Journal of Engineering Science and Technology
Vol. 12, No. 8 (2017) 2213 - 2228

STATISTICAL APPROACH FOR MULTI CRITERIA OPTIMIZATION OF CUTTING PARAMETERS OF TURNING ON HEAT TREATED BERYLLIUM COPPER ALLOY

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Abstract

In machining operations, achieving desired performance features of the machined product, is really a challenging job. Because, these quality features are highly correlated and are expected to be influenced directly or indirectly by the direct effect of process parameters or their interactive effects. This paper presents effective method and to determine optimal machining parameters in a turning operation on heat treated Beryllium copper alloy to minimize the surface roughness, cutting forces and work tool interface temperature along with the maximization of metal removal rate. The scope of this work is extended to Multi Objective Optimization. Response Surface Methodology is opted for preparing the design matrix, generating ANOVA, and optimization. A powerful model would be obtained with high accuracy to analyse the effect of each parameter on the output. The input parameters considered in this work are cutting speed, feed, depth of cut, work material (Annealed and Hardened) and tool material (CBN and HSS).

Keywords: Multi objective optimization, Beryllium copper, Metal removal rate, Cutting forces, Surface roughness, Response Surface methodology.

1. Introduction

Metal cutting is one of the most important methods of removing the unwanted material in the production of mechanical components. This treatment identifies the major problem areas and relates observed performance to fundamentals of physics, chemistry, materials behaviour and the engineering sciences of heat transfer, solid mechanics and surface science. Since material removal is a work-

Nomenclatures

d	Depth of cut, mm
f	Feed rate, mm/min
F_c	Cutting force, KN
ht	Heat treatment
MRR	Metal removal rate, mm^3/min
Ra	Surface roughness, microns
s	Spindle speed, rpm
T	Interface temperature, ^0C
tm	Tool material

Abbreviations

ANOVA	Analysis of Variance
DOE	Design of Experiments
MOO	Multi Objective Optimization
RSM	Response Surface Methodology

shop related activity where very strong economic or production rates pertain, it is important that the selection of tools, fluids, operating conditions, etc., be based on a rational optimization procedure.

Beryllium copper alloy, now-a-days, is widening its area of applications in various fields, due to its extensive properties. In spite of its cost, the alloy is increasingly proving the material of choice in applications spanning the automotive, aerospace, electronics, electrochemical, computer, tele-communications, hydrocarbon, appliance and medical industries. Copper-beryllium alloys offer a combination of mechanical and electrical properties which is unique for copper alloys. The mechanical strength achieved after heat treatment ranks highest among all copper alloy materials and is combined with an electrical conductivity which outperforms that of bronzes. The high strength beryllium copper alloys, which have good electrical and thermal conductivity, are used in applications such as springs, electronic connectors, bearings, moulds and corrosion resistant hardware. As many applications require machining, the Be-Cu alloy satisfies all the requirements of machining criteria. Table 1 gives the general span of mechanical properties of Beryllium copper alloy.

Table 1. Mechanical properties of beryllium copper alloy.

Property	Value
Hardness, Rockwell B	80.0 - 85.0
Tensile strength, ultimate	515 - 585 MPa
Tensile strength, yield	275 - 345 MPa

Recent advances in computer hardware and software technology have led to research in calculation of efficient cutting parameters and design and development of a tool or combination of tools for a specific operation or set of operations. The proposed study aims at evaluating the best process environment which simultaneously gives multi objective optimization. Turning involves different process parameters among which the most influential on the performance of the process are cutting speed, feed, depth of cut and type of work material, tool material, etc, the work piece material, in this work is subjected to annealing and hardening, and is treated as two forms of material. From the past studies, it is provided that beryllium copper alloy can be effectively machined with CBN and HSS tools.

Finally, the effect of five input variables namely cutting speed, feed, depth of cut, work material and tool material on different output parameters is studied in the study. The output variables which give the ultimate performance of the process are Metal Removal Rate, Machinability, Cutting Force, Temperature at tool chip interface, Surface Roughness, etc.

The objective of the proposed study is to extract the simultaneous

- Maximization of metal removal rate and
- Minimization of cutting force, temperature at tool chip interface and surface roughness.

Multi objective optimization (MOO)

Optimal machining parameter determination is an important matter for ensuring an efficient working of a machining process. Multi-Objective Optimization algorithms allow for optimizations that take into account multiple objectives simultaneously. Each objective can be a minimization or a maximization of an output. Criteria of system's efficiency are described by the objective function that is to be either minimised or maximised. The proposed experimental study comes under the MOO category, where, possible evolutionary algorithms like Genetic Algorithms, Ant Colony Optimization, Neural Networks, Response Surface Methodology, etc. can be developed to solve the problem.

The correct selection of manufacturing conditions is one of the most important aspects to take into consideration. Turning is one of the manufacturing processes that is used to produce rotational, typically axi-symmetric, parts that have many features, such as holes, grooves, threads, tapers, various diameter steps, and even contoured surfaces. Parts that are fabricated completely through turning often include components that are used in limited quantities, perhaps for prototypes, such as custom designed shafts and fasteners. Turning is also commonly used as a secondary process to add or refine features on parts that were manufactured using a different process.

