International Journal of Technical Innovation in Modern Engineering & Science (IJTIMES)
Impact Factor: 5.22 (SJIF-2017), e-ISSN: 2455-2585
Volume 4, Issue 10, October-2018

MULTI OBJECTIVE OPTIMIZATION OF CUTTING PARAMETERS IN MACHINING OF HEAT TREATED BERYLLIUM COPPER ALLOY

MANDA SREEJA[1], Dr.B.DURGA PRASAD[2], K.DEVAKI DEVI[3]

[1]*Department of Mechanical Engineering, JNTUA, Anantapuramu, India*
[2]*Department of Mechanical Engineering, JNTUA, Anantapuramu, India*
[3]*Department of Mechanical Engineering, G Pulla Reddy Engineering College, India*

Abstract*— Increase in productivity, consistently has become the sole aim of Engineers of concerned Technical Industries along with the welfare of Environment. In order to increase the efficiency of the process it is pre-requisite to identify optimal machining parameters. The effect of machining process parameters is correlated to achieve desired performance features of the machined product. This project is to present an effective method for the determination of optimal machining parameters in turning operation of heat treated beryllium copper alloy. To obtain the optimal cutting parameters, experiment is designed to minimize the surface roughness, cutting force along with the maximization of metal removal rate. Heat treated beryllium copper alloys have good mechanical and electrical properties. This work is extended to multi criteria optimization, design of matrix and ANOVA analysis is prepared by response surface methodology which results to an effective model to analyse the effect of each parameter on output. The input parameters used in this work are speed, feed, depth of cut, nose radius, workpiece material (hardened and untreated).

Keywords*—Multi objective optimization, Beryllium copper, Genetic algorithm, Response surface methodology, ANOVA, Material removal rate, Surface roughness, Cutting force.

I. INTRODUCTION

Manufacturing plays main role in industrial development. Whereas manufacturing a product includes machining. A machining process with all the necessary features like adaptability, precision and assisted by computers includes upgradation in industrial manufacturing.
The main aim is to improve machining yield and the nature of machined segments, it is important to pick the most apt cutting conditions. It is excessively perplexing, making it impossible to accomplish the most noteworthy execution with a machine as there are many impacting machining parameters. In request to address these machining issues, there is a need to fabricate comprehensive techniques to decide on cutting conditions and geometry of the cutting tool for simple machining of metals.

II. LITERATURE REVIEW

Rony Mohan [1] described in his paper about optimization of surface roughness of bearing steel during CNC hard turning process as AISI 52100 is chiefly used to produce direction. The procedure for assembling bearing incorporates turning process taken after by three unique phases of pounding activity. These days crushing task are supplanted by hard turning process and it has been demonstrated that hard turning process are 30% reduced cost. The machining parameters (depth of cut, speed and feed) are advanced with variations of surface roughness. Taguchi's ideas of symmetrical exhibits, flag to commotion (S/N) proportion and ANOVA are utilized to improve the surface roughness for rapid CNC turning process.
As defined by Ajay Mishra [2] about Multi criteria optimization in his paper, The Taguchi's approach is a quality outline method whose application in deciding the ideal settings of controllable parameters in different single-target streamlining have been as of late abused. In many cases, the wide range of the item or procedures have a few quality attributes of intrigue. This paper explores the multi-target streamlining of the turning procedure of steel tube(AISI 1045) shaped bars to yield the base apparatus flank wear width, surface roughness and roundness using the mix of Taguchi strategy and Utility idea. Nine test runs in view of Taguchi's L9 symmetrical exhibit were performed and flag to commotion (S/N) proportions, investigation of change (ANOVA) and utility qualities were utilized with speed, feed, depth of cut as turning process parameters and with device flank wear width, surface unpleasantness and roundness as reaction factors. The ideal qualities acquired amid the examination utilizing the multi-target enhancement with the assistance of Taguchi technique and utility idea have been approved by affirmation tests.
Shihab [3] presented, a study on cutting temperature while hard turning by using RSM as an endeavor was made to explore the impact of cutting parameters on cutting temperature while hard turning of compound steel utilizing multilayer covered carbide (TiN/ TiCN/ Al2O3/ TiN) embed. For performing machining analyses, the Central composited design (CCD) was utilized to gather information. A few analytic tests were performed to check the legitimacy of suspicions. Importance of cutting parameters was decided utilizing measurable investigation of difference (ANOVA). The model condition to foresee the cutting temperature is moreover proposed. RSM was used to decide ideal benefits of cutting parameters. The ANOVA results depicted that the three cutting parameters have

noticeable impact on cutting temperature. Results additionally uncovered that inside the range examined, the cutting temperature is profoundly touchy to cutting pace and feed rate

Prashant waydande [4] introduces an exploratory investigation of hard turning with PVD covered carbide instrument of AISI 52100 bearing steel, with the h.ardness of 45-47 HRC. The fundamental motivation behind given examination is to build up the impact of cutting condition on cutting powers and surface roughness. The fundamental concentrated on connection between cutting parameter i.e. cutting velocity , feed rate, depth of cut and machining yield factors i.e. cutting powers and surface roughness through the reaction surface procedure i.e. central composite design plan. The impact of cutting parameters on machining yield factors is to look at utilizing ANOVA.

Devaki Devi [5] explained in her paper about multi objective optimization of cutting parameters of turning on heat treated beryllium copper alloy as, in machining operations, accomplishing and execution of the machined components, is extremely a challenging work. Since, these quality highlights are profoundly corresponded and are relied upon to be impacted specifically or in a turning by the immediate impact of process parameters or their intelligent impacts. This paper presents a powerful technique and to decide ideal machining parameters in a turning task on heat treated Beryllium copper alloy to limit the surface roughness, cutting force and interface temperature alongside the expansion of metal expulsion rate. The extent of this work is stretched out to Multi Objective Optimization. Response Surface Methodology is picked setting up the plane lattice, producing ANOVA, and improvement. A great model would be acquired with high exactness to dissect the impact of every parameter on the yield. The input parameters considered in this work are cutting velocity, feed, depth of cut, work material (Annealed and Hardened) and apparatus material (CBN and HSS).

