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Gray Relational Based Analysis of Al-6351&AISI 1040

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Abstract: CNC End Milling Machining is a widely accepted material removal process used to manufacture components with complicated shapes and profiles. The quality of the surface plays a very important role in the performance of milling because good-quality milled surface significantly improves fatigue strength, corrosion resistance, or creep life. The surface generated during milling is affected by different factors such as vibration, spindle run–out, temperature, tool geometry, feed, cross-feed, tool path and other parameters. In the present study, experiments are conducted on aluminium 6351 and AISI 1040 materials to see the effect of process parameter variation in this respect. An attempt has also been made to obtain Optimum cutting conditions with respect to roughness parameters and Material removal rate .In order to carry out the multi objective optimization Gray relational analysis is used which gives gray relational grade and from the analysis it can be concluded that tool diameter is the most significant parameter for the combined objective function while, feed is the least significant parameter.
Keywords-Surface roughness parameter, optimum conditions

I. INTRODUCTION

A. Background

CNC End Milling Machining is a widely accepted material removal process used to manufacture components with complicated shapes and profiles. The surface generated during milling is affected by different factors such as vibration, spindle run–out, temperature, tool geometry, feed, cross-feed, tool path and other parameters. The most important interactions, that effect surface roughness of machined surfaces, are between the cutting feed and depth of cut, and between cutting feed and spindle speed. In order to obtain better surface roughness, the proper setting of cutting parameters is crucial before the process takes place. Material removal rate (MRR) is an important control factor of machining operation and the control of machining rate. MRR is a measurement of productivity & it can be expressed by analytical derivation as the product of the width of cut, the feed velocity of milling cutter and depth of cut. The non-linear nature of the machining process has compelled engineers to search for more effective methods to attain optimization. It is therefore imperative to investigate the machinability behavior of different materials by changing the machining parameters to obtain optimal results. This experiment gives the effect of different machining parameters like spindle speed, feed, depth of cut, tool diameter on material removal rate and Surface finish in end milling. This experimental investigation outlines the Gray-Taguchi optimization methodology.

B. Problem statement

The present work focus on optimization of AL-6351& AISI 1040 considering the various process parameters the objectives of the current is as follows; To find the optimum values for the input parameters like speed (N), feed (f) ,depth of cut(d),tool diameter and its effect on the surface finish for achieving the minimum surface roughness**.** Objective function for first objective is to Minimize Surface roughness (R_a) subjected to minimum and maximum range of input parameters like speed (N), feed (f), depth of cut (d), and tool diameter. To select the order of input parameters to get the maximum MRR. The Objective function is to; Maximize Material removal rate (MRR) subjected to minimum and maximum range of input parameters like speed (N), feed (f), and depth of cut (d) & tool diameter.

C. Scope

Surface roughness and MRR are very important which rely on many parameters, its need of hour to have the experimental investigation for optimum values by satisfying the desired constraints to achieve particular objective.

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II. LITERATURE REVIEW

Table 2.1Summary of Literature Review

Sr No	Author	Investigation	Findings/Observations/Remark
1	Palani&Natarajan (2011)	Prediction of surface roughness in CNC end milling by machine vision system using artificial neural network based on 2D Fourier transform.	Using trained ANN, the experimental result had shown that the surface roughness of milled parts predicted by machine vision system over a wide range of machining conditions obtain with a reasonable accuracy compared with those measured by traditional stylus method.
2	Thepsonthi&Ozel(2012)	Multi-objective process optimization for micro-end milling of Ti-6Al-4V titanium alloy	The average surface roughness minimized while burr formation reduced concurrently.
3	Hamdan, Sarhan&Hamdi (2012)	An optimization method of the machining parameters in high-speed machining of stainless steel using coated carbide tool for best surface finish	The feed rate is found to be more significant followed by the cutting speed and the depth of cut, while, the lubrication mode was found to be statistically insignificant for surface roughness.
4	Kumar & Jerald (2014)	Process parameters optimization for micro end-milling operation for CAPP applications	AI & GA used for the optimization of surface roughness and machining time.
5	Freiburg, Hense, Kersting (2016)	Determination of force parameters for milling simulations by combining optimization and simulation techniques	The combination of a geometric milling simulation with the BFGS optimization algorithm as a tool for the determination of force parameters was presented
6	Xu& Shin(2008)	An adaptive fuzzy controller for constant cutting force in End-Milling processes	The control algorithm implemented using a real-time control in an open architecture control environment, where high metal removal rates achieved and the cycle time reduced by up to 34%.
7	Fard, Hsi-Yung (2010)	Effective determination of feed direction and tool orientation in five-axis flat-end milling	The toroidal surface inscription method can efficiently determine a feed direction and tool orientation, corresponding to a near maximum machining strip width.
8	Arokiadas, Palaniradj, et al	Bi-Performance optimization of end milling characteristics of Al/SiCp composites using NSGA	The NSGA used for optimization to achieve better multiple performances. The second-order polynomial model was developed for tool flank wear
9	Dhandapai, Thangaras, Sureshkannan (2015)	Investigation on effect of material hardness in high speed CNC end milling process	The prediction method suggested is based on various experimental analyses of parameters in different compositions of input conditions which would benefit the industry on standardization of high speed CNC end milling processes
10	Madic, Markovic, Radovanovic (2013)	Comparison of meta-heuristic algorithms for solving machining optimization problems	Four meta-heuristic algorithms taken into consideration, namely, real coded genetic algorithm (RCGA), simulated annealing (SA), improved harmony search algorithm (IHSA) and cuckoo search algorithm (CSA).

