	0.000	-	-
Cor total	139900	14	-	-	-

*Significant

Fig. 2 indicates response surface of MRR by varying the Speed and Feed, while DOC is held constant at low level (Fig 2.a), medium level (Fig 2.b), and high level (Fig 2.c). Fig. 2.a indicates that with low DOC (180 mm), high MRR is achievable with high speed and high feed. The maximum MRR is found to be 397×10^3 mm³/min. Fig. 2.b indicates that with medium DOC (190 mm), high MRR is achievable at high speed and high feed. The maximum value of MRR obtained with this combination is 397×10^3 mm³/min. Fig. 2.c indicates that with high DOC (200 mm), the high MRR is achievable at high speed and high feed. The maximum MRR is found to be 398×10^3 mm³/min. By comparing the influence of different levels of DOC from the Fig. 2, it is observed that high DOC results in high MRR. This may be due to the fact that, while in higher depth of cut, more machining area is exposed to drilling operation. Hence high DOC results in high Metal Removal Rate.

Fig. 3 indicates response surface of MRR by varying the Speed and DOC, while Feed is maintained constant at low level (Fig 3.a), medium level (Fig 3.b), and high level (Fig 3.c). Fig. 3.a indicates that with low Feed(0.07 mm/rev), high MRR is achievable with high speed and high DOC. The maximum MRR is found to be 110×10^3 mm³/min. Fig 3.b indicates that with medium Feed (0.16 mm/rev), high MRR is achievable at high speed and high DOC. The maximum MRR obtained is 260×10^3 mm³/min. Fig 3.c indicates that with high Feed (0.25 mm/rev), high MRR is achievable at high speed and high DOC. The maximum MRR is found to be 398×10^3 mm³/min. By comparing the influence of different levels (low, medium and high) of Feed from the Fig 3, it is observed that high Feed (0.25 mm/rev) results in high MRR. This may be due to the fact that at high feed, the rate of metal removed per unit time is also high. Hence high feed results in high Metal Removal Rate (MRR).

Fig. 4. indicates response surface of MRR by varying the Feed and DOC, while Speed is maintained constant at low level (Fig 4.a), medium level (Fig 4.b), and high level (Fig 4.c). Fig. 4.a indicates that with low Speed (1000 rpm), high MRR is achievable with high Feed and high DOC. The maximum MRR is found to be 135×10^3 (mm^3/min). Fig 4.b indicates that with medium Speed (2000 rpm), high MRR is achievable at high Feed and high DOC. The maximum value of depth of cut obtained is 260×10^3 (mm^3/min). Fig 4.c indicates that with high Speed (3000 rpm), high MRR is achievable at high Feed and high DOC. The maximum value of depth of cut obtained is 260×10^3 (mm^3/min). By comparing the influence of different levels (low, medium and high) of speed from the Fig 4, it is observed that high Speed results in high MRR. This may be due to the fact that with high spindle speed, the speed of metal removed in a unit time is also high. Thus high speed results in high Metal Removal Rate (MRR).

From the above study, it is observed that high Speed, high Feed and high DOC result in higher MRR.

ANALYSIS OF R_a

Table. 6 shows the ANOVA results for the R_a. It indicates that among the process parameters studied in this work, the effect of Depth Of Cut are found to be significant. Other effects are found to be insignificant. The relationship between input process parameters and R_a is expressed in the form of regression equation (2) which is given below.

R_a = -5.40692 -9.04722E-005 *N +1.54383 *F +0.055506 *DOC -4.61111E-004 *N*F +7.00000E-007 *N*DOC -7.22222E-003 *F*DOC +1.02500E-008 *N^2 +2.62346 *F^2 -1.42500E-004 *DOC^2 (2)

From the above regression equation (2), the response surface graphs are obtained for different process parameters (Fig 5-7). The results observed from response surface graphs for various combinations are shown in the table . The model F-value model 6.65 implies the model is significant. There is only a 2.52% chance that a "Model F- Value" this large could occur due to noise.