III. RESEARCH AND EXPERIMENTATION

The selection of parameters is based on the influence of parameters over the operations performed on the material chosen. Generally, output parameters performance is dependent on input factors. The selection of these factors is the most important task as the resulting responses are based on the effect of these parameters.

Speed, feed, depth of cut are the basic input factors of turning operation whereas the other factors like work piece material, interface temperature, tool material will influence the experimental results too.

Speed:

Speed is the rate of rotation of the spindle where the tool is held. When we consider speed particularly in turning operation, the surface speed is also noticeable factor. It is measured in revolutions per minute (RPM).

Feed:

Feed is the rate at which the tool is moved into the part or it is the measure of the movement of part into the tool. Feed is measured in feet, inches or millimetres per time period (mm/min).

Depth of cut:

It is the measurement of removal of the work piece material in a single pass. i.e., it is given to be how wide and deep the tool cuts into work piece. Its units are given in millimetres (mm).

Nose radius:

It is the radius value of the cutting tool's tip. Nose radius is given because the sharp edge at the tool tip may lead to breakage due to severe cutting force during machining process. Nose radius is measured in millimetres (mm).

Work piece material:

Beryllium copper alloy also known as copper beryllium or beryllium bronze is a metal alloy of copper and 0.5 to 3 % beryllium and sometimes with other alloying metals. It is a copper alloy with load bearing capacity which is second to none. It is the strongest of all copper alloys. Its unique characteristics and benefits male it an ideal material for use in variety of settings. In use since the 1940s, this alloy was traditionally used in tools and machine parts. However, miniaturization and improved casting and machining have made it possible to use it on electronics and other areas. This has led to an increase in the popularity of beryllium copper.

PHYSICAL PROPERTIES:

- Elastic modulus - 19,000 ksi /131 GPa
- Melting point (solidus) - ~1600 °F/~870 °C
- Density - .302 lb/in3/8.36 g/cm3
- Thermal expansion - 9.7x10-6 in/in °F /17.5x 10-5 °C-1
- Thermal conductivity (100°C) - 90 BTU/hr•f t•°F /155 W/m•K
- Heat capacity - 0.10 BTU/lb•°F /0.44 J/g•K

Beryllium copper alloy is used for experimentation due to its wide range of properties and its specific characteristics. The chemical composition of beryllium alloy is as follows

Beryllium – 1.8 to 2.1%.
Cobalt, nickel - 0.2 %.
Copper – remaining.

Mechanical properties of Be Cu alloy are as follows

Rockwell hardness – B88 to 96.
Ultimate tensile strength – 510 to 594 MPa.
Yield tensile strength – 140 to 190 ksi.
Heat treatment of Be Cu alloy:

Due to heat treatment the strength of beryllium copper increases. After casting the material, the work pieces are cut to required sizes. Heat treatment enables the rearrangement of atoms and does not disturb the mechanical properties except strength of the material. There are types in heat treatment, we employed hardened beryllium copper alloy for experimentation.

For hardening of beryllium copper, the alloy is subjected to heat treatment between 460 and 780C for 2 hours and allowed to retain to normal temperature generally. It takes 2 to 3 days to attain room temperature. The structure has slightly elongated grains of alpha phase as shown whereas strengthening is metastable.

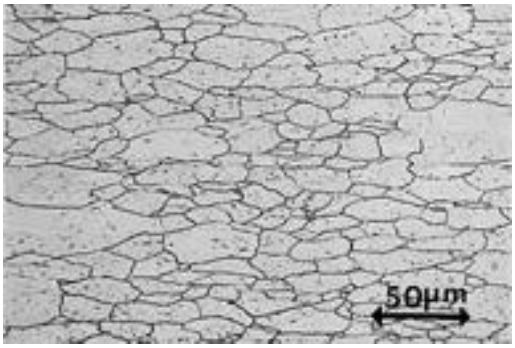


Fig: Microstructure of Hardened beryllium copper alloy.

Tool material:

Tool material is selected based on type of work piece material and machining process. As we chose beryllium copper, we require high strength tools so we are supposed to opt for carbide tools.

Carbide tools give good surface finish at various cutting speeds and feed. Following are the images of the carbide tools used for this project.



Fig: carbide tools (TNMG160404, 08, 12).

Surface roughness: Surface roughness is the dreary or arbitrary deviation from the nominal surface that structures the three-dimensional (3D) topology of the surface. For the most part, surface roughness is shaped by deviations of short wavelength in the surface, portrayed by local maxima or local minima. Surface roughness is measured by using profilometer. It is given in terms of Ra with microns as units.

Material removal rate (MRR): The material removal rate, MRR, can be characterized as the volume of material evacuated or isolated by the machining time. Material removal rate is the rate at which the cross-sectional region of material being expelled travels through the workpiece. Its units are mm^3/min.

Cutting force:

Cutting force is to be measured by lathe tool dynamometer.



Fig : lathe tool dynamometer.

Cutting force cannot be measured directly. When a force acts on a material, it undergoes a particular deformation.

Experimental details:

Experiments are generally conducted in almost all the fields of inquisition, normally to explore some facts about a specific process or system. To define in general, an experiment is a trial or series of trials in which the input factors of a process or system are intentionally changed to observe the reasons for variations in the responses shall be understood and appreciated.

