





#### Optimization of Surface Roughness and M.R.R in End milling on 20MnCr5 Using RSM & MOGA Method

#### **Under The Guidance Of**

Internal Guide :-Prof. Rishi kumar (Mech Dept.)

**Team No: 8519** 

External Guide :-Mr. Chetan Jani (Ammann Apollo Executive HR.)

By Jay R. Soni(11me109) Dhaval D. Prajapati (11me79) Dhaval J. Sindhav (11me78) Mukesh V. Chaudhary (11me69)

# **CONTENTS**

Introduction

- Milling Operation
- Literature Survey
- Objective
- Research Methodology
  - i) Machine tool, work piece and coolant
  - ii) Design of experiment
  - iii) Measurements
  - iv) Response surface modeling
  - v) Genetic Algorithm

Results and Discussion i) Analysis of Variance for MRR and Ra ii) Mathematical modeling for MRR and effect of factors iii) Mathematical modeling for Ra and effect of factors iv) Multi-objective optimization using GA

#### Confirmation Test

**Conclusions** 

## **INTRODUCTION**

- Machining is the manufacturing process by which parts can be produced to the desired dimensions and surface finish from a blank by gradual removal of the excess material in the form of chips with the help of a sharp cutting tool.
- Almost all of the engineering components undergo some kind of machining during manufacture. Hence, it is very important to design those parts in such a way that would increase the efficiency of the machining process, increase the tool life and reduce the overall cost of machining. With the aim of achieving these objectives, a brief knowledge of various machining processes is required. A brief classification of various machining processes that are widely used in the manufacturing and fabrication industries of all kinds is shown in Fig.1.1

## **Milling Operation**

- Milling is a versatile and useful machining operation.
- Milling is a process of producing flat and complex shapes with the use of multi-point (or multi-tooth) cutting tool.

# **Milling Machine**



# Two basic types of milling operations

#### **Down Milling:**

• When the cutter rotation is in the same direction as the motion of the workpiece being fed.

#### Up Milling:

• The workpiece is moving towards the cutter, opposing the cutter direction of rotation.



Schematic depiction of (a) Down milling and (b) Up milling operations

# **Depending on the orientation of** <u>the milling tool</u>

#### 1. Peripheral Milling

- Operation performed by milling cutter to produce a machined surface parallel to axis of rotation of cutter.
- It can be either UP milling or DOWN milling.



#### **2.Face Milling**

• The face milling cutter is rotated about an axis perpendicular to the work surface.

#### **3. End Milling**



- Cutter has teeth both on end face and periphery.
- Vertical milling machine is most suitable for end milling operation.



Copyright © 2007 CustomPartNet



### **Literature Survey**

**Narayana Reddy. A R et. al(Sept. 2014)** The effect of process parameters cutting speed, Feed, Depth of cut and Tool Hardness on response Characteristics MRR and Surface roughness were studied on 20MnCr5 steel alloy in CNC Turning.. The experimental results showed that the Taguchi parameter design is an effective way of determining the optimal cutting parameters for achieving low surface roughness and maximum material removal rate. The relationship between cutting parameters (cutting speed, feed, depth of cut and hardness of cutting tool) and the performance measures (surface roughness and material removal rate) are expressed by multiple regression equation which can be used to estimate the expressed values of the performance level for any parameters levels.[1]

Sahoo, P. et. al (2011) The three level rotatable central composite designs are employed for developing mathematical models for predicting surface roughness parameters in CNC turning of AISI 1040 mild steel It is seen that the surface roughness parameters Ra and Rsm decrease with increase in depth of cut and spindle speed but increase with increase in feed. Genetic Algorithm is used to determine the optimum machining parameters in order to obtain the best possible surface quality. [9]

## **Literature Survey (continued)**

**K.Kadirgama et.al(2010)** This research illustrates the machining of aluminium alloy (AA6061-T6) with end-milling methods and predicting their subsequent surface roughness. There is becoming a need for investigating the machining of various types of aluminium and their surface roughness, which in turn can be useful in developing more cost effective personalised products. The authors have shown the use of RACO to formulate an optimised minimum surface roughness prediction model for end machining of AA6061-T6.[2]