11	Joshi, Kothiyal (2013)	Investigating effect of machining parameters of CNC milling on surface finish by taguchi method	ANOVA for SR optimization showing percentage contribution of each factor
12	Bajic, Lele and Zivkovic (2008)	Modeling of machined surface roughness and optimization	Feed is most dominating factor for optimization.
13	Zhang Joseph C. et al (2007)	Surface roughness optimization in an end-milling operation using the taguchi design method	spindle speed and feed rate are more significant for surface roughness
14	Gologlu, Cevdet and, Nazim (2008)	The effects of cutter path strategies on surface roughness of pocket milling of 1.2738 steel based on taguchi method	Cutting parameters have significant effect on surface roughness & study is for pocket milling.
15	Kopac and Krajnik (2007)	Robust design of flank milling parameters based on grey-taguchi method	Gray based taguchi techniques is used for AL alloy for injection mould
16	Nair &Govindan (2013)	Optimization of CNC end milling of brass using hybrid taguchi method using PCA and grey relational analysis	PCA for the optimization with taguchi is used to solve multi-attribute optimization of CNC end milling
17	Kumar &Thirumurugan (2012)	Optimization of machining parameters for milling titanium using taguchi method	Studied optimization of titanium alloy concluded that tool grade and spindle speed is most significant.
18	Rawangwong, Chatthong (2013)	An investigation of optimum cutting conditions in face milling nodular cast iron FCD 400 using carbide tool	Optimization of face milling for the carbide tool used practically for automotive industry is carried out.
19	Khorasani, Yazdi (2011)	Tool life prediction in face milling machining of 7075 Al by using Artificial Neural Networks(ANN) and taguchi design of experiment	study was to discover the role of machining parameters in tool life by ANN &taguchi
20	Periyanan,Natarajan, Yang (2011)	A study on the machining parameters optimization of micro-end milling process	To focus the taguchi technique for the optimization in for MRR shows speed is most important factor
21	Rao et al (2012)	Taguchi based grey relational analysis to optimize face milling process with multiple performance characteristics	Optimization for Inconel 718 considering speed, feed, and depth of cut, gray relational is used

III. EXPERIMENTAL METHODOLOGY

A. *Design Of Experiments*

Design of experiments (DOE) is a powerful tool that can be used in a variety of experimental situations. DOE techniques enable designers to determine simultaneously the individual and interactive effects of many factors that could affect the output results in any design. To achieve a thorough cut it was required that the combinations of the process variables give the jet enough energy to penetrate through the specimens. In the present study four process parameters were selected as control factors. The parameters and levels were selected based on the actual Machining setup and literature review of some studies that had been documented on end milling. But considering all practical limitation with actual machining centre Speed, Feed, Depth of cut and tool diameter are selected for experimentation. For designing the experiment “Minitab 17 software” is used. Following are the details of experiment design.

Number of Experimental factors:
Number of blocks: 1
Number of responses: 2
Number of run s: 9, including 9 slots over the entire length of work piece
Error degrees of freedom: 8

B. *Machine Specifications*

The technical specifications are of which are as follows.