More the number of process parameters considered, more will be the number of experiments to be carried out. Response surface optimal design methodology is found suitable to resolve this problem.

Design of Experiments (DOE):

Design of experiments is an effective technique which allows modelling and analysis of the effect of the process parameters on the response variables. The response variable is an anonymous function of the process parameters, called design variables. The following are the features of great importance in DOE:

Significance test (ANOVA):

The main technique adopted for the analysis and interpretation of the data collected from an experiment is analysis of variance technique which essentially consists of partition in the total variation in an experiment into components ascribable to different sources of variation due to the controlled factors and error. Adequacy of the constructed regression model for the responses in the experiment can be efficiently checked using Analysis of variance (ANOVA). ANOVA helps in calculating the ratio of the mean square and the mean square error of the regression, which is called F-ratio. The F-ratio is also called the variance ratio, the ratio of variance due to the effect of a factor to the variance due to the residual term.

Experimental plan:

In this context machining models, based on the minimized cutting force, surface roughness, maximized metal removal rate are proposed for single pass turning in single-tool applications. Some formulations of these conditions presented in this work are found in the literature. The others are developed and presented in this chapter. Based on optimal central composite design in response surface methodology, 30 preliminary experiments have been conducted with the minimum and maximum ranges of the input factors and are presented in the table.

Name	Units	Type	Std. Dev.	Low	High
s	rpm	Factor	0	700	1200
f	mm/rev	Factor	0	0.053	0.129
doc	mm	Factor	0	0.2	0.6
ns	mm	Factor	0	0.4	1.2
ht		Factor	N/A	-1	1
MRR	mm^3/min	Response	550.676	633	8216
Ra	microns	Response	0.08875	0.075	1.335
Fc	Newtons	Response	32.9912	26	183

Table : Input and output factors.

	Factor 1	Factor 2	Factor 3	Factor 4	Factor 5	Response 1	Response 2	Response 3
Run	A:s	B:f	C:doc	D:ns	E:ht	MRR	Ra	Fc
	Rpm	mm/rev	mm	mm		mm^3/min	Microns	Newtons
1	910	0.053	0.4	0.8	1	1923	0.112	84.928
2	1200	0.129	0.2	0.4	-1	853	1.335	52.271
3	1200	0.053	0.4	1.2	-1	2219	0.075	130.72
4	700	0.129	0.2	0.4	1	1792	1.335	26.086
5	700	0.053	0.6	0.4	1	2152	0.225	111.1
6	700	0.129	0.2	1.2	-1	1561	0.445	94.7
7	700	0.129	0.2	0.4	1	1788	1.335	39.2
8	700	0.053	0.6	0.4	1	2062	0.225	166.7

9	1200	0.129	0.2	1.2	1	3063	0.445	45.8
10	700	0.129	0.6	0.4	-1	4657	1.335	124.1
11	700	0.053	0.2	0.4	-1	633	0.225	45.7
12	1200	0.053	0.2	0.4	1	1134	0.225	35.9
13	1200	0.053	0.6	0.4	-1	3144	0.225	39.2
14	1200	0.129	0.4	0.8	-1	5261	0.667	88.2
15	700	0.053	0.6	1.2	-1	1796	0.075	160.1
16	1200	0.053	0.6	1.2	1	3743	0.075	117.7
17	1200	0.092	0.2	0.8	-1	1817	0.339	62
18	1200	0.129	0.6	1.2	-1	7282	0.445	166.7
19	1200	0.129	0.6	0.4	1	8216	1.335	150.3
20	700	0.129	0.6	0.4	-1	4396	1.335	183
21	910	0.092	0.4	0.4	-1	2541	0.679	75.1
22	1200	0.092	0.4	1.2	1	4206	0.226	71.9
23	700	0.053	0.6	1.2	-1	1753	0.075	114.3
24	1200	0.053	0.2	0.4	1	1091	0.225	26
25	700	0.053	0.2	1.2	1	692	0.075	55.5
26	700	0.092	0.2	0.8	-1	959	0.339	55.5
27	910	0.053	0.2	1.2	-1	729	0.075	39.2
28	910	0.092	0.6	0.8	1	2541	0.679	75.1
29	700	0.129	0.6	1.2	1	4157	0.339	55.5
30	700	0.092	0.4	1.2	1	2084	0.226	75.1

Experimental validation:

Table : ANOVA table for MRR

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	9.732E+07	15	6.488E+06	21.40	< 0.0001	Significant
A-s	1.429E+07	1	1.429E+07	47.12	< 0.0001	
B-f	2.732E+07	1	2.732E+07	90.10	< 0.0001	
C-doc	4.424E+07	1	4.424E+07	145.90	< 0.0001	
D-ns	59977.75	1	59977.75	0.1978	0.6633	
E-ht	6.815E+05	1	6.815E+05	2.25	0.1561	
AB	1.594E+06	1	1.594E+06	5.26	0.0379	
AC	4.734E+06	1	4.734E+06	15.61	0.0014	
AD	5.770E+05	1	5.770E+05	1.90	0.1894	
AE	5.862E+05	1	5.862E+05	1.93	0.1861	
BC	5.932E+06	1	5.932E+06	19.56	0.0006	

BD	55596.14	1	55596.14	0.1833	0.6750	
BE	45732.58	1	45732.58	0.1508	0.7036	
CD	5.474E+05	1	5.474E+05	1.81	0.2005	
CE	5.014E+05	1	5.014E+05	1.65	0.2194	
DE	9.574E+05	1	9.574E+05	3.16	0.0973	
Residual	4.245E+06	14	3.032E+05			
Lack of Fit	4.205E+06	9	4.673E+05	58.46	0.0002	Significant
Pure Error	39967.50	5	7993.50			
Cor Total	1.016E+08	29				

Observations:

The **Model F-value** of 21.40 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise.