**V. Tandon et. al(2006)** This work has presented a new approach to optimizing the cutting conditions in end milling (feed and speed) subject to a near to comprehensive set of constraints. The original set of seventeen constraints was reduced to an equivalent set (of only three equations). Next, a production cost objective function was used to define the parameter to optimize (in this case, minimize).[4]

**Tung- Hsu Hou et. al (2007)** The fitness function of GA was obtained by RSM and was applied to find the optimal parameters for a nano-particle milling process. This integrated approach resulted in very good output responses in the nano-particle wet milling process. [6]

## **Literature Survey (continued)**

**P.V.S. Suresh et. al(2002)** The two-stage effort of obtaining a surface roughness model by surface response methodology, and optimiz- ation of this model by Genetic Algorithms, has resulted in a fairly useful method of obtaining process parameters in order to attain the required surface quality. This has validated the trends available in the literature, and extended the data range to the present operating con- ditions, apart from improving the accuracy and model- ling by involving the most recent modelling method.[5]

**Franci Cus et .al(2003)** This paper presents a genetic algorithm optimization approach for solving the machining operations problem with milling. The results obtained from comparing the proposed genetic algorithm optimization approach with those taken from recent literature prove its effectiveness. The results of the proposed approach are compared with results of simulated annealing, fuzzy possibilistic-genetic algorithm, linear-programming approaches.[7]

### **Literature Survey (continued)**

**M.Subramanian1 et. al(2013)**In this work, response surface methodology and genetic algorithm have been utilized for establishing optimum end mill process parameter guiding to minimum cutting force during shoulder mill Aluminium 7075-T6 with different cutting condition. Shoulder mill cutting parameters cutting speed, cutting feed, axial depth of cut used to conducting experiments. A response surface methodology was developed to regression model cutting force by manipulating experimental measurements found from these cutting forces. The established RSM model was further coupled with an established genetic algorithm to novelty the optimum end mill cutting parameter prominent to the minimum cutting force value.[8]

**S. Gopalakannan et. al(2013)** A novel ultrasonic cavitation method used for bulk fabrication of nano-composites.Enhanced properties were obtained with lower volume fraction of nanoparticles.Machining of nano-composites with better surface finish can be obtained with EDM.Effects of process parameters were investigated using response surface methodology.Research finding provides technical database for aerospace, military applications.[10]

## **Objectives**

#### The objectives of present research are as follows:

- 1. To determine optimum surface roughness in milling process to maximize the production rate, quality of product and minimum production cost in industry.
- 2. To predict the surface roughness in milling process to make an optimization.
- 3. Analysis of experimental results using statistical methods and developing mathematical models either first or second order response surfaces with better fittings. ANOVA is performed to find the most influential parameters on both MRR and Ra.
- 4. Optimum parameter selection for overall improvement in milling performance using multi objective genetic algorithm.
- 5. Multi objective Genetic algorithm (MOGA) to obtain pareto-optimal setting.

### **Methodology**



### **Research Methodology**

#### Machine tool, Work piece and coolant

20MnCr5 is categorized as case hardened steel produced by casting, it is easily machinable and can have a wide variety of surface finishes. It also has high strength and stiffness. It is used in the field of high stressed components in automobile industry like small gear, shafts, crankshafts, connecting rods, cam shafts, piston bolts, spindles and other mechanical controlling parts. The experiment was performed on 20mncr5 of cross section 130mm×94mm×15mm. The chemical, physical and mechanical properties of 20mncr5 is shown in Table 3.1(a), 3.1(b) and 3.1(c) respectively.

С	Si	Mn	Ρ	S	Cr	Ni
0.22%	0.40%	1.40%	0.035%	0.035%	1.30%	0.019%

Table 3.1(a) Chemical Composition of 20MnCr5 (Wt %)[22]

#### Table 3.1(b) Physical Properties[22]

Density	7.81 g/cm^3				
Melting Point	1400°C				
Thermal Expansion	10 <sup>-8</sup> °C <sup>-1</sup> /K				
Modulus of Elasticity	210 Gpa				
Thermal Conductivity	42 W/m.K				
Electrical Resistivity	$0.16 \Omega .\mathrm{m}m^2/m$				
Table 3.1(c) Mechanical Properties[22]					

UTS	658.17 MPa
Tensile Strength	1200 MPa
Elongation A5	28%
Shear Strength	80 GPa
Yield Point	48KN
Break Point	56KN

# **Tool**

• To conduct the experiment, the tool used is cobalt bonded cemented carbide End milling cutter tool (Fig 3.3) of 10 mm diameter having six numbers of flutes and teeth on both side and periphery of the cutter. The coolant used is S 500 CF which is water soluble and chlorine free.