The three primary factors in any basic turning operation are speed, feed, and depth of cut. Other factors such as kind of material and type of tool have a large influence, of course, but these three are the ones the operator can change by adjusting the controls, right at the machine.

In design of experiments, number of trials to be conducted is determined by optimal design method (in response surface designs) and design matrix is constructed. After getting design matrix, ANOVA (Analysis of Variance) is carried out to determine the percentage contribution of each factor. In the present work, DESIGN EXPERT 9.1 software is used to analyze the above aspects. The work material selected is beryllium copper Alloy, due to its wide range of applications in manufacturing areas. The final optimal values obtained were again experimented and compared.

2. Literature Review

Pytlak presented in their paper, the results of multicriteria optimization of hard finish turning operation parameters of hardened 18CrMo4 steel in a view of chosen parameters of surface roughness [1]. The following cutting parameters were subjected to the optimization: v_c, f and a, while as optimization criteria were assumed selected parameters of surface roughness: R_a, R_z and R_{max}. The research was performed with the help of the Modified Distance Method (MDM), from the point of view of mating of machined surface with sealing rings (Simmering rings). Obtained set of Pareto-optimal solutions comprises 6 solutions only.

According to Lan, deduced a general optimization scheme which was deemed to be necessary for the industry [2]. Kolohan et al. proposed Multi objective optimization of machining processes for simultaneous achievement of several goals such as increased product quality, reduced production time and improved production efficiency [3]. This article presented a combinatorial approach of grey relational analysis and regression modelling to convert the values of multi responses obtained from Taguchi method design of experiments into a multi objective model. The proposed approach was implemented on turning process of St 50.2 Steel. This study illustrated that regression analysis can be used for high precision modelling and estimation of process variables.

Gupta and Kumar presented a report on experimental analysis and optimization of performance characteristics in unidirectional glass fiber reinforced plastic composites using Taguchi method and Grey relational analysis [4]. Performance characteristics such as surface roughness and material removal rate are optimized during rough cutting operation. Process parameters including tool nose radius, tool rake angle, feed rate, cutting speed, cutting environment and depth of cut were investigated using mixed L18 orthogonal array. Grey relation analysis is used to optimize the parameters and Principal Component Analysis is used to find the relative significance of performance characteristics. Depth of cut has great influence on surface roughness and material removal rate, followed by feed rate. The percentage contribution of depth of cut is 54.399% and feed rate is 5.355%.

Sridhar and Venkateswarlu suggested Taguchi and Grey Relational Analysis to optimize the machining parameters for turning of EN8steel on lathe machine to yield minimum cutting forces and surface roughness [5]. The process parameters such as rotational speed, feed, depth of cut and cutting fluid have been selected. In this study, the experiments were carried out as per Taguchi experimental design and L_9 orthogonal array was used. Analysis of variance (ANOVA) was also used to find out the most influence of processing parameters on the responses. The regression equations were also established between the process parameters and responses. The results indicate that the depth of cut is the most significant factor affecting the cutting force and surface roughness followed by a feed, speed and cutting fluid.

AbdelouahhabJabri and Abdellah El Barkany [6], applied a genetic algorithm based multi-objective-optimization technique for optimal cutting parameters (depth of cut, feed rate and cutting speed) in multi-pass turning. The objective functions were cutting cost and tool life time subject to specified constraints. Pareto frontier plot was built from the Pareto optimal solutions. Somashekara and Swamy studied on optimal setting of turning parameters (Cutting speed, Feed and Depth of Cut) which results in an optimal value of Surface Roughness while machining Al 6351-T6 alloy with Uncoated Carbide Inserts. Several statistical modelling techniques were used to generate models including Genetic Algorithm, Response Surface Methodology [7]. An attempt was made to generate a model to predict Surface Roughness using Regression Technique. Optimization of the process parameters was done using Taguchi Technique. S/N ratio and ANOVA analysis were performed to obtain significant factors influencing Surface Roughness.

Kazancoglu et al. investigated the multi-response optimization of the turning process for an optimal parametric combination to yield the minimum cutting forces and surface roughness with the maximum material-removal rate (*MRR*) using a combination of a Grey relational analysis (GRA) and the Taguchi method [8]. The objective functions were selected in relation to the parameters of the cutting process: cutting force, surface roughness and *MRR*. The Taguchi approach was followed by the Grey relational analysis to solve the multi-response optimization problem. The significance of the factors on the overall quality characteristics of the cutting process was also evaluated quantitatively using the analysis-of-variance method (ANOVA). Optimal results were verified through additional experiments. It was concluded that a proper selection of the cutting parameters produces a high material-removal rate with a better surface roughness and a lower cutting force.

Kumar et al. studied the influence of cutting parameters (cutting speed, feed per tooth, axial depth of cut and radial depth of cut) during ball-end milling of Al2014-T6 under dry condition. The experimental plan was based on face centred, rotary central composite design (RCCD) [9]. Three cutting force components i.e. tangential, radial and axial forces were measured and then analysis of variance (ANOVA) is performed. It has been found that the quadratic model is best fitted for prediction of the force components. The analysis of result showed that the cutting forces increases as increase in feed per tooth and axial depth of cut but decreases with increase in cutting speed. Radial depth of cut had significant effect on the cutting force components.

