Machining Parameters Optimization for End Milling of Stainless Steel 304

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Abstract - Machines increases the efficiency of a manufacturing plant in terms of time, quality or quantity. It becomes very difficult to get both quality and quantity at the same time so we need a balanced value to attain maximum efficiency. It is possible only if machining parameters are optimized to do so. This paper puts an attempt to review milling machining parameters optimization for surface roughness, material removal rate, Production cost etc. using various techniques like Taguchi, Genetic Algorithm (GA), Response Surface Methodology (RSM) Artificial Neural Network (ANN), ANOVA, Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO) and provide an idea how input parameters are optimized using above techniques to fulfill our objectives.

Keywords: Optimization techniques, milling machining, surface roughness, material removal rate, depth of cut.

I. INTRODUCTION

Milling machine is one of the most common machines used in industry and machine shops for machining parts to precise sizes and shapes. A milling machine is considered superior to other machines in terms of accuracy and better surface finish. Every manufacturing industry is trying to achieve the high-quality products in a very short period of time with less input. In a milling machine, there are many process parameters like spindle speed, feed rate, depth of cut, coolant, geometry of tool etc. which affect required quality parameters and hence these must be optimized. Optimization doesn't mean to achieve maximum or minimum values of something rather it is that random value corresponding which we get best results. So in this paper, we had made an attempt to review the literature available on optimization of milling machining parameters using various techniques.

We observe that each pioneer was following some certain steps for optimization which were similar to each other and can be given as:

- Determination of optimization objective/objectives.
- Design of experimentation and Data Collection.
- Analysis using selected technique.
- Experimentation
- Confirmatory Test
- Result Interpretation

Many researchers have optimized various parameters according to objectives of optimization using different DOE technique sand analysis methods:

M.Tolouei Rad et.al [1] in 1997 focused on minimizing production time and cost. Using constraints as machining power, surface finish requirement and cutting force permitted by the rigidity of tool. He used the method of feasible directions as an optimization technique. The method of feasible direction chosen by him was the

quickest method of solving optimization models till date. He found that NC machines can reduce lead time considerably but the machining time is almost the same as in conventional machining when machining parameters are selected from machining databases or handbooks. That's why he went for this optimization. After optimization using proposed technique, he found 38% cost saving 42% time saving and 350% increase in total profit rate.

V. Tandon et.al [2] in 2002 focused on production cost reduction using Particle Swarm Optimization (PSO) coupled with Artificial Neural Network (ANN) as a predictive model. According to them in order to increase productivity process parameters should be assigned according to the NC tool path in addition to the condition of the part, tool, setup, and machine. To optimize the cutting time and cutting cost he used cutting velocity, feed per tooth and cutting force as constraints. After experimentation, he found that cutting time reduced by 35% and the cutting cost dropped to 4.086$ corresponding to spindle speed of 1500RPM, the feed rate of 122.39mm/min, the force of 0.3N and 12 effective number of generation.

J.A.Ghani et.al [3]in 2007 have optimized spindle speed, feed rate and depth of cut in order to achieve minimum Surface Roughness(Ra) and cutting forces (Fc) on CNC end milling. DOE used is Taguchi while analysis is done using S/N ratio approach. Optimized values of parameters are: cutting speed 355m/min (level 2), feed rate 0.1mm/tooth (level 0) and depth of cut 0.5 mm (level 1) [for min. Ra], 0.3 mm (level 0) [for min. Fc]. According to Pareto ANOVA confirmatory analysis, it was concluded that for low values of Ra and Fc we should use low feed rates, low depth of cut and high spindle speed to remove more material. Order of significance can be given as interaction between feed rate and depth of cut > spindle speed > depth of cut > feed rate.

Julie Z. Zhang et.al [4] in 2009introduced a new optimization parameter i.e. noise with 3 levels similar to as that of cutting speed, feed rate and depth of cut. The analysis was done using Taguchi technique and optimized values are found by plotting graphs of S/N ratio and surface roughness VS optimization parameter. Results were interpreted as 3500 rpm spindle speed (level 3), feed rate 762mm/min (level 2) and depth of cut 0.60μm (level 3). The confirmatory test found surface roughness of .58μm after 15 confirmation which is very close to 0.60 μm found experimentally and also proved that if noise factor, tool wear would be negligible then another noise factor that is temperature variation would be insignificant too (certain range).

C.C.Taso [5] in 2009 optimized the cutting speed, feed rate, depth of cut, different coatings, helix angle, primary relief angle, cutter diameter and width of cut in order to get low flank wear and surface roughness in end milling process. Grey-Taguchi method was used for optimization. He found order of significance of input parameters for individual optimization objective parameter and from that he concluded composite factor significance order as: cutter diameter (50.3% significance)> feed rate (15.3%significance)> helix angle (12.5%significance)> primary relief angle (5.1%significance) while coating typing, spindle speed, width of cut and depth of cut were having negligible significance. The optimization reduced flank wear from 0.177mm to 0.0667mm and surface roughness from 0.44μm to 0.24μm.