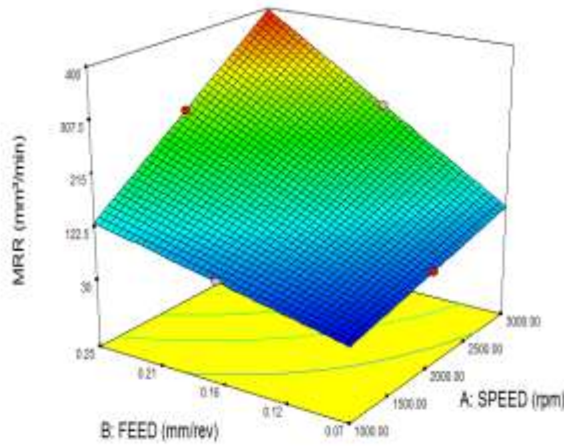
Table 6. ANOVA for Surface Roughness (R_a)

Source	**Sum of squares**	**df**	**Mean square**	**F value**	**p- value Prob> f**
Model	0.014	9	12.04	6.65	0.0252
A-Speed	760496	1	72.05	3.36	0.1261
B- Feed	511996	1	47.2	2.26	0.1927
*C- DOC	204797	1	17.48	9.06	0.0298
*AB	688897	1	65.89	30.47	0.0027
AC	195996	1	15.6	0.87	0.3946
BC	168996	1	12.9	0.75	0.4268
A^2	387896	1	34.79	1.72	0.2472
*B^2	166697	1	13.67	7.37	0.0420
C^2	749796	1	70.98	3.32	0.1282
Residual	113097	5	18.61	-	-
Lack of fit	107497	3	31.82	12.79	0.0734
Pure error	559995	2	23	-	-
Cor total	0.015	14	-	-	-

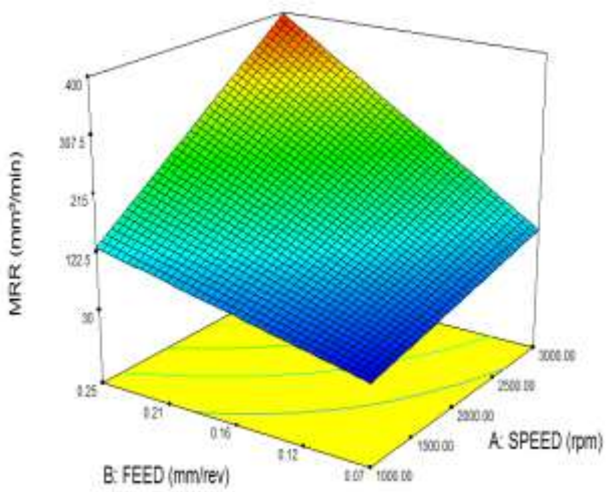
*Significant

Values of "Prob> F" less than 0.05 indicates model terms are significant. Value greater than 0.1 indicates model terms are not significant.

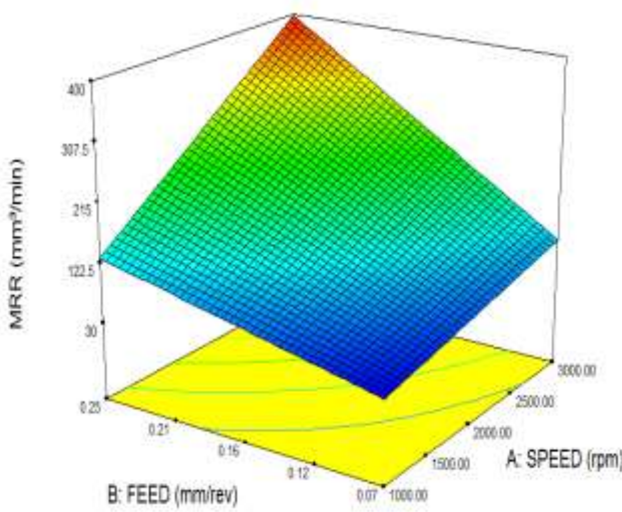
Fig 5. indicates the response surface of R_a which is obtained by varying the Speed and Feed from low level to high level while DOC is held constant at low level (Fig 5.a), medium level (Fig 5.b) and high level (Fig 5.c). Fig 5.a indicates that at low DOC (180 mm), when at low Feed rate and at low Speed, the R_a is found to be lower. The lower R_a that can be achievable by this combination is found to be 0.015 µm. Similar trends are observed with medium DOC (190 mm) (Fig 5.b) and high DOC (200 mm) (Fig 5.c). The R_a value that can be achieved with these combinations is found to be 0.040 µm and 0.045 µm respectively. By comparing the influence of different levels of DOC, it was observed that low DOC results in lower R_a. This may be due to the fact that, at lower DOC the wear rate of tool is less because of lower drilling area. As lesser as tool wear, the surface quality is fine. Thus low DOC(180 mm) results in low R_a.