#### Figure 3.3 End Milling Tool[23]

## **Surface Roughness**

 Roughness is defined as the arithmetic value of the profile from the centerline along the length and can be expressed as

$$\operatorname{Ra} = \frac{1}{L} \iint y(x) |d(x)|$$

where L is the sampling length, y is the profile curve and x is the profile direction. The average "Ra" is measured within L = 0.8 mm.



Surface roughness measurement was carried out using a portable stylus type profilometer, Talysurf (Taylor Hobson, Surtronic 3+) as shown in Figure.



Roughness measurements were carried out in the transverse direction. The measured profile was digitized and processed through the dedicated advanced surface finish analysis software

The roughness measuring conditions are shown in Table

Condition	Value				
Probe tip radius	0.005 mm				
Measuring range	0.800 mm				
Traverse length	4.000  mm				
Speed	1.000  mm/s				
Filter	2 CR				

#### **Roughness measuring condition**

The MRR for every parameter setting was measured by the weight loss method in volumetric scale using digital single pan balance with a precision of 0.001 g and a maximum capacity of 500 g. By weighing work piece before and after each experiment, average value of MRR was calculated using equation 1

$$MRR = \frac{w(i) - w(f)}{p * t}$$

Where, w(i) = initial weight before experiment W(f) = final weight after experiment p =density of 20MnCr5 alloy t= machining time in minutes

### **Measurement Of MRR.**

The weight of work piece and tool has taken by high precision balance Figure whose capacity is 1960 gram and accuracy is 0.001 gram. By weighing work piece before and after each experiment, average value of MRR was calculated using equation 3.7

$$MRR = \frac{w(i) - w(f)}{p * t}$$
(3.7)

Where w(i) = initial weight before experiment,

W(f) = final weight after experiment,



Figure 3.7 Weight Measuring Instrument[24]

## **Design Of Experiment (DOE)**

- The objective of any experimental activity is to obtain the maximum realistic information about a system with the minimum number of well designed set of experiments. An experimental program identifies the major "factors" that affect the outcome of the experiment. The factors may be identified by observing at all the quantities that may affect the outcome of the experiment. The most important among these may be identified using a few exploratory experiments or from past experience or based on some underlying theory or hypothesis. The next thing one has to do is to select the number of levels for each of the factors. The data is gathered for these values of the factors by conducting the experiments by maintaining the levels at these values. Hence in brief, we can say that the selection Process is known as Design of Experiments.[12]
- Design of experiments (DOE), or statistically designed experiments (SDE), is defined as a scientific approach that allows the experimenter to understand process and to determine how the input variable (factors) affects the output or quality characteristic. In other words it is a systematic approach to process optimization. [12]

### **Response surface modeling of process measures**

- The response surface method developed by Box and Wilson in the early 1950 s is a collection of mathematical and stastical techniques that are used to model and analyze engineering applications in which a response of interest is usually influenced by several factors and the objective is to find the combination of factors that can optimize the response.
- In general, the procedure of RSM consists of the following steps:-

**Step 1.** Design and conduct a series of experiments to find adequate and reliable measurements of responses of interest.

**Step 2.** Develop mathematical models of the first and second order response surfaces with best fittings.

**Step3.** Find the optimal set of process parameters that produce optimized value of the response.

**Step 4.** Represent and analyze the direct and interactive effects of the process parameters

## <u>Machining parameters and design of</u> <u>experiment</u>

• In order to determine the working characteristics of milling machine, a number of preliminary experiments were conducted. Four controllable milling parameters namely velocity, feed, depth of cut, coolant speed were chosen to evaluate the process efficiency in terms of MRR (mm^3/min). Table 3.1(d) summarizes the pertinent machining conditions in both coded and actual form. Table 3.1(e) lists all the parametric settings of experimental runs along with their obtained corresponding responses. Fig. 3.4 to Fig 3.6 shows Work piece after Experiment.