R. Jalili Saffar et.al [6] in 2009 added a new optimization objective i.e. tool deflection along with surface roughness and tool life. However, tool deflection was only significant for the tools having a low diameter. Determination of cutting forces and tool deflection was done on the basis of conventional models and formulas. Parameters were optimized using Genetic Algorithm with 0.8-6.3μm range of surface finish, min tool life of 60-120 min, max 500N cutting force and max vibration amplitude of 2μm as constraints. The result found after experimentations were: 23.56m/min cutting speed,25mm/min feed rate,3mm axial depth of cut and 1.5mm radial depth of cut.

O. Zarei et.al [7] in 2009 optimized the multi pass face milling via harmony search algorithm. He found optimum values for a number of passes, speed, depth of cut and feed for each pass to yield minimum production cost. Harmony search algorithm was compared with genetic algorithm and results found were better than a genetic algorithm. The values of parameters to be optimized by HS algorithm found as: No. of passes = 3, feed per tooth = 0.453 mm/tooth, spindle speed = 60.75mm/min, surface roughness = 6.59 μm and cost was 0.446$ and for GA are: No. of passes = 4, feed per tooth = 0.319 mm/tooth, spindle speed = 60mm/min, surface roughness = 3.2 μm and cost is 0.536$ Hence cost reduced by HS Algorithm.

Sanjit Moshat et.al [8] in 2010used Principle Component Analysis (PCA) based Taguchi method for multi objective optimization of CNC end milling process. They used PCA based Taguchi as they found their optimization objectives i.e. Surface roughness and Material Removal Rate are highly co-related however Taguchi assume that output is not co-related. Using PCA they converted the correlated response to Principle components and out of 2 components one having Accountability Proportion (AP) 0.951 was taken into account and other (.049) was neglected. The disadvantage of this technique is the difficulty in interpreting principle components physically as if these are mathematical only. Optimized values of input parameters were: spindle speed 300rpm (level 1), feed rate 70mm/min (level 3) and depth of cut 0.8mm (level 3).

R.Venkata Rao and Pawar [9] in 2010 focused over maximization of production rate, as large industries have attempted to introduce the FMS (flexible manufacturing system) to sustain in the competitive market. The optimization was done using artificial bee colony (ABC), particle swarm optimization (PSO), simulated annealing (SA) techniques with arbor strength, arbor deflection and cutting power as their constraints. Feed rate, cutting speed and depth of cut were optimized by them and results were 3.240 min, 3.240 min and 3.263 min for ABC, PSO and SA respectively. Results concluded that ABC and PSO required less iteration than SA.

M.R.Yazdi and A.Khorram [10] in 2010 used Response surface methodology (RSM) and Artificial neural network (ANN) for optimizing cutting speed, feed rate and depth of cut to improve surface finish and material removal rate. They used 3 levels of factors for finishing and rough machining. Results were interpreted using both techniques and found to be very close to each other. For rough machining case, both of them depicted that as speed increases and feed decreases the value of surface roughness goes down while with an increase in depth of cut, feed ratio and their relation the MRR increases. For the finishing case, both techniques show that with an increase in feed rate, depth of cut and their relation MRR increases. From their results, it can be concluded that data coverage and accuracy of ANN is more than RSM.

Wen-an Yang [11] in 2011 optimized the multi pass face milling by using particle swarm intelligence. In order to reduce production time and decrease the cost of production and enhance profit rate by controlling parameters like Machine power, Cutting Force, Feed rate and surface roughness. Yang concluded the results in comparison to experiment performed by Shanmugam, Saha, An chen by using the values of total stock removal of 8mm & 15 mm, so by comparing and plotting results, he concluded that results were better using Particle Swarm Optimization technique.

Tao Fu et.al [12] in 2012 focused three directional cutting forces (feed force, radial force and tangential force) optimization objective. In their experimentation, they evaluated spindle speed, feed per tooth and depth of cut using Taguchi method and grey relational analysis coupled with PCA. They used grey relational analysis to reduce multi objective problem to single objective problem and PCA was used to find weightage factor. After experimentation, Reduced 3 directional cutting forces were found for values corresponding to spindle speed 2400 rpm, feed per tooth 0.10mm per tooth and 0.2 mm depth of cut.