Das et al. made an attempt has been made to evaluate the performance of multilayer coated carbide inserts during dry turning of hardened AISI 4340 steel (47 HRC) [10]. The effect of machining parameters (depth of cut, feed and cutting speed) on surface roughness (Ra) was investigated by applying ANOVA. The experiments were planned based on Taguchi's L_{27} Orthogonal array design. Results showed that surface roughness (Ra) mainly influenced by feed and cutting speed, whereas depth of cut had negligible influence on surface roughness. The experimental data were further analyzed to predict the optimal range of surface roughness (Ra). Finally, a second order regression model was developed to find out the relationship between the machining parameters and surface roughness.

3. Materials and Method

3.1. Materials

Beryllium copper alloy with two types of heat treatments is being considered for study. The work material is subjected to annealing and hardening, and is considered as two forms of material. The properties of annealed and hardened Becu alloy are put up in Table 2 and the micro structures are represented in Fig. 1. Beryllium copper bars of diameter 30 mm and length 40 mm with input dimensions are subjected to turning process to get the desired dimensions.

Table 2. Properties of annealed and hardened Be-Cu alloy.

Alloy composition (wt.%)	Heat treatment	Tensile strength (MPa)	Yield strength (MPa)	Rockwell hardness (B scale)
Be (2%)+ Cu (98%)	Annealed (A)	496.42	193	B60
	Hardened (H)	827.37	620.52	B95

The secret of strength of beryllium copper lies in its heat treatment. The material is first cast and then drawn to sizes. Heat treatment process dissolves the beryllium completely into the copper, like salt in warm water. Even spacing of beryllium atoms in the alloy does not change the mechanical properties except strength. After heat treatment, beryllium copper is as strong as cold rolled steels. Two types of heat treatment are performed in this work- Annealing and precipitation hardening.

Annealing involves heating a material to above its critical temperature of 650˚C, maintaining a suitable temperature, and then cooling. Annealing time has been set to 3 hours for obtaining maximum property benefit. Annealing can induce ductility, soften material, relieve internal stresses, refine the structure by making it homogeneous, and improve cold working properties.

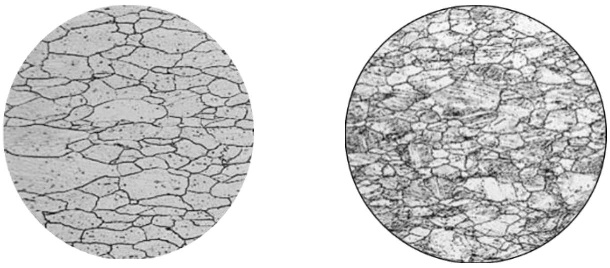

Fig. 1. Microstructures of annealed and hardened alloys.

Precipitation hardening begins in solid/liquid solution with the matrix metal is precipitated out of solution with the metal as it is quenched, leaving particles of that phase distributed throughout to cause resistance to slip dislocations. This is achieved by first heating the metal to a temperature of 340˚C where the elements forming the particles are soluble then quenching it, trapping them in a solid solution. In this work, the soaking of the alloy has been taken in salt solution for 3 hours, so that the elements would form precipitates. The elevated temperature allows the dissolved elements to diffuse much faster, and form the desired precipitated particles. The quenching is required since the material otherwise would start the precipitation already during the slow cooling. This type of precipitation results in few large particles rather than generally desired profusion of small precipitates.

Methodology of proposed work is divided in to the following phases:

- Investigation of the significant machining parameters that affects on the process performance noted as Metal Removal Rate, Tool Wear, Machinability, cutting force, temperature at tool chip interface and surface roughness.

- Experiments conducted on lathe (shown in Fig. 2) with the selected cutting parameters as per the design matrix using Response Surface Methodology.
- Mathematical relation between the input and output variables are developed from Design of Experiments.
- Optimization problem is set to get the best optimal combination of input variables on the application of Response Surface Methodology.

Fig. 2. CNC lathe fixed with strain gauge dynamometer.

3.2. Method

3.2.1. Design of experiments

In general usage, design of experiments (DOE) or experimental design is the design of any information-gathering exercises where variation is present, whether under the full control of the experimenter or not. Experimental designs play an important role in the engineering world in process development and process trouble shooting to improve performance. The objective in many cases may be to develop a robust process. In any experiments, the results and the conclusions that can be drawn depend to a large extent on the manner in which the data was collected. Thus, the method of data collection has adverse effect on the conclusions that can be drawn from the experiment. Response surface methodology is one of the methods in the design of experiments and it has its own advantages in the optimization over various techniques and the detailed view of the RSM is discussed below.

3.2.2. Response surface methodology

In statistics, Response Surface Methodology (RSM) explores the relationships between several explanatory variables and one or more response variables. The method was introduced by G. E. P. Box and K. B. Wilson in 1951. The main idea of RSM is to use a sequence of designed experiments to obtain an optimal response. Box and Wilson suggest using a second-degree polynomial model to do this. They acknowledge that this model is only an approximation, but use it because such a model is easy to estimate and apply, even when little is known about the process.