Parameter	Unit	Level				
		-1	0	+1		
Speed (A)	m/min	74.35	160.74	247.14		
Feed (B)	mm/min	50	75	100		
<b>Depth of Cut (C)</b>	mm	0.4	0.8	1.2		
<b>Coolant Speed (D)</b>	Litters Per Min.	0	2	4		
			<b>T</b> 1			

 Table 3.1(d) Milling Parameters & Their Levels

## **Design layout and experimental results**

Run Order	Speed (RPM)	Feed (mm/min)	Depth of Cut (mm)	Coolant speed (Lt./hr)	Machine time (Min.)	MRR (mm3/min)	Ra(µm)
1	160.74	100	0.8	2	1.17	642.73	0.365
2	160.74	75	0.8	2	1.09	689.91	0.280
3	160.74	75	0.8	2	1.15	653.91	0.261
4	247.14	50	1.2	0	1.05	1074.28	0.200
5	74.35	75	0.8	2	1.06	709.43	0.322
6	160.74	75	1.2	2	1.38	817.39	0.241
7	160.74	75	0.8	4	1.13	665.49	0.255
8	74.35	50	0.4	0	0.63	595.25	0.265
9	74.35	50	1.2	4	1.13	998.23	0.247
10	247.14	75	0.8	2	1.23	611.38	0.162
11	247.14	50	1.2	4	1.30	867.69	0.175
12	74.35	100	0.4	4	0.68	544.92	0.435
13	160.74	75	0.8	2	1.38	637.28	0.251
14	160.74	75	0.8	0	1.10	683.64	0.350
15	247.14	100	1.2	4	1.44	783.33	0.235
16	247.14	50	0.4	4	0.84	446.73	0.111
17	247.14	100	1.2	0	1.	980.86	0.321
18	160.74	75	0.4	2	0.80	469.02	0.260

### **Design layout and experimental results**

19	160.74	75	0.8	2	1.09	689.91	0.250
20	74.35	100	0.4	0	0.64	584.45	0.470
21	160.74	75	0.8	2	1.11	677.47	0.260
22	247.14	100	0.4	4	0.84	445.85	0.250
23	160.74	75	0.8	2	1.09	675	0.286
24	74.35	50	0.4	4	0.67	557.03	0.225
25	160.74	75	0.8	2	1.12	671.43	0.270
26	247.14	50	0.4	0	0.85	438.06	0.215
27	160.74	50	0.8	2	1.12	671.42	0.218
28	247.14	100	0.4	0	0.88	425.66	0.335
29	74.35	100	1.2	4	1.13	998.23	0.452
30	74.35	50	1.2	0	1.11	1016.22	0.317
31	74.35	100	1.2	0	1.11	1016.22	0.480

## **Analysis of Variance**

The most powerful analytical tool for identifying the main and interaction effects is analysis of variance (ANOVA). This is a tool used for subdividing the total variation in the data into useful and meaningful component of variation. In the context of orthogonal array experiments, ANOVA is a useful tool to sub-divide the total variation into variation due to main effect, variation due to interaction effects and variation due to error. Therefore, mathematically, we can write as,[13]

Total variation=Vm +Vi +Ve;

A low P- value ( $\leq 0.05$ ) indicates statistical significance for the source on the corresponding response ( $\alpha = 0.05$ ) or 95% confidence level • The model with the rest of the terms after backward elimination process in order to discard the insignificant terms (p-value greater than 0.05) so as to adjust the fitted quadratic model is illustrated in tables for MRR. It can be observed that the p-values of all these terms are less than  $\alpha$ -value which means that they are significant hence these are included in the model.