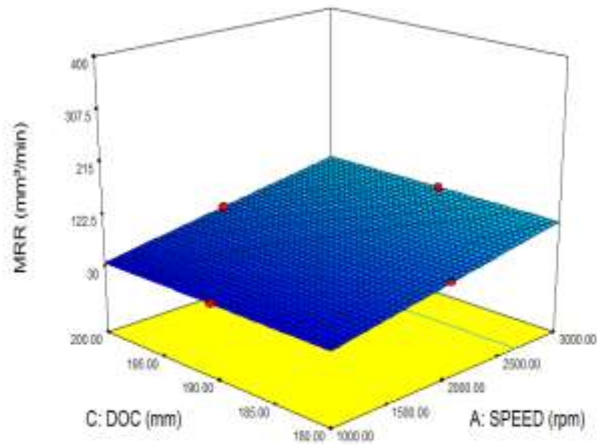
2.a Speed vs Feed at low DOC



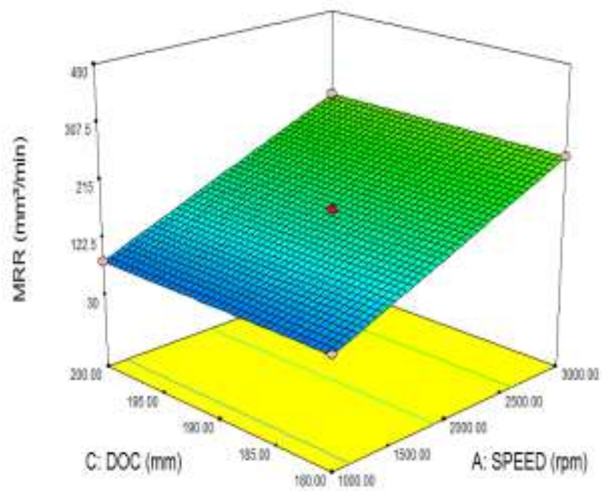
2.b: Speed vs Feed at medium DOC



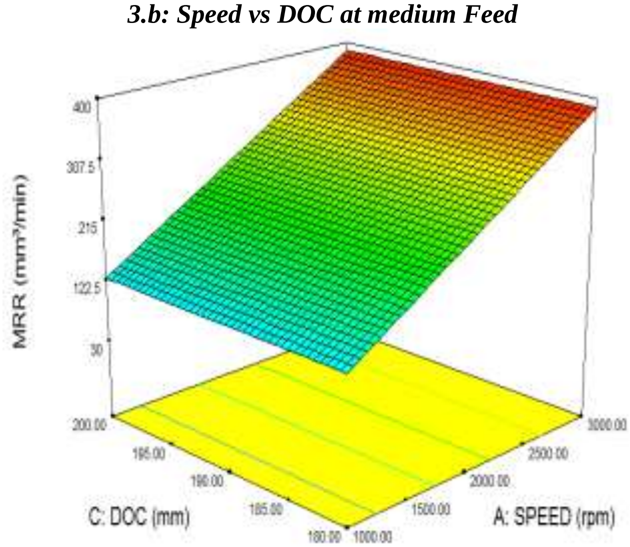
2.c: Speed vs Feed at high DOC
Fig 2. Response surface of MRR at various DOC levels