3.2.3. Experimental design

By considering the above said parameters, a response surface central composite design matrix with 24 runs is being designed after which experiments were conducted. The performance parameters *MRR*, *Ra*, chip tool interface temperature and cutting force. The input factors with their ranges are shown in Table 3. The response surface design matrix with performance parameters is given in Table 4.

Table 3. Input factors with their ranges.

Factor	Name	Units	Type	Subtype	Minimum	Maximum
A	s	rpm	Numeric	Continuous	500	1800
B	f	mm/min	Numeric	Continuous	60	110
C	d	mm	Numeric	Continuous	0.2	0.5
D	tm		Categoric	Nominal	CBN	HSS
E	*ht*		Categoric	Nominal	A	H

Table 4. Experimental design matrix.

A:s	***B:f***	***C:d***	***D:tm***	***E:ht***	***MRR***	***Ra***	***T***	***Fc***
rpm	**mm/min**	**mm**			**mm^3/min**	**microns**	**$^{\circ}$C**	**kN**
1800	60	0.2	CBN	A	6030.3	0.17581	37.2	108.053
700	96	0.2	HSS	A	2584.2	2.97598	39.4	640.76
1600	110	0.5	CBN	H	24072.8	0.74787	52	171.99
1500	100	0.5	CBN	H	13684.6	0.70323	56.8	427.714
1400	60	0.5	CBN	H	10280.2	0.29062	46.1	18.207
1800	90	0.3	CBN	A	8712.5	0.39557	45.5	680.85
700	60	0.2	HSS	A	1945	1.16249	32.45	5.55
1800	80	0.2	CBN	H	4943.2	0.31255	33.95	259.636
1800	72	0.5	CBN	A	13168.5	0.25316	33.4	9.609
600	80	0.3	HSS	A	2377.4	2.81294	31.85	11.531
500	70	0.3	HSS	H	2112	3.10127	31.55	10.763
1430	80	0.3	CBN	H	6277.6	0.49521	32.9	10.982
1400	68	0.2	CBN	H	2492.2	0.37329	31.4	35.405
1400	60	0.2	CBN	H	3079.3	0.29062	31.2	3.844
620	68	0.2	HSS	A	1438	1.90334	31.75	3.844
1638	78	0.2	CBN	H	3219.3	0.35879	31.25	5.766
1800	72	0.4	CBN	A	6538.5	0.25316	31.75	7.688
1400	80	0.5	CBN	A	6613.4	0.51666	31.25	11.531
650	78	0.2	HSS	A	1193.2	2.27848	31.65	5.766
700	68	0.4	HSS	A	2165.7	1.49315	39	7.688
700	80	0.3	HSS	H	1789.9	2.06665	32.35	7.688
850	80	0.5	HSS	A	3508.3	1.4016	33.95	7.688
600	80	0.4	HSS	A	1819.9	2.81294	35.9	7.688
1800	68	0.4	CBN	H	6339.6	0.22582	44.85	7.688

Analysis of variance is a method of partitioning total variation into accountable sources of variation in an experiment. It is a statistical method used to interpret experimented data and make decisions about the parameters under study. The ANOVA tables for polynomial regression for the four considered output parameters with interpretations are given in Tables 5 to 8 respectively.

Table 5. Analysis of variance for *MRR*.

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	6.218E+008	15	4.145E+007	13.02	0.0005
A-s	2.009E+007	1	2.009E+007	6.31	0.0363
B-f	2.880E+007	1	2.880E+007	9.05	0.0169
C-d	1.617E+006	1	1.617E+006	0.51	0.4963
D-tm	1.421E+007	1	1.421E+007	4.47	0.0675
E-ht	5.675E+006	1	5.675E+006	1.78	0.2186
AB	2.795E+007	1	2.795E+007	8.78	0.0181
AC	**7.176E+005**	**1**	**7.176E+005**	**0.23**	**0.6476**
AD	**6.551E+006**	**1**	**6.551E+006**	**2.06**	**0.1893**
AE	**1.703E+005**	**1**	**1.703E+005**	**0.053**	**0.8229**
BC	**9.077E+005**	**1**	**9.077E+005**	**0.29**	**0.6079**
BD	2.763E+007	1	2.763E+007	8.68	0.0185
BE	1.937E+007	1	1.937E+007	6.09	0.0389
CD	**35255.83**	**1**	**35255.83**	**0.011**	**0.9188**
CE	**2.646E+006**	**1**	**2.646E+006**	**0.83**	**0.3885**
DE	**1.607E+005**	**1**	**1.607E+005**	**0.050**	**0.8278**
Residual	2.547E+007	8	3.183E+006		
Cor Total	6.472E+008	23			

Table 6. Analysis of variance for *Ra*.