Table 3.1- Machine details

Make and Model	MAKINO-S 56
Controller	Fanuc
Technical	Specifications
Table size	1000*500mm
Spindle RPM	13000
Maximum Work piece	890*500*450
Maximum Payload	1100lbs
ATC Capacity	20

C. *Material*

For the present work the material use are block of Steel EN8 and Aluminum 6351 in the dimensions 160mm × 100 mm × 32 mm for AL 6351 & 160mm × 100 mm × 20 mm for EN8 The physical properties of the material are as follows.

Table 3.2.Physical properties of materials

Physical Properties	Al6361	AISI 1040
Density	2710Kg/m3	7844 Kg/m3
Hardness(Brinell)	95	149
Hardness(Knoop)	120	169
Hardness(Rockwell B)	40	80
Ultimate Tensile strength	250MPA	620MPa
Yield strength	207MPA	415MPa

Table 3.3: The chemical compositions of the materials Al 6351

Component	Al	Fe	Mn	Si	Cu	Mg	Ti	Zr	Pb	Ca	Sn
Composition	95.51	0.12	0.52	0.8	0.051	0.75	0.017	0.013	0.012	0.051	0.004

Table 3.4: Chemical Composition of EN 8(AISI 1040)

Component	C	Si	Mn	S	P	Fe
Composition	0.36-0.44	0.10-0.40	0.6-1	Max-0.05	Max-0.05	Max 98.84

D. *Cutting Tool*

In this experiment the HSS end mill cutter of varying diameter like 8mm, 10mm & 12mm is used to make the grove of 12mm in the work piece for given speed, feed & depth of cut.

E. *Selection Of Orthogonal Array*

Orthogonal arrays are special standard experimental design that requires only a small number of experimental trials to find the main factor effects on output. The minimum number of experiments to be conducted shall be fixed which is given by: NTaguchi = 1+ NV (L – 1) where, N Taguchi = Number of experiments to be conducted, NV = Number of variables = Number of levels. Four machining parameters are considered as controlling factors namely, cutting speed, depth of cut, feed rate, Tool diameter and each parameter has three levels – namely low, medium and high, denoted by 1,2 and 3, respectively. Standard OAs available are L4, L8, L9, L12, L16, L18, L27, etc once the orthogonal array is selected, the experiments are selected as per the level combinationsBased on these values and the required minimum number of experiments to be conducted 9, the nearest Orthogonal Array fulfilling this condition is L9 (3^4)[11]

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IV. GREY BASED ANALYSIS FOR COMBINE OBJECTIVE

GRA was proposed by Deng in 1989 as cited in is widely used for measuring the degree of relationship between sequences by grey relational grade. Grey relational analysis is applied by several researchers to optimize control parameters having multi-responses through grey relational grade, steps are as follows;
Identify the performance characteristics and cutting parameters to be evaluated.
Determine the number of levels for the process parameters.
Select the appropriate orthogonal array and assign the cutting parameters to the orthogonal array.
Conduct the experiments based on the arrangement of the orthogonal array.
Normalize the experiment results of cutting force, tool life and surface roughness.
Perform the grey relational generating and calculate the grey relational coefficient.
Calculate the grey relational grade by averaging the grey relational coefficient.
Analyze the experimental results using the grey relational grade and statistical ANOVA.
Select the optimal levels of cutting parameters.
Verify the optimal cutting parameters through the confirmation experiment [12].

A. *Data pre-processing.*

In grey relational analysis, the data pre-processing is the first step performed to normalize the random grey data with different measurement units to transform them to dimensionless parameters. Thus, data pre-processing converts the original sequences to a set of comparable sequences. Different methods are employed to pre-process grey data depending upon the quality characteristics of the original data. The original reference sequence and pre-processed data (comparability sequence) are represented by $xx0\ (0)(kk)$ and $xxii\ (0)(kk)$, i =1,2,….,m; k =1,2,.....,n respectively, where m is the number of experiments and n is the total number of observations of data. Depending upon the quality characteristics, the three main categories for normalizing the original sequence are identified as follows:

If the original sequence data has quality characteristic as 'larger-the-better' then the original data is pre-processed as 'larger-the-best:

$$xi(k) = \frac{\mathrm{yi(k) - min\ yi(k)}}{\mathrm{max\,yi(k) - min\ yi(k)}}$$

If the original data has the quality characteristic as 'smaller the better', then original data is pre-processed as 'smaller-the best':

$$xi(k) = \frac{\mathrm{max\ yi(k) - \ yi(k)}}{\mathrm{max\,yi(k) - min\ yi(k)}}$$

Xi=Compatibility sequence

B. *Sample Calculation Of Compatibility Sequence For Roughness Value*

$$xi(k) = \frac{\text{Max CT} - \text{First Value of CT}}{\text{Max CT} - \text{Min CT}}$$

$$xi(k) = \frac{16.6881 - 7.7867}{16.6881 - 6.3661} xi(k) = 0.8622$$

Table 4.1 Normalized S/N data (Grey relational generation)

Sr no	S/N Ra	S/N MRR	Xi	Δ Xi	Xi MRR	ΔMRR
1	8.93	26.36	0.75	0.25	1	0
2	7.78	33.13	0.86	0.137	0.25	0.75
3	8.95	35.42	0.74	0.25	0	1
4	8.61	32.73	0.78	0.217	0.296	0.703
5	11.38	29.67	0.51	0.487	0.635	0.364
6	12.70	33.25	0.38	0.615	0.239	0.760
7	16.67	29.48	0	1	0.655	0.344
8	11.81	33.39	0.47	0.528	0.224	0.775
9	6.366	35.33	1	0	0.009	0.907

Similarly all values of compatibility sequence for surface roughness and material removal rate can be Calculated All values are show in Table 4.1.

Where xi (k) is the value after the grey relational generation, min yi (k) is the smallest value ofyi (k) for the k^{th} response, and max yi (k) is the largest value of yi (k) for the k^{th} response. An ideal sequence is x0(k) (k=1, 2) for two responses. The definition of the grey relational grade in the grey relational between the twenty-seven sequences (x0(k) and *xi* (k), i=1, 2 . . . 27; k=1, 2). The grey relational coefficient ξi(k) can be calculated as:

C. Sample Calculation Of Grey Relation Coefficient For Roughness Value

$$\xi i(k) = \frac{\min\Delta + \theta * \max\Delta}{\Delta i(k) + \theta * \max\Delta}$$

ξi(k) =The grey relational coefficient

θ is the distinguishing coefficient which is taken as 0.5

$$\xi i(k) = \frac{0 + (0.5 * 1)}{0.1378 + (0.5 * 1)}$$

ξi(k) = for second value = 0.7839

Similarly, all values of grey relation coefficient for roughness and material removal rate are calculated and tabulated in the table given below.

D. Sample calculation of grey relation grade for roughness value and mrr.

After averaging the grey relational coefficients, the grey relational grade γi can be computed as,

$$Yi = \frac{1}{n}\sum_{k=1}^{n} = \xi i[k]$$

$$Yi = \frac{1}{2}(0.7839 + 0.4)$$

First reading of grey relation grade is, Yi = 0.5919

Similarly all values of grey relation grade of nine experiments are carried out and tabulated in table givenbelow,Yi =grey relational grade,Where n = number of process responses. The higher value of grey relational grade corresponds to intense relational degree between the reference sequence x0 (k) and the given sequence xi (k). The reference sequence x0 (k) represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal**.**

Table 4.2: Grey Relation Grade, coefficient and Order

Experiment no	Ra	MRR	GRC For Ra	GRC For MRR	GRG	Gray order
1	0.3575	20.0764	0.6666	1	0.8333	1
2	0.408	45.3319	0.7839	0.4	0.5919	3
3	0.3565	59.8045	0.6655	0.3333	0.4994	6
4	0.371	43.2495	0.6964	0.4153	0.5558	4
5	0.2695	30.4462	0.5065	0.5781	0.5423	5
6	0.2315	46.0105	0.4483	0.3965	0.4424	8
7	0.15	29.8065	0.3333	0.592	0.4626	7
8	0.2565	46.7199	0.4888	0.392	0.4404	9
9	0.4805	58.4783	1	0.3552	0.6776	2

E. Sample Calculation Of Compatibility Sequence For Roughness Value For Aisi 1040

$$xi(k) = \frac{\text{Max CT} - \text{First Value of CT}}{\text{Max CT} - \text{Min CT}}$$

$$xi(k) = \frac{5.705024 - 3.267189}{5.705024 - 1.89879}, xi(k) = 0.640484$$

Similarly all values of compatibility sequence for surface roughness and MRR can be calculated as