3.a Speed vs DOC at low Feed

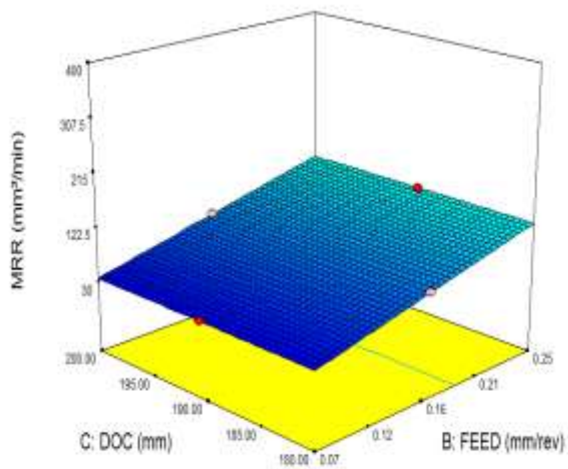


3.b: Speed vs DOC at medium Feed

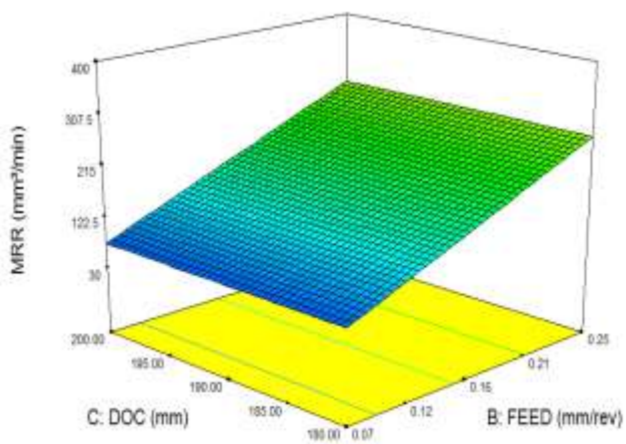


3.c: Speed vs DOC at high Feed

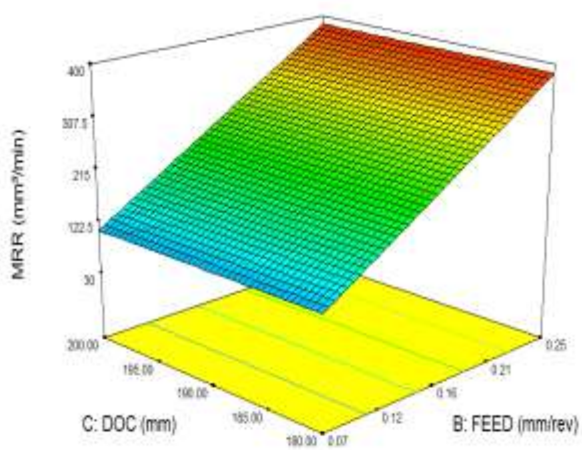
Fig 3. Response surface of MRR at various Feed levels