The **Lack of Fit F-value** of 58.46 implies the Lack of Fit is significant. There is only a 0.02% chance that a Lack of Fit F-value this large could occur due to noise.

Table: ANOVA table for Ra

Source	Sum of Squares	df	Mean Square	F-value	p-value	
Model	6.09	15	0.4059	51.53	< 0.0001	Significant
A-s	0.0002	1	0.0002	0.0297	0.8655	
B-f	2.81	1	2.81	356.19	< 0.0001	
C-doc	0.0069	1	0.0069	0.8818	0.3636	
D-ns	1.59	1	1.59	202.25	< 0.0001	
E-ht	0.0146	1	0.0146	1.85	0.1951	
AB	0.0001	1	0.0001	0.0105	0.9199	
AC	0.0009	1	0.0009	0.1125	0.7423	
AD	0.0001	1	0.0001	0.0168	0.8988	
AE	0.0042	1	0.0042	0.5314	0.4780	
BC	0.0004	1	0.0004	0.0469	0.8317	
BD	0.7257	1	0.7257	92.14	< 0.0001	
BE	0.0004	1	0.0004	0.0457	0.8338	
CD	0.0008	1	0.0008	0.1071	0.7483	
CE	0.0037	1	0.0037	0.4647	0.5066	
DE	0.0027	1	0.0027	0.3398	0.5692	
Residual	0.1103	14	0.0079			
Lack of Fit	0.1103	9	0.0123			
Pure Error	0.0000	5	0.0000			
Cor Total	6.20	29				

Observations:

The **Model F-value** of 51.53 implies the model is significant. There is only a 0.01% chance that an F-value this large could occur due to noise. **P-values** less than 0.0500 indicate model terms are significant

Table: ANOVA Table for Fc

Source	Sum of Squares	Df	Mean Square	F-value	p-value	
Model	36471.28	5	7294.26	6.70	0.0005	Significant

A-s	181.49	1	181.49	0.1667	0.6866	
B-f	372.28	1	372.28	0.3420	0.5641	
C-doc	31991.57	1	31991.57	29.39	< 0.0001	
D-ns	416.52	1	416.52	0.3827	0.5420	
E-ht	2629.53	1	2629.53	2.42	0.1332	
Residual	26122.02	24	1088.42			
Lack of Fit	21657.92	19	1139.89	1.28	0.4258	not significant
Pure Error	4464.10	5	892.82			
Cor Total	62593.30	29				

Observations:
Factor coding is **coded**.
Sum of squares is **Type III - Partial**
The **Model F-value** of 6.70 implies the model is significant. There is only a 0.05% chance that an F-value this large could occur due to noise. **P-values** less than 0.0500 indicate model terms are significant. The **Lack of Fit F-value** of 1.28 implies the Lack of Fit is not significant relative to the pure error. There is a 42.58% chance that a Lack of Fit F-value this large could occur due to noise.
R- Squared analysis:

Std. Dev.	0.0887	**R^2**	0.9822
Mean	0.4917	**Adjusted R^2**	0.9632
C.V. %	18.05	**Predicted R^2**	0.8394
		Adeq Precision	20.6300

Table: R-squared analysis for Metal Removal Rate(MRR)

Observations:
The **Predicted R^2** of 0.5960 is not as close to the **Adjusted R^2** of 0.9134 as one might normally expect; i.e. the difference is more than 0.2. This may indicate a large block effect or a possible problem with your model and/or data. Things to consider are model reduction, response transformation, outliers, etc. All empirical models should be tested by doing confirmation runs.

Table: R- squared analysis for surface roughness (Ra)

Std. Dev.	550.68	**R^2**	0.9582
Mean	2674.83	**Adjusted R^2**	0.9134
C.V. %	20.59	**Predicted R^2**	0.5960
		Adeq Precision	17.9359

Observations:
The **Predicted R^2** of 0.8394 is in reasonable agreement with the **Adjusted R^2** of 0.9632; i.e. the difference is less than 0.2.

Table: R- squared analysis for cutting force (Fc)

Std. Dev.	32.99	**R^2**	0.5827
Mean	85.59	**Adjusted R^2**	0.4957
C.V. %	38.55	**Predicted R^2**	0.3020
		Adeq Precision	7.3436

Observations:
The **Predicted R^2** of 0.3020 is in reasonable agreement with the **Adjusted R^2** of 0.4957; i.e. the difference is less than 0.2.

Regression Equations (In terms of coded equations):
Final Equation in Terms of Coded Factors

1) MRR= 2861.43 + 761.254 * A + 1117.84 * B + 1417.86 * C + 51.463 * D + 155.017 * E + 283.448 * AB + 496.635 * AC + 165.126 * AD + 155.674 * AE + 558.162 * BC + 53.3607 * BD + 46.7163 * BE -169.616 * CD -150.893 * CE -303.423 * DE.

2) Ra=0.492279 + -0.00308211 * A + 0.358185 * B + 0.0177638 * C -0.265209 * D + 0.0226772 * E-0.00203968 * AB + 0.00679461 * AC + 0.00249756 * AD + 0.0131537 * AE -0.00440294 * BC -0.192783 * BD + 0.00414548 * BE-0.00665701 * CD -0.012892 * CE -0.0107554 * DE.

3) Fc= 85.7339 + -2.65931 * A + 3.97654 * B + 36.6915 * C + 4.10864 * D -9.39718 * E.