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	24.11	15	1.61	69680.60	0.0001
A-s	1.30	1	1.30	56326.83	0.0001
B-f	1.91	1	1.91	82691.33	0.0001
C-d	0.035	1	0.035	1518.13	0.0001
D-tm	0.12	1	0.12	5413.55	0.0001
E-ht	0.012	1	0.012	516.47	0.0001
AB	0.023	1	0.023	1014.29	0.0001
AC	0.021	1	0.021	925.52	0.0001
AD	1.46	1	1.46	63157.06	0.0001
AE	0.033	1	0.033	1432.07	0.0001
BC	0.027	1	0.027	1191.52	0.0001
BD	**4.672E-005**	**1**	**4.672E-005**	**2.03**	**0.1925**
BE	0.028	1	0.028	1216.34	0.0001
CD	0.018	1	0.018	761.35	0.0001
CE	0.016	1	0.016	677.48	0.0001
DE	0.030	1	0.030	1297.58	0.0001
Residual	1.845E-004	8	2.307E-005		
Cor Total	24.11	23			

Table 7. Analysis of variance for *T*.

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	1147.45	5	63.75	1017.94	< 0.0001
A-s	4.44	1	4.44	70.86	0.0004
B-f	9.97	1	9.97	159.18	0.0001
C-d	71.06	1	71.06	1134.74	0.0001
D-tm	0.47	1	0.47	7.51	0.0407
E-ht	2.52	1	2.52	40.21	0.0014
Residual	0.31	18	0.063		
Cor Total	1147.76	23			

Table 8. Analysis of variance for *Fc*.

Source	Sum of Squares	df	Mean Square	F Value	p-value
Model	6.979E+005	5	46523.43	10.57	0.0011
A-s	22802.55	1	22802.55	5.18	0.05
B-f	1.818E+005	1	1.818E+005	41.30	0.0002
C-d	25580.04	1	25580.04	5.81	0.0425
D-tm	9081.67	1	9081.67	2.06	0.0189
E-ht	79011.27	1	79011.27	17.95	0.0029
Residual	35220.05	18	4402.51		
Cor Total	7.331E+005	23			

The F-test and p-test conducted on *MRR*, *Ra*, *T* and *Fc* in relation to the input parameters s, f, d, tm and ht give a significant variance on the model.

- Feed rate influenced the most and the interactions s×d, s×tm, s×ht, f×d, d×tm, d×ht and tm×ht do not show any significance on *MRR* when observed F-Value in Table 5. Therefore, the relation has been formulated by aliasing the above interaction effects for better prediction.
- From Table 6, highest F-value for speed shows the higher influence on surface roughness. The interaction f×tm is insignificant, which is not included in the model.
- Temperature was influenced the most by depth of cut when observed from Table 7.
- Feed rate can be considered as the important factor for deciding cutting force (Table 8).

3.2.4. Regression models

After subjected to regression, the mathematical models are developed by relating the mutually independent input parameters and output parameters given below (in coded form).

$$MRR = 35009.20 + 1.206E{+}005 \times A + 32887.19 \times B + 2590.71 \times C + 98942.86 \times D + 40027.95\, E + 1.324 \times E{+}\,005 \times AB + 1.114E{+}005 \times BD + 44503.84 \times BE \qquad (1)$$

$$Ra = 4.14-5.91\times A+4.97\times B+1.15\times C-0.65\times D-1.42\times E -4.34\times AB-0.33\times AC-1.96\times AD-0.36\times AE +1.26\times BC-1.58\times BE-0.29\times CD-0.088\times \mathrm{CE}-0.32\times DE \quad (2)$$

$$T = 71.01+3.58\times A+37.41\times B+3.13\times \mathrm{C}+1.74\times D+1.50\times E \quad (3)$$

$$Fc = 1770.4+88.90\times A+1868.98\times B -85.29\times C+12.95\times D-41.8\times E \quad (4)$$

4. Graphical Interpretation

4.1. Main effects corresponding to *MRR*

Figure 3 shows that the Metal Memoval Rate increases with speed up to 1638 RPM and is reduced with further increase in speed. Highest *MRR* is obtained at a feed of 110 mm/min and depth of cut of 0.5 mm. Hardened job process is shown to give more *MRR* compared to annealed job, when turned. Similarly, CBN tool performs better for obtaining high *MRR*.