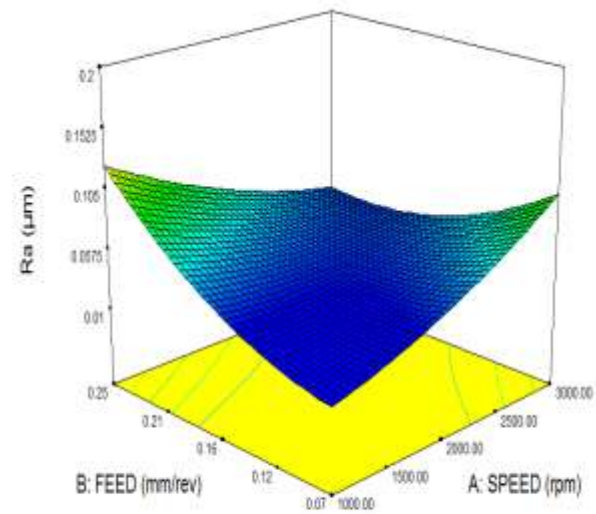
4.a: Feed vs DOC at low Speed



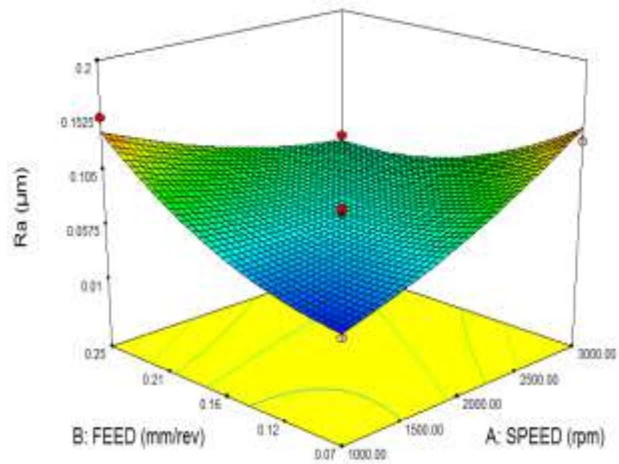
4.b: Feed vs DOC at medium Speed



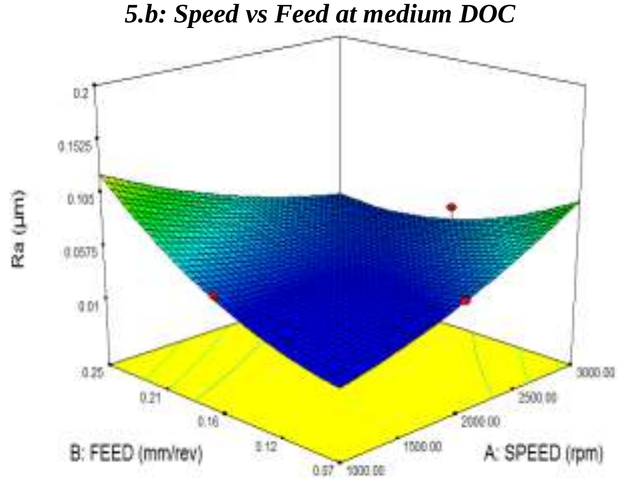
4.c: Feed vs DOC at high Speed
Fig 4. Response surface of MRR at various Speed levels