Graphical analysis:

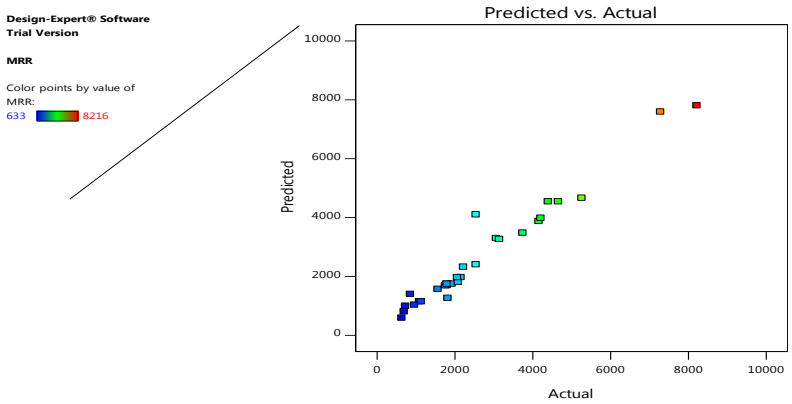


Fig: Residual plot for MRR.

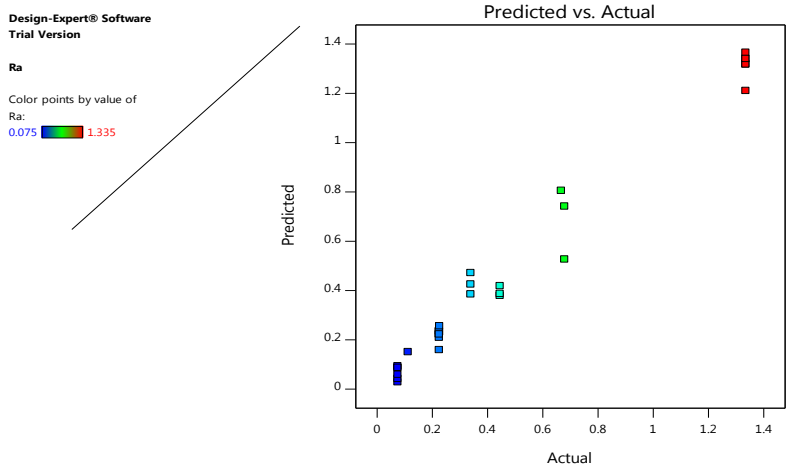


Fig: Residual plot for MRR.

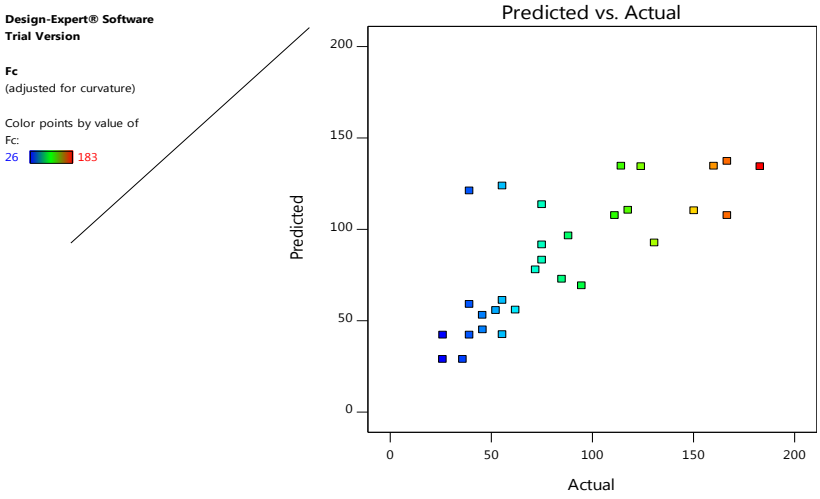


Fig : Residual plot for Fc.

Response Surface Optimization:

Desirability plots:

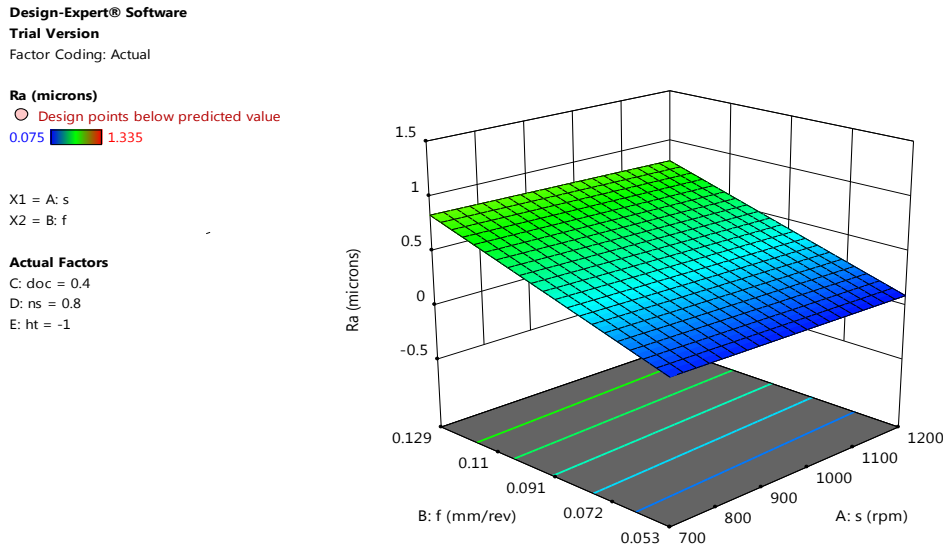
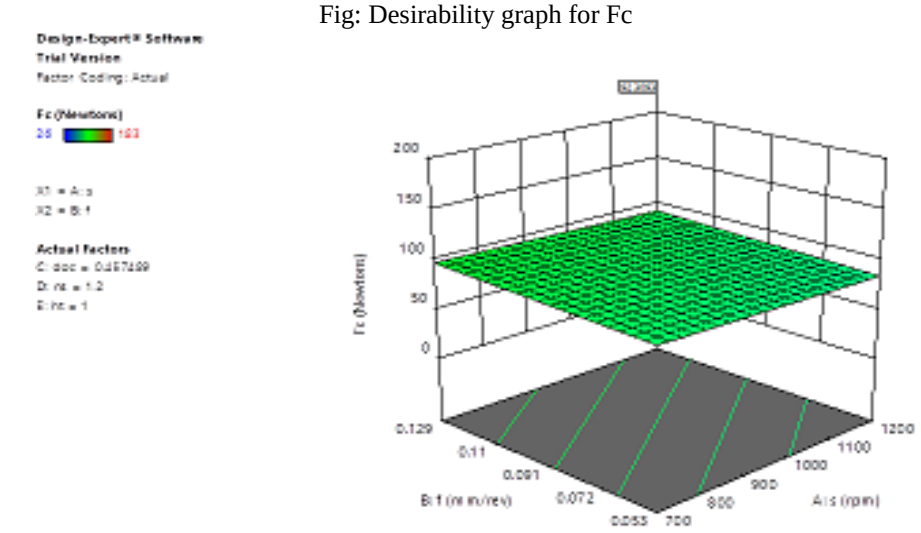