Table 4.3: Normalized S/N data (Grey relational generation)

S/N Ra	Xi Ra	Δ Ra	S/N Rz	Xi Rz	Δ Rz	S/N MRR	Xi MRR	Δ MRR
5.71	0	1	8.761	1	0	8.19	0	1
3.27	0.64	0.36	11.2	0.27	0.73	16.8	0.71	0.29
3.84	0.49	0.51	10.03	0.62	0.38	20.2	1	0
3.01	0.71	0.29	11.24	0.26	0.74	12.5	0.36	0.64
1.9	1	0	12.13	0	1	20.1	0.99	0.01
2.9	0.74	0.26	10.56	0.47	0.53	12.8	0.38	0.62
5	0.19	0.81	9.731	0.71	0.29	17.6	0.78	0.22
5.3	0.11	0.89	9.243	0.86	0.14	10.8	0.22	0.78
4.44	0.33	0.66	10.69	0.43	0.57	18.7	0.87	0.13

F. Sample Calculation Of Grey Relation Coefficient For Roughness Value

$$\xi i(k) = \frac{\min\Delta + \theta * \max\Delta}{\Delta i(k) + \theta * \max\Delta}$$

$\xi i(k)$ =The grey relational coefficient

θ is the distinguishing coefficient which is taken as 0.5

$$\xi i(k) = \frac{0 + (0.5 * 1)}{0.359516 + (0.5 * 1)}$$

ξi (k) = for second value = 0.581712

G. Sample calculation of grey relation grade for roughness value and mrr.

After averaging the grey relational coefficients, the grey relational grade γi can be computed as,

$$Yi = \frac{1}{n}\sum_{k=1}^{n} = \xi i[k]$$

$$Yi = \frac{1}{3}(1 + 0.333333 + 0.983295)$$

Reading of grey relation grade is, Yi = 0.7722093

Similarly all values of grey relation grade of nine experiments are carried out and tabulated in table given below, Yi = grey relational grade,Where n = number of process responses. The higher value of grey relational grade corresponds to intense relational degree between the reference sequence x0 (k) and the given sequence xi (k). The reference sequence x0 (k) represents the best process sequence. Therefore, higher grey relational grade means that the corresponding parameter combination is closer to the optimal.

Table 4.4: Grey relation grade, coefficient and order for AISI 1040.

Speed	Feed	DOC	Diameter	Ra	Rz	MRR	GRC Ra	GRC Rz	GRC MRR	GRG	Gray order
2500	300	0.1	8	0.52	2.74	2.57	0.33	1	0.33	0.56	5
2500	400	0.2	10	0.69	3.63	6.91	0.58	0.41	0.64	0.54	6
2500	500	0.3	12	0.64	3.17	10.3	0.49	0.57	1	0.69	2
3000	300	0.2	12	0.71	3.65	4.21	0.63	0.4	0.44	0.49	9
3000	400	0.3	8	0.8	4.04	10.2	1	0.33	0.98	0.8	1
3000	500	0.1	10	0.72	3.37	4.34	0.66	0.48	0.45	0.53	7
3500	300	0.3	10	0.56	3.07	7.58	0.38	0.63	0.69	0.57	3
3500	400	0.1	12	0.54	2.9	3.47	0.36	0.78	0.39	0.51	8
3500	500	0.2	8	0.6	3.43	8.57	0.43	0.47	0.79	0.56	4

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V. ANALYSIS OF THE COMBINED OBJECTIVE BY USING TAGUCHI

Table 5.1: Response Table for Taguchi analysis

Sr	Speed	Feed	DOC	Diameter	GRG	SNRA1
1	2000	300	1	8	0.8333	-1.5839
2	2000	500	1.25	10	0.5919	-4.5550
3	2000	700	1.5	12	0.4994	-6.0310
4	3000	300	1.25	12	0.5558	-5.1016
5	3000	500	1.5	8	0.5423	-5.3152
6	3000	700	1	10	0.4424	-7.0837
7	4000	300	1.5	10	0.4626	-6.6958
8	4000	500	1	12	0.4404	-7.1230
9	4000	700	1.25	8	0.6776	-3.3805