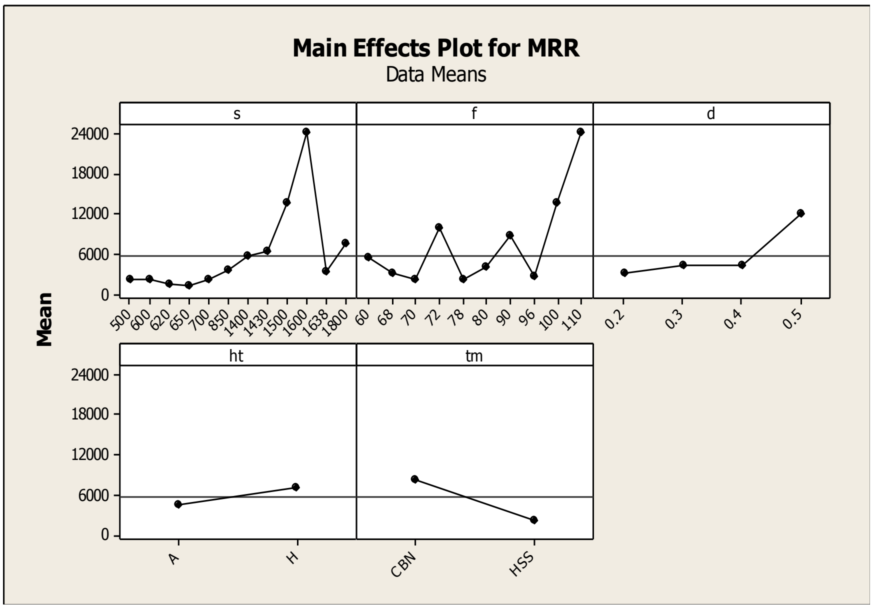

Fig. 3. Main effects plot for *MRR*.

4.2. Main effects corresponding to Ra

From Fig. 4, it is observed that surface roughness decreased as the speed is increased. Feed has random effect on *Ra*. *Ra* was minimum at 0.5 mm depth of cut. Fine surface finish was obtained with hardened work piece and CBN tool.

4.3. Main effects corresponding to T

Chip tool interface temperature, from Fig. 5, was minimum at a speed of 620 rpm, feed of 72 mm/min, 0.2 depth of cut, for annealed component and on HSS tool.

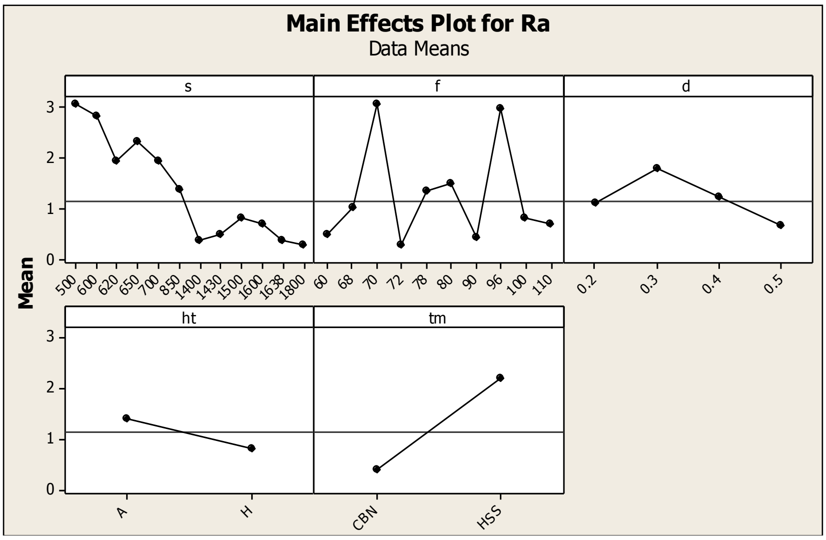

Fig. 4. Main effects plot for *Ra*.

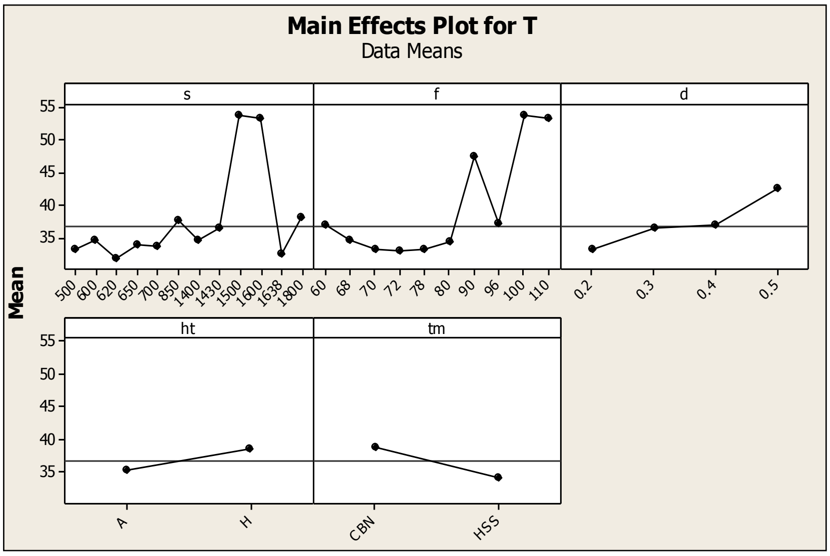

Fig. 5. Main effects plot for *T*.

4.4. Main effects corresponding to *Fc*

Speed has a variable effect on cutting force, showing minimum value at 620 rpm. Cutting force randomly increased with feed and reached maximum at 90 mm/min. Minimum cutting force was observed at a feed of 68 mm/min and 0.4 mm depth of cut. Hardened piece and HSS tool were shown to consume minimum force (Fig. 6).

4.5. Interaction plots

These plots represent the combined effect due to any two factors of the set of input factors. A statistical interaction occurs when the effect of one independent variable on the dependent variable changes depending on the level of another independent variable. in the present case, the four output factors are analysed with the interactions of different input parameters shown in Figs. 7 and 8. Interactions do not exist for *T* and *Fc*.