Milon D.Selvam et.al [13] in 2012 used Taguchi Technique for experiment design and analysis was done using S/N Ratio first and then by Genetic Algorithm for face milling. Results obtained by Taguchi and Genetic Algorithm for surface roughness was 0.975 µm with 4.308% error and 0.88µm with 4.625% error from predicted value respectively. Genetic Algorithm served the purpose to fine tune the results obtained by Taguchi and confirms the results as both the values were very close. Parameters optimized by them according to their significance order was spindle speed> no. of passes> feed rate> depth of cut. Optimum values for these parameters were: 3 for no. of passes, 0.1162 for depth of cut, 1999rpm for spindle speed and 497.7mm/min for feed rate.

Thepsonthi et.al [14] in 2012 worked for multi objective optimization of micro milling. It was seen that most of the parameters which were insignificant in the macro milling became significant for micro milling like vibration, temperature, tool deflection, micro structure of work piece etc. They used titanium alloy as work piece which is difficult to process but have wide applications in medical devices and implant. He has taken surface roughness and burr formation as optimization objective and concerned to lower the both Particle Swarm optimization (PSO) is used as an optimization technique. Burr formation was measured with burr width and it was more in up milling than down milling. Optimized result has shown that it is better to go with spindle speed tested (60k rpm) and at the highest feed per tooth (50 µm).The significance of parameters can be given in order of Axial Depth of Cut (ADOC)> Feed Rate> Spindle Speed.

Jihong Yan and Li [15] in 2013 apart from traditional optimization focused on non-conventional optimization as they considered cutting energy as one of the optimization objectives. They presented factors analysis affecting the cutting energy, material removal rate and surface roughness at face milling. For these optimization objectives, spindle speed, feed rate, depth of cut and width of cut were evaluated and optimized using Grey-Taguchi Method and optimized values were 1000rpm for spindle speed(level 1), 300mm/min for feed rate(level 3), 15mm for width of cut(level 3) and 0.4mm for depth of cut(level 3). After optimization they found that parameters were significant according to order: Width of cut> Depth of cut> Feed rate> Spindle speed. Using this optimization technique they were able to reduce the cutting energy by 18.1% as compared to traditional objective optimization.

Lohithaksha et.al [16] in 2013 worked over reducing surface roughness and increasing material removal rate for end milling process. They used Taguchi for experiment planning, grey relational analysis for combining multiple responses into one numerical score and to determine the optimum value of evaluated parameters. ANOVA was used by them as a confirmatory test and to find a most significant factor. Cutting speed, feed rate and Depth of cut were the parameters optimized by them. They found optimum values as: 75m/min for spindle speed (level 3), 0.06mm/tooth for feed rate (level 1) and 0.4mm for depth of cut (level 2). Corresponding to these optimum values Surface Roughness was found to be 0.19µm and 7.21cu.mm/sec. Experimentation after using optimized values found 64.8% improvement in MRR and 9.52 % improvement in surface roughness. Order of significance was concluded as cutting speed> feed rate> depth of cut.

Emel Kuramet. al. [17] in 2013 optimized tool wear, forces on tool and surface roughness by varying spindle speed, feed per tooth and depth of cut. First, the experiments were carried out using a micro mill on aluminum alloy. The design of experimentation was done using Taguchi's L9 orthogonal array. In the second stage, S/N ratio analysis was done in order to reduce the signal to noise ratio. Then single optimization of parameters was done using ANOVA (Analysis Of Variance). However, in order to achieve multi optimization of the parameter, grey relational analysis was used and significance of these results was done from ANOVA results. It was concluded that spindle speed was a most significant factor for all responses except surface roughness. From surface roughness, the feed rate was a more significant factor. From multi objective optimization results it was found that best combination values minimizing tool wear, Fx, Fy and Ra were spindle speed of 10,000 rpm, feed per tooth of 0.5µm and depth of cut of 50µm.

Ali R .Yildiz [18] in 2013introduced a new optimization technique that is hybrid differential evolution algorithm. He optimized the machining parameters using this technique and compared the result with other techniques. Like other researchers, his objective function is also production time and cost and constraints were: Machining power, Cutting force permitted by tool rigidity and surface finish requirement. Using proposed approach results were found to be better than other techniques like Method of feasible direction, Genetic algorithm etc. Final values for reduced cutting cost, time and overall cutting rate were 10.90$, 5.00 min, 2.82/minute respectively.

Reddy Sreenivasulu [19] in 2014 studied the effect of cutting speed, feed rate and depth of cut on delamination, damage factor and surface roughness using end milling. He had used Taguchi technique for desirability function analysis. He found that as spindle speed increases desirability factor decreases, desirability first decrease and then increase as feed rate increases and for increasing depth of cut desirability factor increase and from here he concludes that optimum parameter combination for least delamination and surface roughness were: 1000rpm for cutting speed(level 1), 200mm/min for feed rate(level 1) and 1.5 mm for depth of cut (level 3).Order of significance was concluded as feed rate> depth of cut > cutting speed.