5.a: Speed vs Feed at low DOC

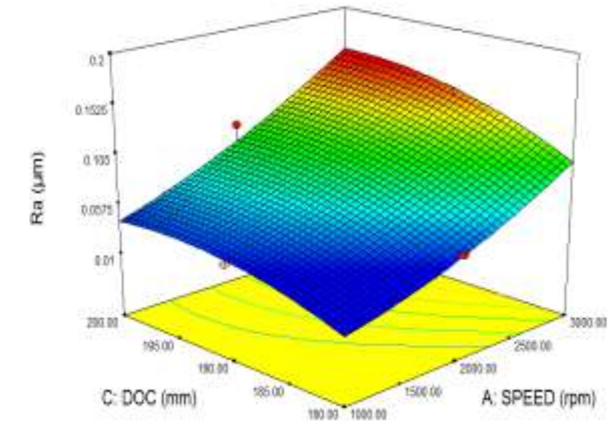


5.b: Speed vs Feed at medium DOC

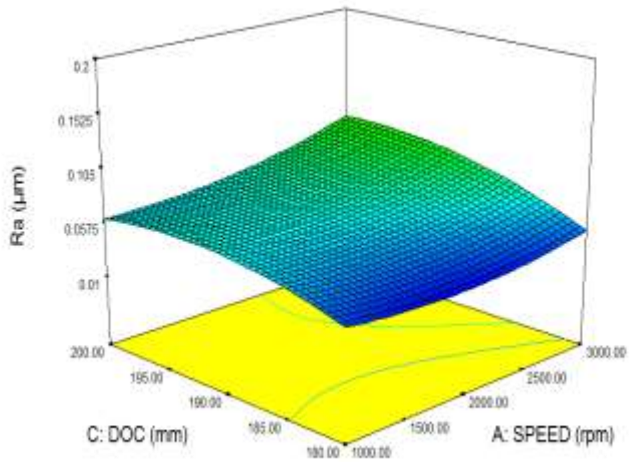


5.c: Speed vs Feed at high DOC

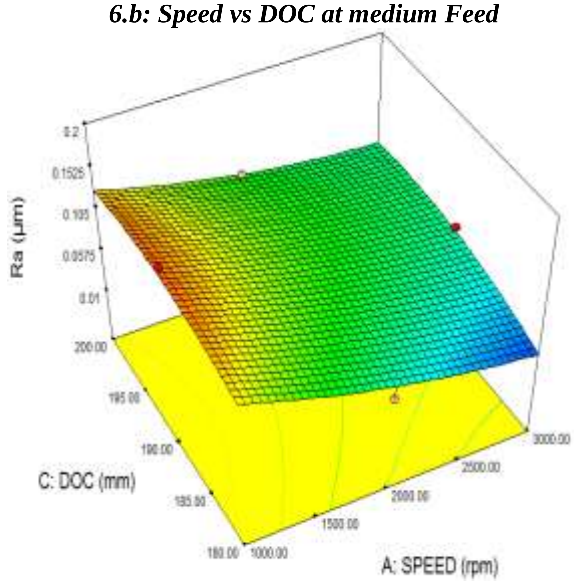
Fig 5. Response surface of R_a at various DOC levels



6.a: Speed vs DOC at low Feed

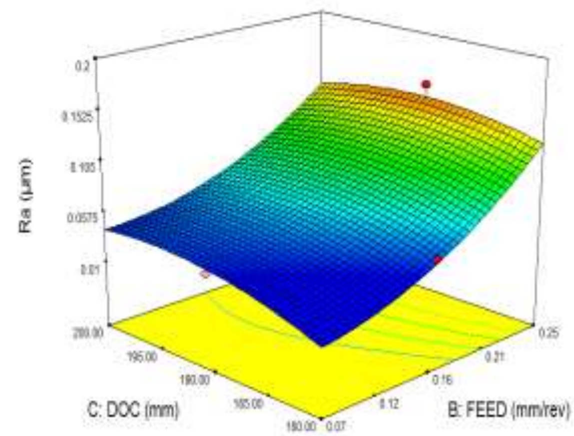


6.b: Speed vs DOC at medium Feed

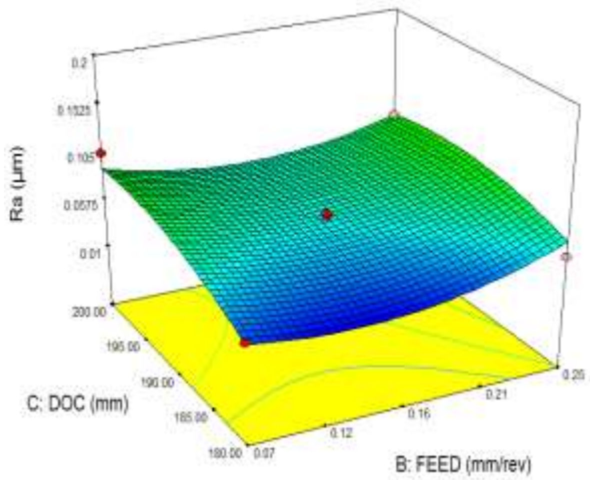


6.c: Speed vs DOC at high Feed

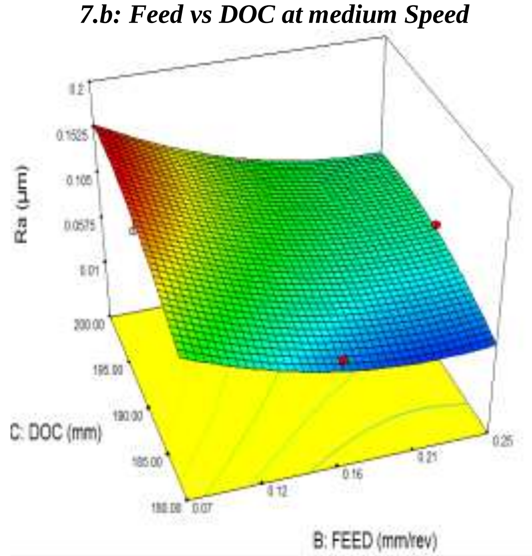
Fig 6. Response surface of R_a at various Feed levels