Term	Coeff	SF Coeft	T- Value	P- Value
		SE COUR	I varae	1 Vuide
Constant	514.096	12.61	52.046	0.000
Speed	-1.250	10.02	-5.246	0.000
Feed	-3.3261	10.02	-1.346	0.197
DOC	592.9506	10.02	22.432	0.000
CS	-11.34	10.02	-2.812	0.013
CS*DOC	-30.563	10.63	-2.301	0.035

#### **Table 5.2 Test results for the independent MRR**

S = 42.51, R-Sq = 97.3%, R-Sq(adj) = 94.9%

#### **Table 5.3 Test results for the independent Ra**

Term	Coefficient	SE Coefficient	T- Value	P- Value	
Constant	0.1025	0.00553	47.733	0	
Speed	-0.0012	0.00443	-15.032	0	
Feed	0.0042	0.00443	17.301	0	
DOC	0.004	0.00443	1.153	0.261	
CS	-0.0508	0.00443	-7.246	0	
SPEED*SPEED	-0.008	0.01114	-2.34	0.029	
FEED*FEED	-0.001	0.1142	2.102	0.047	
CS*CS	0.0344	0.01114	3.089	0.005	
SPEED*FEED	-0.022	0.0047	-4.694	0	

S = 0.01880, R-Sq = 96.6%, R-Sq(adj) = 95.4%

#### <u>Mathematical modeling for MRR and effect</u> <u>of factors</u>

Mathematical modeling for MRR and effect of factors are as following. The mathematical relation obtained on the basis of RSM analysis for analyzing the influences of the various dominant machining parameters on MRR is given by[13],

# MRR= 514.096+ (-1.250)\*SPEED+ (-3.3261)\* FEED+ (592.9506)\*DOC+ (-11.34)\*CS + (-30.563)\*DOC\*CS.

Fig. 5.1 shows the main effect plot for MRR which can be used to graphically assess and compare the magnitude of the main effects of the factors when it is dealt with multiple factors. The points are the means of the response variables at different levels of each factor with a reference line drawn at the grand mean of the response data. It can be seen that depth of cut are the most influencing parameters as there is sharp increase in MRR. [16]



**Figure 5.1 Main Effects Plot for MRR** 

### Mathematical modeling for Ra and effect of factors

•On the basis of RSM analysis, the mathematical relationship for correlating the surface roughness Ra for analyzing the influences of various parameters on Ra is given by

> Ra= 0.1025+ 0.0000\*Speed - 0.00424\*Feed-0.004\*DOC-0.0508\*(CS)+0.0080\*(CS) \*(CS)-0.0001\*Speed\*(Feed)

•The main effect plot for Ra is shown in figure 5.2 It can be seen that speed and coolant speed have significant effect on Ra which is supported by ANOVA results. However coolant speed is the most influencing parameter showing a sharp decrease in Ra from 0.35  $\mu$ m to 0.25  $\mu$ m when coolant speed increase from 0 to 2 liters per min.



#### **Figure 5.2 Main Effects Plot for RA**

## **Normal Probability Plot of the Residuals for MRR**

Fig. 5.3 shows the variation between residuals and their expected value. It indicates that the residuals are following a normal distribution.



Figure 5.3 Normal Probability Plot of the

**Residuals for MRR** 

## **Normal Probability Plot of the Residuals for Ra**

Fig. 5.6 shows the variation between residuals and their expected value. It indicates that the residuals are following a normal distribution.



**Figure 5.6 Normal Probability Plot of the** 

**Residuals for Ra** 

#### **Optimization of milling process using GA**

•The genetic algorithm (GA), introduced by John Holland (1971) is a stochastic search technique based on the mechanism of natural selection and natural genetics for solving difficult optimization problems with high complexity and an undesirable structure.

• This approach represents a powerful, general purpose optimization paradigm in which the computational process mimics the theory of biological evolution.

#### •Implementation of GA

GA approach in solving an optimization problem can be summarized as follows

#### Coding

In order to use GAs to solve the problem, variables  $x_i$ 's are first coded in same strings which has only ones and zeros.

#### **Fitness Function**

A fitness function F(x) is derived from the response function and is used in successive operations.

#### •Reproduction

This is the first operator applied on a population.

In this process, copies of individual strings are copied into a separate string called the 'mating pool', in proportion to their fitness values.

•The strings which have higher fitness values will have higher probability of contributing more strings as the search progress

#### • Crossover

•This is the second operator among genetic operator applied after reproduction; the population is enriched with good strings from the previous generation.

• It swaps the parent strings partially causing offspring's to be generated in order to create better strings.

•The total number of participative strings in crossover is controlled by crossover probability which is the ratio of total strings selected for mating and the population size.