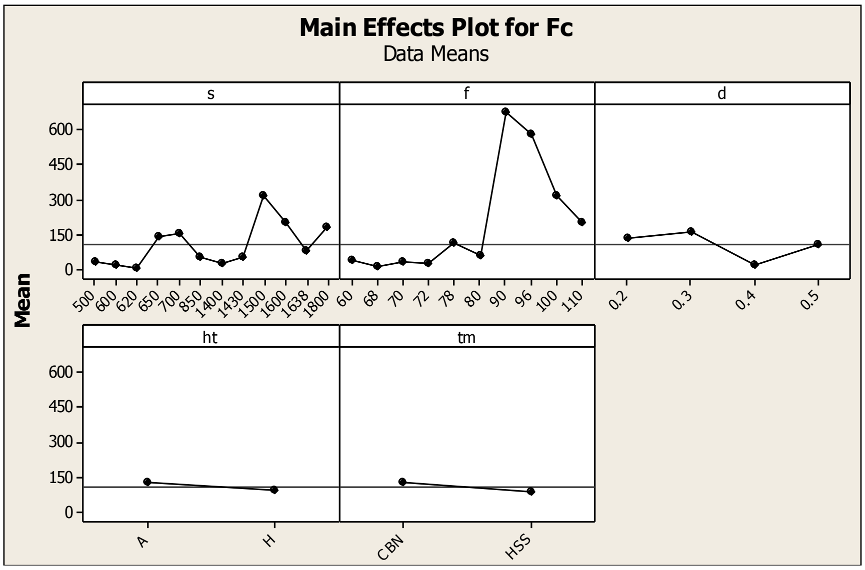

Fig. 6. Main effects plot for *Fc*.

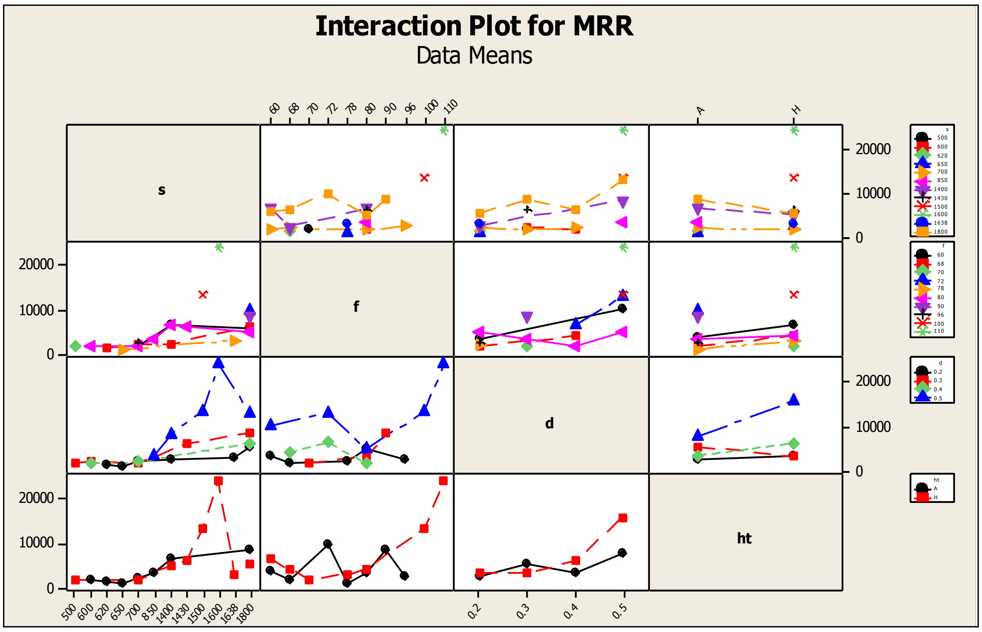

Fig. 7. Interaction effects plot for *MRR*.

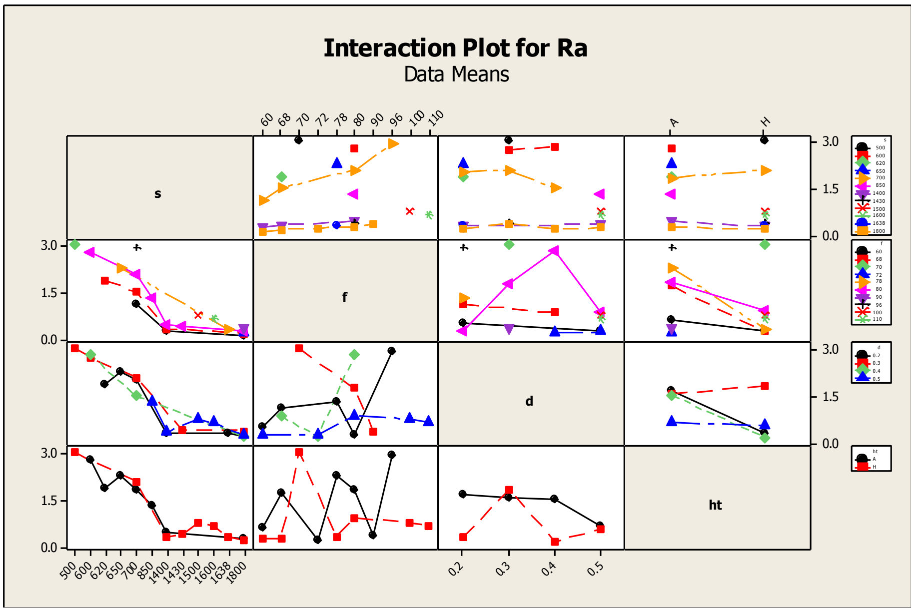

Fig. 8. Interaction effects plot for *Ra*.