A. *Analysis Of The Combined Objective By Using Taguchi*

Table 5.2: Response Table for Taguchi analysis

Sr.No	Speed	Feed	DOC	Diameter	GRG	S/NRA
1	2500	300	0.1	8	0.56	-5.11
2	2500	400	0.2	10	0.54	-5.32
3	2500	500	0.3	12	0.69	-3.24
4	3000	300	0.2	12	0.49	-6.17
5	3000	400	0.3	8	0.8	-2.25
6	3000	500	0.1	10	0.53	-5.54
7	3500	300	0.3	10	0.57	-4.88
8	3500	400	0.1	12	0.51	-5.87
9	3500	500	0.2	8	0.56	-5.01

B. *Main Effect Plot For Combine Objective*

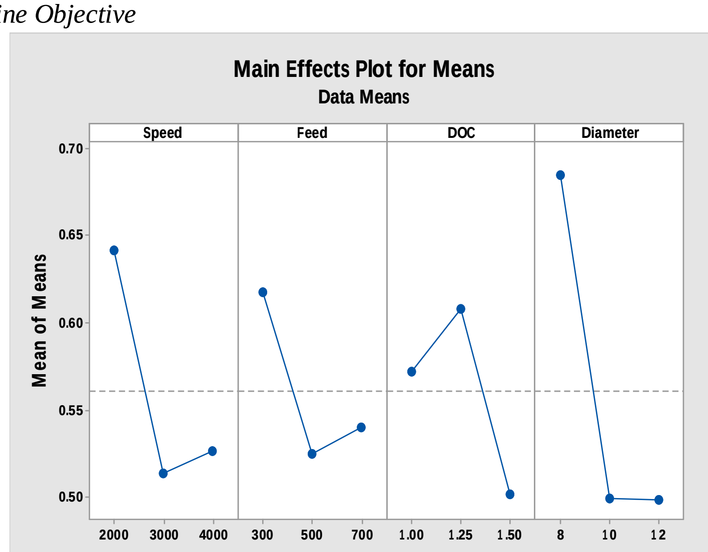

Fig 5.1Fig: Main effect plot for Mean

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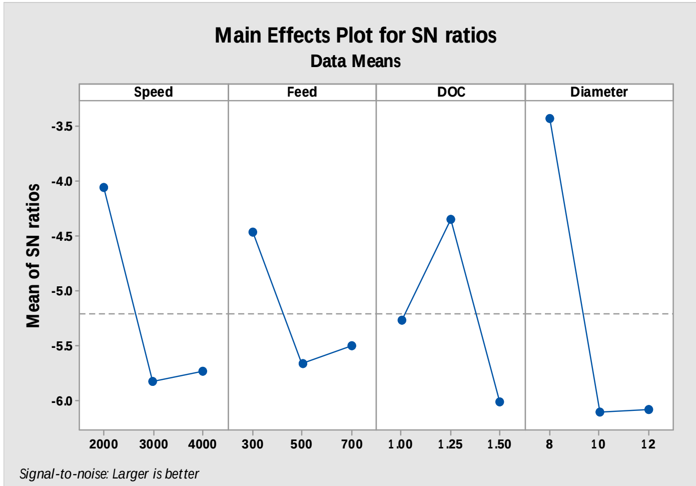