7.a: Feed vs DOC at low Speed



7.b: Feed vs DOC at medium Speed



7.c: Feed vs DOC at high Speed

Fig 7. Response surface of R_a at various Speed level

Fig 6. indicates the response surface of R_a which is obtained by varying the Speed and DOC from low level to high level while Feed is held constant at low level (Fig 6.a), medium level (Fig 6.b) and high level (Fig 6.c). Fig 6.a indicates that at low Feed (0.07 mm/rev), when at low Speed and at low DOC, the R_a is found to be low. The lower R_a that can be achievable by this combination is found to be 0.013 µm. Similar trends are observed in medium Feed rate (0.16 mm/rev) (Fig 6.b) and high Feed rate (0.25 mm/rev) (Fig 6.c). The R_a value that can be achieved with these combinations is found to be 0.035 µm and 0.045 µm respectively. By comparing the influence of different levels of Feed rate (low, medium and high), it was observed that low Feed rate results in lower R_a. This may be due to the fact that, at low feed rate the speed of metal removing per unit time is also less. During lesser feed rate, time exposed to lapped wear pads of BTA tool is high. Hence low feed rate results (0.07 mm/rev) in low R_a.

Fig 7 indicates the response surface of R_a which is obtained by varying the Feed rate and DOC from low level to high level while Speed is held constant at low level (Fig 7.a), medium level (Fig 7.b) and high level (Fig 7.c). Fig 7.a indicates that at low Speed (1000 rpm), when at low Feed rate and at low DOC, the R_a is found to be low. The lower R_a that can be achievable by this combination is found to be 0.012 µm. similar trends are observed in medium Speed (2000 rpm) (Fig 7.b) and high Speed (3000 rpm) (Fig 7.c). The R_a value that can be achieved with these combinations is found to be 0.045 µm and 0.040 µm respectively. By comparing the influence of different levels of Speed (low, medium and high), it was observed that low Speed results in lower R_a.(This is due to the fact that during low speed, the area and time exposed to wear pads are high. Hence low speed (1000 rpm) results in low R_a.

From the above studies, it is observed that low Speed, low Feed rate and low DOC results in lower $R_{a.}$

MULTI OBJECTIVE OPTIMIZATION

From the ANOVA and response surfaces the combinations of significant input process parameters and their levels for achieving higher MRR and lower R_a individually are determined. Therefore, in order to verify the above combinations of input process parameters and to improve the productivity multi-objective optimization is carried out using RSM technique to achieve higher MRR and lower R_a together. The solution of multi objective optimization using RSM is shown in the table 7.

Table 7. Multi Objective Optimization Solutions

Sl.No	**Speed (rpm)**	**Feed (mm/ rev)**	**DOC (mm)**	**MRR ×10^3 (mm^3/ min)**	**R_a (µm)**
1	3000	0.25	180.00	398.19	0.045
2	2988.0	0.25	180.00	396.55	0.045
3	3000.0	0.25	180.00	393.27	0.044
4	2978.3	0.25	180.00	395.32	0.045
5	2966.2	0.25	180.00	393.71	0.045
6	3000.0	0.24	180.00	387.58	0.043
7	3000.0	0.25	180.63	398.19	0.047
8	3000.0	0.23	180.00	370.58	0.042
9	3000.0	0.23	180.00	365.03	0.042
10	3000.0	0.25	185.61	398.01	0.065
11	2999.9	0.25	191.47	398.19	0.077
12	3000.0	0.25	200.00	398.19	0.078
13	3000.0	0.25	199.89	398.19	0.078
14	3000.0	0.25	192.84	398.19	0.079
15	3000.0	0.25	198.30	398.19	0.079

And we have set of graphs by setting criteria set as Maximized for Metal Removal Rate(MRR) and Minimized for R_a and have obtained desirability graphs for combined MRR and R_a as per the defined criteria set. Those graphs are shown in the Fig 8 and Fig.9.