Fig: Desirability graph for optimum values (Ra)

Fig: Desirability graph for Fc



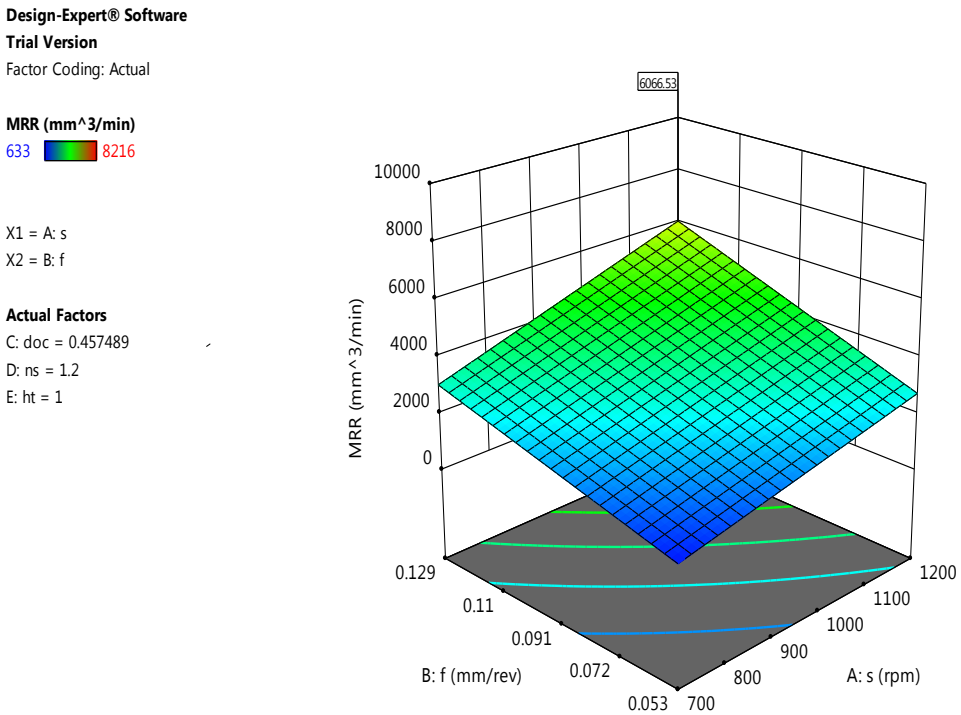


Fig: Desirability graph for MRR

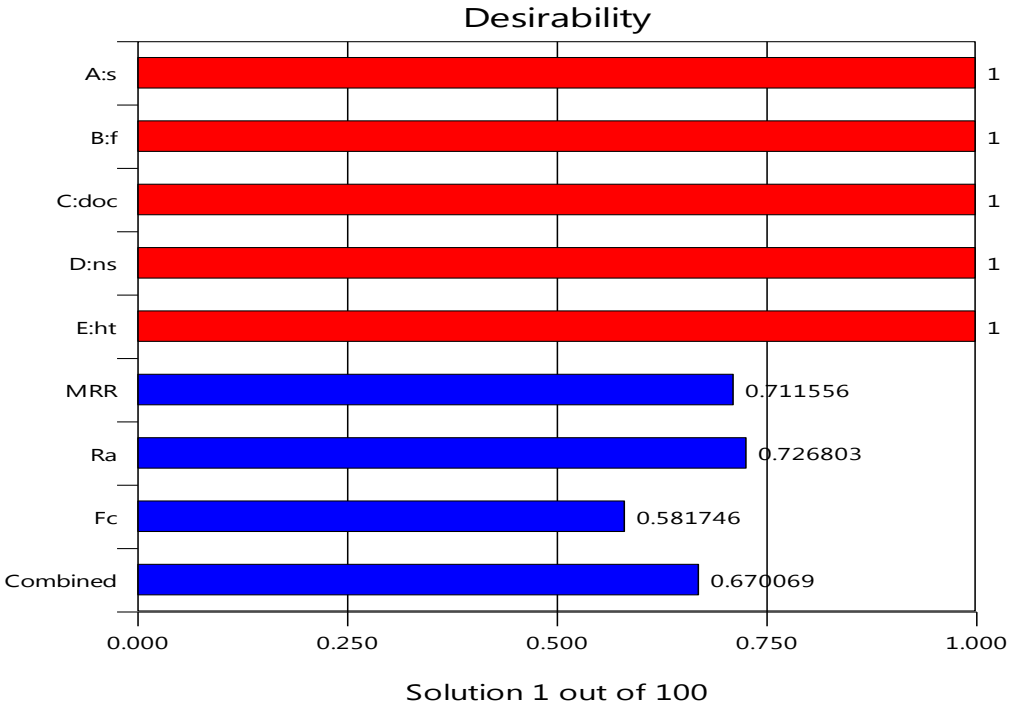


Fig: Desirability Histogram for optimum conditions of machining parameters with response surface methodology.