#### To use the GA Tool, we must first enter the following information

- Fitness function The objective function you want to minimize. Enter the fitness function in the form @multiga, where multiga.m is an M-file that computes the fitness function.
- Number of variables The length of the input vector to the fitness function
- To run the genetic algorithm, click the Start button. The tool displays the results of the optimization in the Status and Results pane.
- In order to convert the responses into single characteristic, it is suitably modified. The objective functions after modification are given below.

Objective 1 = Ra = f(1)

Objective 2 = -(MRR) = f(2)

A Start Ready	multiga Ln 1 Col 1 OVR
	Activate Windows Go to PC settings to activate Windows.
fz, >>	
Click here if you do not want to see this message again.	
from the active settings drop-down list. For more information, see <u>Help</u> .	
To customize keyboard shortcuts, use <u>Preferences</u> . From there, you can also restore previous default settings by selecting "R2009a Windows Default Set"	
across the desktop.	
In addition, many keyboard shortcuts have changed for improved consistency	
MATLAB desktop keyboard shortcuts, such as Ctrl+S, are now customizable.	
Command Window	× 5 ⊡ ±
multiga.m × multiga.m ×	
5 end	
$\begin{array}{l} 3 - f(1) = & 0.1025 - 0.0000*x(1) + & 0.0042*x(2) - & 0.0004*x(3) - & 0.0508*x(4) - & 0.0080*x(4)*x(4) - & 0.000*x(1)*x(2); \\ 4 - & f(2) = - & (514.096 - 1.250*x(1) - & 3.326*x(2) + & 592.95*x(3) - & 11.34*x(4) - & 30.563*x(3)*x(4)); \end{array}$	
2 Function f= multiga(x)	
*=	ce
🖺 😂 🖩 👗 🤊 🝽 🍓 🖅 - 🛤 🌩 🔶 😥 - 🗟 🐮 🖷 🖷 🗊 🗐 🕼 Stack: Base 🗸 🏂	ار الله الله الله الله الله الله الله ال
Editor - C:\Users\jay soni\Desktop\multiga.m	× 5 ⊡ * ×
Shortcuts Z How to Add Z What's New	

File Help

Problem Setup and Results						Options				>>			
Solver: gamultiobj - Multiobjective optimization using Genetic Algorithm											^		
Problem													
Fitness function:	@multiga								E Stopping criteri				
Number of variables:	4								Generations:				
Constraints:										O Spec	ify:		
Linear inequalities:	A:			b:					Time limit:	Use d	efault: Inf		
Linear equalities:	Aeq:			beq:						O Same	if		
Bounds:	Lower: [74.35	50 0.4 0]		Upper:	[247.14 100	1.2 4]				⊖ spec	ny:		
<b>D</b> 1 1 1									Fitness limit:	Use d	efault: -Inf		
Kun solver and view res	uits									O Spec	ify:		
Use random states	from previous	run							Stall generations:	🖲 Use d	efault: 100		
Start Pause	Stop									O Shor	if a		
Current iteration: 280							Clea	ar Reculto		O spec	ny:		
									Function tolerance:	🖲 Use d	efault: 1e-4		
								^		O Spec	ify:		
Optimization running.									Plot functions				
Optimization terminated: a	average change	in the spread of Par	eto solutions less than	options.T	olFun.				Distister al		1		
											I		
								۷	Distance		Genealogy	Score diversity	
Pareto front - function	values and de	cision variables							Selection		Stopping	✓ Pareto front	
Index f1		f2	x1 3	x2	x3		x4 🔺		Average Pareto	distance	Rank histogram	Average Pareto spread	
5	0.314	-938.767	93.677		50.737	1.2		0.021 🔺	Custom function	n:			
17	0.285	-912.571	94.763		50.587	1.199		0.541				A structo Mindours	
21	0.273	-902.82	94.524		50.514	1,199		0.737	Output function	n		Activate windows	
20	0.200	-050.047	0/ 0/2		50.51	1 100		1 V	History to new w	vindow	Interval: 1	Go to PC settings to activate Wind	<del>OWS.</del>
													Y