Fig 5.2: Main effect plot for GRGfor AL

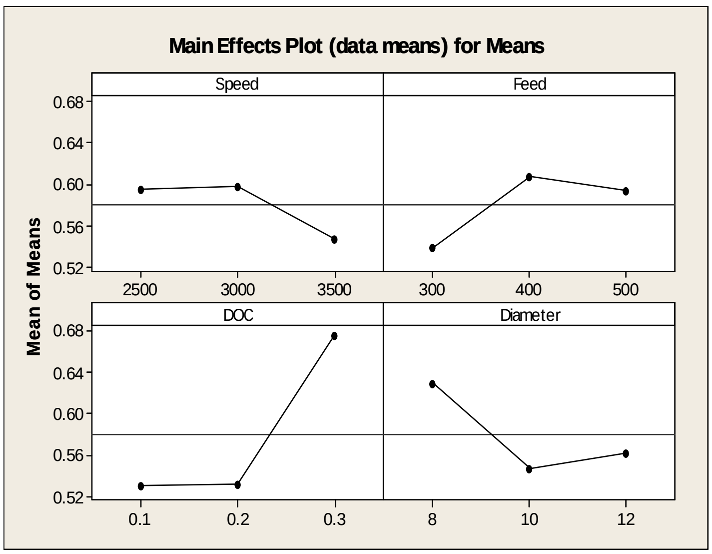

Fig 5.3: Main effect plot for Mean

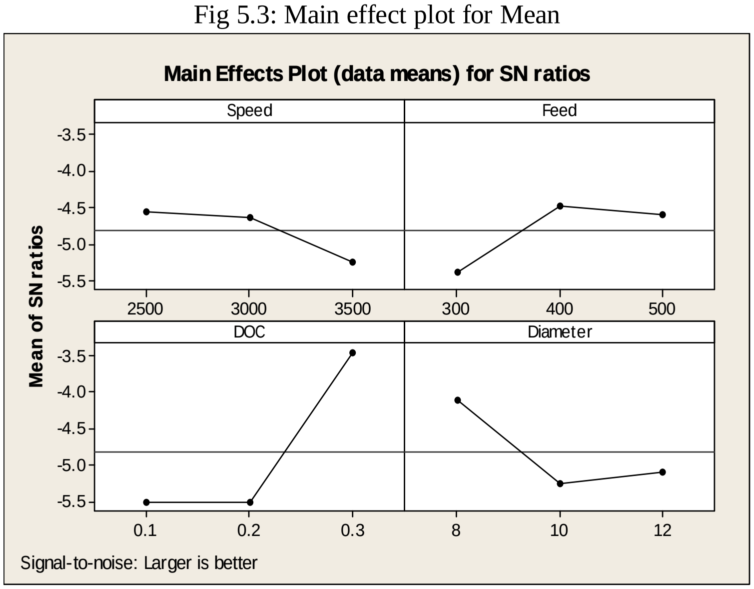

Fig 5.4: Main effect plot for combined Objective for AISI 1040

Table 5.3.Response table for S/N ratio for combined Objective

Level	Speed	Feed	DOC	Diameter
1	-4.057	-4.460	-5.26	-3.427
2	-5.83	-5.664	-4.346	-6.112
3	-5.733	-5.498	-6.014	-6.085
Delta	1.777	1.204	1.668	2.685
Rank	2	4	3	1

Table 5.4.Response table for Mean

Level	Speed	Feed	DOC	Diameter
1	0.6415	0.6172	0.5720	0.6844
2	0.5135	0.5249	0.6084	0.4990
3	0.5269	0.5398	0.5014	0.4985
Delta	0.1280	0.0924	0.1070	0.1859
Rank	2	4	3	1

Table 5:5.Response table for S/N ratio for combined Objective

Level	Speed	Feed	DOC	Diameter
1	-4.555	-5.388	-5.503	-4.119
2	-4.652	-4.477	-5.499	-5.246
3	-5.253	-4.594	-3.456	-5.094
Delta	0.698	0.91	2.047	1.127
Rank	4	3	1	2

Table 5.6:.Response table for Mean

Level	Speed	Feed	DOC	Diameter
1	0.595	0.539	0.531	0.63
2	0.597	0.608	0.532	0.547
3	0.547	0.593	0.677	0.563
Delta	0.051	0.069	0.146	0.083
Rank	4	3	1	2

V. CONCLUSIONS

Existing experiment and its analysis provides following remarkable point

A. Considering the objective like MRR and roughness eighteen experiments were successfully conducted and then its analysis is done with the help of Minitab software

B. The present work has successfully demonstrated the application of Taguchi based Grey relational analysis for multi objective optimization of process parameters in CNC end milling process for two different materials subjected to various conditions.

C. In grey relational analysis higher the grey relational grade of experiment says that the corresponding experimental combination is optimum condition for multi objective optimization and gives better product quality. Also form the basis of the grey relational grade, the factor effect can be estimated and the optimal level for each controllable factor can also be determined.

D. Thus this experimentation successfully optimize the end milling process for two different materials considering various process parameters, which will help to improve the efficiency by selecting the optimum parameters.

VI. FUTURE SCOPE

Tool conditioning monitoring (TCM) of the end milling for the different materials will be the scope for the future work till then only 6% work is till done on TCM of the end milling.

Nontraditional algorithm like RCGA can be applied to optimize end mill parameters

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