Optimal Solutions derived from RSM:

Solutions for 2 combinations of categoric factor levels

Number	s	f	doc	ns	ht	MRR	Ra	Fc	Desirability	
1	**1199.998**	**0.129**	**0.452**	**1.200**	**1**	**6006.974**	**0.419**	**91.296**	**0.670**	**Selected**
2	1199.996	0.129	0.451	1.200	1	5994.235	0.419	91.078	0.670	
3	1199.950	0.129	0.455	1.200	1	6041.225	0.419	91.884	0.670	
4	1199.993	0.129	0.447	1.200	1	5951.478	0.419	90.349	0.670	
5	1199.997	0.129	0.459	1.200	1	6079.984	0.419	92.538	0.670	
6	1200.000	0.129	0.445	1.200	1	5933.008	0.419	90.031	0.670	
7	1199.961	0.129	0.465	1.200	1	6142.327	0.419	93.708	0.670	
8	1199.622	0.129	0.448	1.200	1	5945.682	0.418	90.490	0.670	
9	1199.409	0.129	0.450	1.200	1	5965.930	0.418	90.865	0.670	
10	1199.608	0.129	0.464	1.200	1	6114.093	0.418	93.384	0.670	
11	1200.000	0.129	0.474	1.200	1	6244.852	0.419	95.349	0.670	
12	1199.962	0.129	0.425	1.200	1	5714.019	0.419	86.304	0.669	

Genetic Algorithms:

Genetic Algorithm Parameters Selected in the Work

the parameters are given as:

Sample size = 18

Crossover probability (Pc) = 0.8

Mutation probability (Pm) = 0.01

Number of generations = 611

Population type: Double vector

Population size = 60

Length of Chromosome = 6

Selection operator: Rank order

Crossover operator: Single point operator

Crossover probability = 0.75

Mutation probability =0.1

Fitness parameters: speed, feed, depth of cut, work piece material (coded to a numerical value: -1 for untreated and 1 for hardened piece), nose radius.
Selection function: Tournament
Mutation function: Adaptive feasible
Crossover function: Heuristic
Hybrid function: fgoalattain

Implementation of GA:

- Step-1: Initialization
- Step-2: Evaluation
- Step-3: Selection and Reproduction
- Step-4: Crossover
- Step-5: Mutation

Fitness function is as follows:

- Y(1)=1/(1+(2861.43+761.25*x(1)+1117.84*x(2)+1417.86*x(3)+51.46*x(4)+155.02*x(5)+283.45*x(1)x(2)+496.64*x(1)x(3)+165.13*x(1)x(4)+155.67*x(1)x(5)+558.16*x(2)x(3)+53.36*x(2)x(4)+46.72*x(2)x(5)-169.62*x(3)x(4)-150.89*x(3)x(5)-203.42*x(4)x(5)));
- Y(2)=+0.4923-0.031*x(1)+0.3582*x(2)+0.0178*x(3)-0.2652*x(4)+0.0227*x(5)-0.0020*x(1)x(2)+0.0068*x(1)x(3)+0.0025*x(1)x(4)+0.0132*x(1)x(5)-0.0044*x(2)x(3)-0.1928*x(2)x(4)+0.0041*x(2)x(5)-0.0067*x(3)x(4)-0.0129*x(3)x(5)-0.0108*x(4)x(5);
- Y(3)=+85.73-2.66x(1)+3.98*x(2)+36.69*x(3)+4.11*x(4)-9.40*x(5);Y(1) is MRR, Y(2) is Ra, Y(3) is Fc, X(1) is speed, X(2) is feed, X(3) is doc, X(4) is nose radius, X(5) is work piece material(+1 or -1).

Parameter setup in GA tool:

The GA parameter tools are as follows

Fig: setting options in multi objective genetic algorithm.