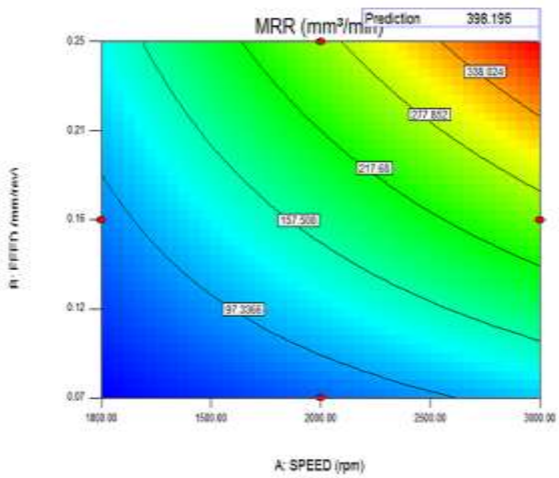


Fig 8. High MRR at Optimum Parameters

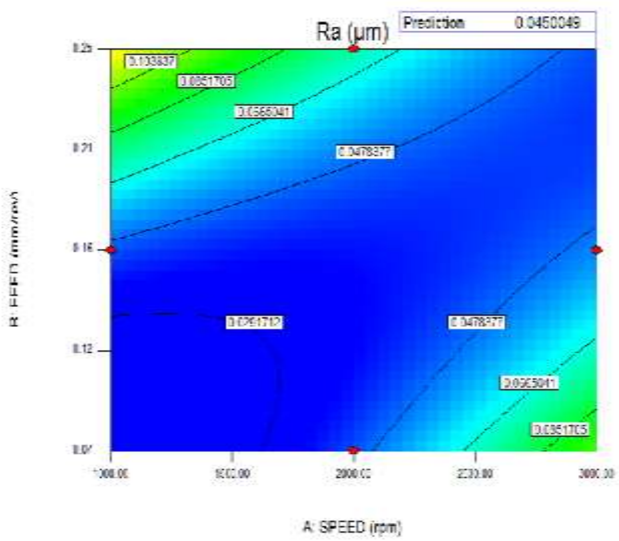


Fig. 9 . Low R_a at Optimum Parameters

Fig. 8 predicts the graph of MRR at optimum parameters of multi objective optimization process. Here the input parameters are considered as per the underlined values in Table 7.

Fig. 9 predicts the Surface roughness (R_a) at optimum parameter of multi objective optimization process as underlined in Table 4.5.

While doing deep hole drilling using the above input parameters, we can get highest Metal Removal Rate (MRR) of 397.91 $\times 10^3$ mm³/min and Surface roughness (R_a) of 0.045 µm can be obtained.

Table 8. Optimum parameters to obtain high MRR and low R_a together

<table>
<tr><th>INPUT PARAMETERS</th><th>UNITS</th><th>VALUE</th><th>MRR $\times 10^3$ mm³/ min</th><th>R_a µm</th></tr>
<tr><td>Speed</td><td>rpm</td><td>3000</td><td rowspan="3">397.9
1</td><td rowspan="3">0.0
45</td></tr>
<tr><td>Feed</td><td>mm/rev</td><td>0.25</td></tr>
<tr><td>Depth Of Cut</td><td>mm</td><td>180</td></tr>
</table>

CONCLUSION

The influence of BTA Deep Hole Drilling process parameters such as Speed (N), Feed rate (F) and Depth Of Cut (DOC) on Metal Removal Rate (MRR) and surface roughness (R_a) are analyzed for machining of Aluminium casting material. The experiments are carried out as per RSM using Box-Behnken method. The significant parameters and their levels are identified for achieving high MRR and low R_a value with the help of ANOVA and response surfaces. From the table 8, It was found that high Speed; high Feed rate and high DOC leads to high MRR and also found that low Speed, low Feed rate and low DOC leads to low surface roughness. Hence these combinations are recommended for BTA Deep Hole Drilling of Aluminium casting material in order to achieve higher MRR and lower R_a. Regression equations are established for MRR and R_a for easier predication. The above study will be useful for the manufacturing engineers to select significant BTA Deep Hole Drilling parameters for machining of material**.**

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