4.6. Response surface plots

Surface plots show the behaviour of the selected response with the simultaneous changes in any two selected input factors in a three-dimensional design space. Figures 9 and 10 depict the response surface plots of the *MRR* and *Ra* with the input factors. As per the precision considered, 2nd order polynomial regression equations have been extracted which reflect graphically in surface plots. For cutting temperature and cutting force, linear models are preferred as per the correlations.

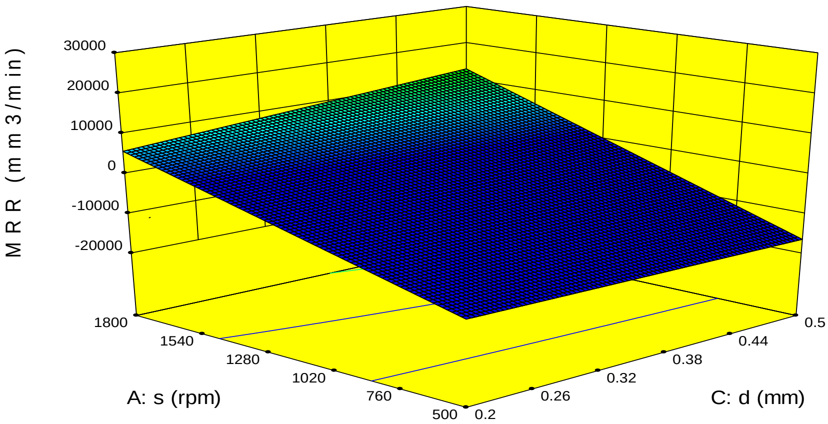

Fig. 9. Surface plot for *MRR*.

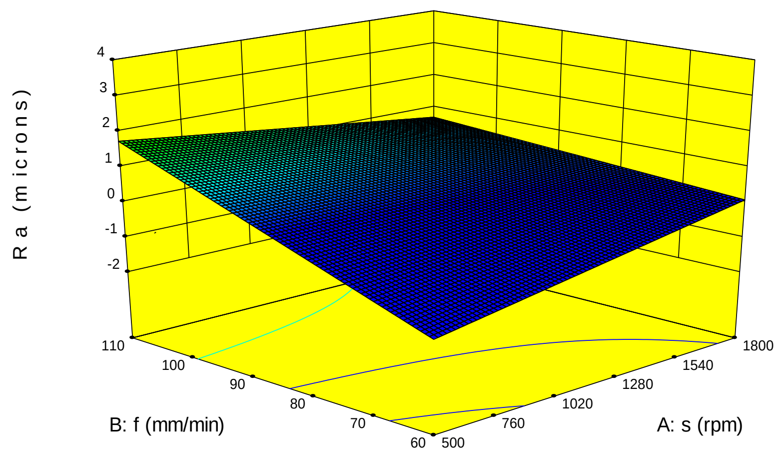

Fig. 10. Surface plot for *Ra*.

5. Optimization

Optimal process parameters are setup through RSM, which can be classified clearly according to the combination of the work and tool materials, given in the Table 9. Desirability function is one of the statistical approach widely used for multi response optimization techniques. Its value will be functionally set between 0 to 1, for which ideal value of a performance parameter will have desirability value of 1 and 0 for unacceptable values. The overall desirability of 0.823 expresses a satisfied outcome of the experimentation, to which the optimal set of input and output parameters correspond.

Table 9. Optimal settings of the process parameters.

s	*f*	*d*	*tm*	*ht*	*MRR*	*Ra*	*T*	F_c	**Desirability**
1800	110	0.282	CBN	H	2 3569	0.014	34.53	69.55	0.823
907	75	0.5	HSS	A	1808.6	0.71	36.8	50	0.801

6. Conclusion and Scope for Future Work

This paper presented a successful employment of Response Surface Methodology for finding the optimum performance parameters with the setup of optimal input parameters. Also, the individual and combined effects of the input factors on the output factors are studied. The optimal values are extracted for two different combinations, i.e. for CBN tool- hardened beryllium copper and HSS tool - annealed material, are predicted as the best combination for turning process with the above optimal setting of the input parameters.

Confirmation experiments were conducted for testing the efficiency of optimization, which was proved efficient with ±5% errors. There always exists a scope for extension in every research work and as a part, heuristic techniques with the addition of other parameters like tool signature, other tool materials can be implemented for betterment of the process and generalization of applications of beryllium copper alloy.

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