#### **Optimal Combination of Parameters**[17]

Sr No:	Ra(µm)	MRR	Speed	Feed	Doc	<b>Coolant Speed</b>
1	0.312988	959.274638	79.37866	50.2402	1.2	1.2354787
2	-0.01914	756.994435	84.47974	50.00796	1.190114	3.999996804
3	0.152179	841.794234	81.54617	50.18571	1.192675	2.316687449
4	0.275792	926.961749	80.26464	50.0899	1.19935	0.653368469
5	0.065254	802.264799	80.66883	50.07707	1.19777	3.225543753
6	-0.01914	756.99461	84.47924	50.00796	1.190113	3.999996788
7	-0.00774	769.719842	80.94813	50.0612	1.198154	3.90192227
8	0.214164	883.69727	80.11501	50.14385	1.199496	1.556614943
9	0.029866	779.838508	84.04803	50.00902	1.19279	3.559606943
10	0.202207	872.804544	83.00599	50.0988	1.199336	1.709578734
11	0.160649	852.982785	79.49163	50.14463	1.199927	2.217391661
12	0.207468	877.389409	81.12425	50.11684	1.197655	1.642793978
13	0.123603	830.235053	80.72163	50.12215	1.197043	2.629918243
14	0.181815	860.119458	81.40143	50.10269	1.194717	1.964104098
15	0.091261	815.245807	79.75996	50.19717	1.197894	2.971474439
16	0.191574	868.570702	80.57072	50.11577	1.197963	1.844688358
17	0.292503	941.337745	79.5423	50.16243	1.199993	0.375421377
18	0.242161	899.916665	81.23552	50.11715	1.19761	1.169487341
19	0.107149	825.068869	79.38616	50.06624	1.199457	2.801982808
20	0.22759	891.387893	79.96538	50.17655	1.197727	1.377715499
21	0.100385	815.337282	80.44886	50.0979	1.189846	2.873710297

## **Optimal Value of MRR & Ra**

•The optimal machining parameters are shown in table below.

Optimal Experimental				Experimental	
Combination				Value	
Speed	Feed	DOC	C.S	M.R.R	Ra(µ m)
				(mm <sup>3</sup> /	
				min)	
84.048	50.00	1.192	3.55960	779.83	0.0298

•The experimental results confirm the validity of the utilized Response surface Methodology (RSM) integrated with GA for improving the machining performance and optimizing the machining parameters.

## **Conclusion**

The effect of process parameters cutting speed, Feed and Depth of cut on response Characteristics MRR were studied on 20MnCr5 steel alloy in End Milling.

- Thirty experiments have been conducted based on RSM with three levels for each four parameters, namely speed, feed, depth of cut and coolant speed. The MRR have been measured for each combination of parameters. Modeling is performed to establish relationship between input machining parameters and the responses of interest (MRR) in order to predict and analyze the responses.
- The analysis of variance revealed that feed and depth of cut are the most influential parameters.
- The result shows that MRR is almost same when coolant is ON and coolant is OFF. Therefore it can be concluded that MRR does not depend much on coolant.
- Interaction effects between cutting speed and depth of cut also possesses a major effect over the surface roughness value
- coolant speed is the most influencing parameter showing a sharp decrease in Ra from 0.35  $\mu$ m to 0.25  $\mu$ m when coolant speed increase from 0 to 2 liters per min.

### **References** [Research Paper/Website/Books]

[1] Optimization of Machining Parameters of 20MnCr5 Steel in Turning Operation using Taguchi technique Narayana Reddy. A R1, Gantt Satya prakash2 1M.Tech student, Dept. of Mech. Egg, CMR Institute of Technology, Hyderabad, India 2 Associate. Prof, Dept. of Mech. Egg, CMR Institute of Technology, Hyderabad, India (2014).

[2] Response Ant Colony Optimization of End Milling Surface Roughness'. Kadirgama 1,\*, M. M. Noor 1 and Ahmed N. Abd Alla 2. Sensors 2010, 10, 2054-2063; doi:10.3390/s100302054 (2010).

[3]Modeling and Optimization of Milling Parameters on Al-6061 Alloy Using Multi- Objective Genetic Algorithm Rishi Kumar1\*, M. K. Pradhan2, Rajesh kumar3 Maulana Azad National Institute of Technology, Bhopal, 462051(2011).