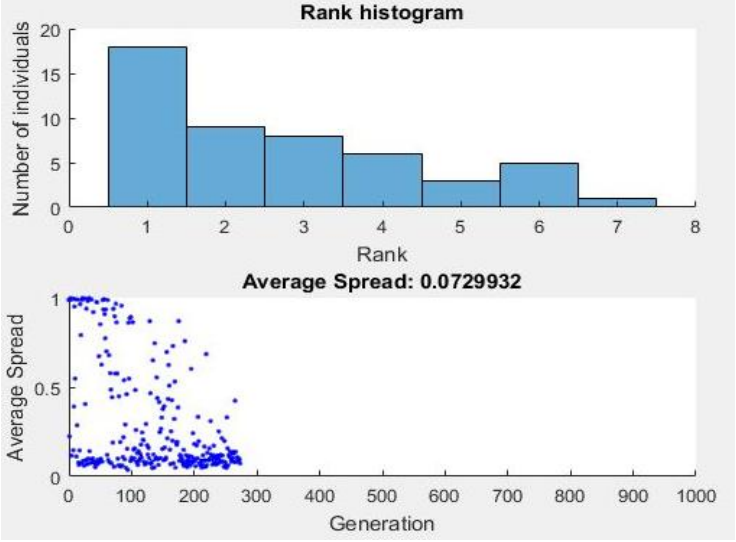
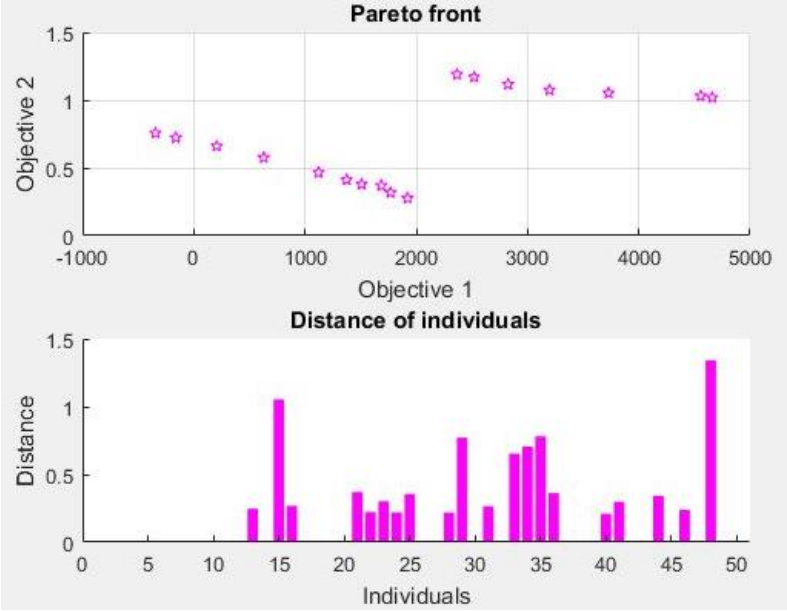


Fig: Histogram and average spread plot.



Pareto optimal solution and average speed:

Table: Pareto Optimal Solution

	MRR	Ra	Fc	s	f	doc	ns	Ht
1	**1964.76**	**0.222**	**101.298**	**716.165**	**0.053**	**0.357**	**0.986**	**-1**
2	-330.75	0.828	-11.279	990.256	0.06	0.2	0.4	-1
3	1020.14	0.31	46.193	720.735	0.053	0.208	0.69	-1
4	656.64	0.388	30.29	772.595	0.053	0.203	0.657	-1
5	11.12	0.583	0.704	889.198	0.053	0.201	0.505	-1
6	153.603	0.577	4.416	901.619	0.054	0.215	0.531	-1
7	926.181	0.383	39.629	792.309	0.053	0.244	0.696	-1
8	475.582	0.484	21.179	825.491	0.055	0.215	0.608	-1
9	-330.75	0.828	-11.279	990.256	0.06	0.2	0.4	1
10	140.606	0.632	0.086	955.462	0.053	0.226	0.5	-1
11	527.599	0.517	2.459	860.889	0.055	0.235	0.604	-1
12	1395.46	0.253	64.922	707.647	0.053	0.24	0.803	-1
13	-316.77	0.719	-15.943	995.738	0.053	0.2	0.411	-1
14	248.409	0.537	12.012	848.852	0.053	0.206	0.562	-1
15	1964.76	0.222	101.298	716.69	0.053	0.357	0.986	-1
16	1554.11	0.242	72.567	708.69	0.053	0.263	0.841	-1
17	1509.03	0.222	77.259	700	0.053	0.24	0.93	1
18	-316.77	0.719	-15.943	995.738	0.053	0.2	0.411	-1

Maximization of material removal rate, minimization of surface roughness, minimization of cutting force.

IV. **Conclusion.**

Comparative results drawn from the optimization techniques and are tabulated as

Number	**s**	**f**	**doc**	**ns**	**ht**	**MRR**	**Ra**	**Fc**	**Desirability**
1	**1199.998**	**0.129**	**0.452**	**1.200**	**1**	**6006.974**	**0.419**	**91.296**	**0.670**
2	1199.996	0.129	0.451	1.200	1	5994.235	0.419	91.078	0.670

Table: Optimal parametric setup using RSM.

	MRR	Ra	Fc	S	f	Doc	ns	Ht
1	**1964**	**0.222**	**101.298**	**716.165**	**0.053**	**0.357**	**0.986**	**-1**

Table: Optimal parametric setup using GA.

Based on the tabular values a conclusion can be drawn that the higher MRR values have been obtained along with the lower surface roughness and low cutting forces. The two optimization techniques Response surface methodology and genetic algorithms are drawn to be effective in the modelling of turning process.

References

[1] Rony Mohan, Optimization of Surface Roughness of Bearing Steel during CNC Hard Turning Process. International Journal of Engineering Trends and Technology (IJETT) – Volume 17 Number 4 – Nov 2014.

[2] Ajay Mishra, Multi-Objective Optimization In Turning Of Cylindrical Bars Of AISI 1045 Steel Through Taguchi's Method And Utility concept. International Journal of Sciences: Basic and Applied Research (IJSBAR) (2013) Volume 12, No 1, pp 28-36.

[3] Suha K. Shihab, RSM Based Study of Cutting Temperature during Hard Turning with Multilayer Coated Carbide Insert. 3rd International Conference on Materials Processing and Characterization (ICMPC 2014) Procedia Materials Science 6 (2014) 1233 – 1242.

[4] Prashant Waydande, Statistical Analysis of Cutting Forces and Surface Roughness Using Response Surface Methodology in Hard Turning of AISI 52100 Steel with PVD Coated Carbide Tool. Journal of Materials and Metallurgical Engineering Volume 1 Issue 2 (2016).

[5] k. Devaki devi, statistical approach for multi criteria optimization of cutting parameters of turning on heat treated beryllium copper alloy. Journal of engineering science and technology vol. 12, no. 8 (2017) 2213 - 2228