[4] NC end milling optimization using evolutionary computation.V. Tandon a, H. El-Mounayri a,\*, H. Kishawy 1,ba Mechanical Engineering Department at Purdue School of Engineering, 723 West Michigan Street, SL 260, Indianapolis, IN 46202-5132, USA b Mechanical Engineering Department, University of New Brunswick, Fredericton, NB, Canada E3B 5A3.(2001)

[5] A genetic algorithmic approach for optimization of surface roughness prediction modelP.V.S. Suresh, P. Venkateswara Rao \*, S.G. DeshmukhMechanical Engineering Department, Indian Institute of Technology, Delhi, New Delhi-110016, India(2001).

[6] Integration of Taguchi method, response surface method (RSM) and genetic algorithm and was applied to set the optimal parameters for a nano- particle milling process.Tung-Hsu Hou,Chi-Hung Su,Wang-Li liu(2007)

[7] Optimization of cutting process by GA approach Franci Cus\*, Joze BalicFaculty of Mechanical Engineering, Production Engineering Institute, University of Maribor, Smetanova ul. 17, P.O. Box 224, SI-2000 Maribor, Slovenia(2003).

[8] Optimization of Cutting Parameters for Cutting Force in Shoulder Milling of Al7075-T6 Using Response Surface Methodology and Genetic Algorithm M.Subramanian1\*, M.Sakthivel2, K.Sooryaprakash3, R.Sudhakaran4(2013).

[9] OPTIMIZATION OF TURNING PARAMETERS FOR SURFACE ROUGHNESS USING RSM AND GA.Sahoo, P. Department of Mechanical Engineering, Jadavpur University, Kolkata 700032, India(2011). [10] Application of response surface method on machining of Al–SiC nanocomposites ;S. Gopalakannan,T. Senthilvelan. Volume 46, Issue 8, October 2013, Pages 2705–2715.(2013).

[11] Optimization of Machining Parameters for End Milling of Inconel 718 Super Alloy Using Taguchi Based Grey Relational Analysis Lohithaksha M Maiyara\*, Dr.R.Ramanujamb, K.Venkatesanc, Dr.J.Jeraldd(2013).

[12] Analysis of cutting Forces and optimization of cutting parameter in high speed ball-end milling using response surface methodology and genetic algorithm.Mithilesh Kumar Dikshit,Asit Baran puri,Atanu Mainty(2014).

[13]Analysis of Varoance(ANOVA) and Response Surface Analysis of Thrust Force And Torque in Drilling Granite Fiber Reinforced Epoxy Composite By using Multi Facct HSS Twist Drill; Jaimon Dennis Quadros, Hanumanthraya, Suhas ,Vaishak N. L.;(2014).

#### **Software**

[16] MINITAB® Release 14.1; Statistical Software.

[17]MATLAB 2010

## Web Site

- [17] <u>http://en.wikipedia.org/wiki/Milling (machining)</u>.
- [18]<u>http://www.americanmachinetools.com/How\_to\_use\_a\_Milling\_Machine\_fi</u> <u>les/Fig8-1.gif</u>.
- [19] <u>http://www.mfg.mtu.edu/cyberman/machining/trad/milling/mill\_spe.gif</u>.
- [20] <u>http://www.mfg.mtu.edu/cyberman/machining/trad/milling/dow\_mill.gif</u>
- [21] <u>http://www.mfg.mtu.edu/cyberman/machining/trad/milling/up\_mill.gif</u>
- [22]http://www.shunitesteel.com/20mncr5-20mncr5s-case-hardening-steel-bar-
- high-strength-alloy-steel/
- [23]<u>http://img.directindustry.com/images\_di/photo-g/roughing-end-milling-</u> <u>cutters-17869-2474581.jpg</u>
- [24] http://fairbanksscales.net/wp-content/uploads/2012/02/weighing-scales.jpg

## **BOOKS**

[25] Workshop technology by hajra choudhary Volume (1&2).

[26] A Textbook Of Workshop Technology : Manufacturing Processes <u>R.S. Khurmi And J.K. Gupta</u>.S. Chand Limited,

[27]Applied Design Of Experiments and Taguchi Method;.K.Krishnaiah,p.SHahabudeen.

[28] Design Of Experiments By DOUGLAS C.MONTGOMERY.