Abhishek Kumbhar et.al [20] in 2015has optimized the parameters of CNC end milling using Grey Taguchi method. Parameters that were chosen for optimization include spindle speed, feed rate and depth of cut and these all were optimized to get low values of surface roughness (Ra) and high material removal rate (MRR). After applying Grey relational analysis result were plotted on the basis of grey relational grade (GRG). The optimized values of parameters are: cutting speed 75m/min (level 2), feed rate 0.15mm /rev (level 1) and depth of cut 1.5mm (level 3). Confirmatory tests were satisfactory and reduce Ra by 24.86% and MRR by 23.99%. Conclusion showed that depth of cut was the most significant factor followed by feed rate and cutting speed.

II. MATERIAL

The material we used for machining is stainless steel-304(30mm*30mm*12mm). Type 304 is the most widely used austenitic stainless steel, and it's also known as "18-8" stainless steel because of its composition. It includes18% chromium and 8% nickel. Type 304 grade stainless steel is found in sinks, tabletops, coffee pots, refrigerators, stoves and various utensils and other cooking appliances. It can withstand corrosion that can be caused by various chemicals found in fruits, meats, and milk. Other areas of use include architecture, chemical containers, heat exchangers, mining equipment, and marine nuts, bolts and screws. Type 304 is also used in mining and water filtration systems and in the dyeing industry.

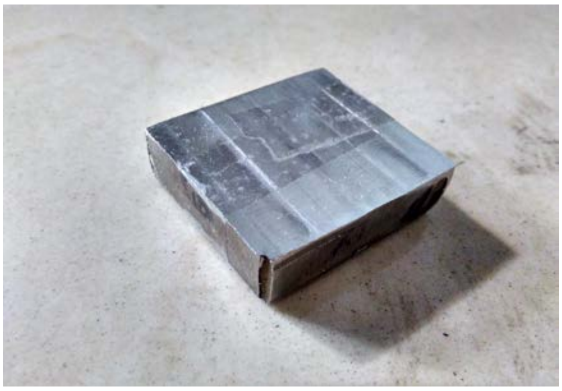

Fig.2.1 Workpiece

Table 2.1 Composition of Steel

Element	Type 304 (%)
Carbon	0.08 max.
Manganese	2.00 max.
Phosphorus	0.045 max.
Sulfur	0.03 max.
Silicon	0.75 max.
Chromium	18.00-20.00
Nickel	8.00-12.00
Nitrogen	0.10 max.
Iron	Balance

Chemical composition is evaluated using chemical spectrometry at CIHT, Jalandhar.

III. METHODOLOGY

Taguchi's method is one of the efficient experimentation techniques in improving quality and cutting down cost at same time. In Taguchi’s method, quality is measured by deviation of a characteristic from its target value. A loss function is developed for this deviation. Since the elimination of the noise factors is impractical and often impossible, the Taguchi method seeks to minimize the effects of noise and to determine the optimal level of important controllable factors based on concept of robustness. Taguchi method uses a special design of orthogonal array to study the entire parameters space with only a small no. of experiments. To determine optimal level of controlled multiple factors simultaneously Grey Relational Analysis method is used. Steps of Grey Relational Analysis are as follow:

Step 1: The first step of grey relational analysis is to normalize (in the range between 0 and 1) the experimental data according to the type of performance response.

If the target value of the original sequence is infinite, it has "the-larger-the-better" characteristic.

Xij = {(Yij) – min (Yij)}/{max (Yij) – min (Yij)}
Eq.1

If the target value of the original sequence is zero, it has "the-smaller-the-better" characteristic.

Xij = {max (Yij) – (Yij)}/{max (Yij) – min (Yij)}
Eq. 2

In this present study, surface roughness was to minimize using "the-smaller-the-better" characteristic and material removal rate was to increase using "the-larger-the –better" characteristic. Where Xij and Yij are the normalized data and observed data, respectively, for i^{th} experiment using j^{th} response. The smallest and largest values of Yij in the responses are min (Yij) and max (Yij), respectively. Larger normalized results mean to the better performance and the best normalized result should be equal to 1. Evaluated values using Eq.1

Step 2: After pre-processing the data, the Grey Relation Coefficient (GRC) for j^{th} the response characteristics in the i^{th} experiment can be expressed as following:

GRC = {Δmin + μΔmax}/{Δi(k)+ μΔmin}
Eq. 3

Where,

Yij = denotes reference sequence.

Xij = denotes the comparability sequence.

Δi(k)=difference in absolute value between Yij and Xij.

Δmin=smallest value of Δi.

Δmax= largest value of Δi.

μ= [0, 1] is the distinguish factor: 0.5 is widely accepted.

Step 3: After calculating GRC, the Grey Relational Grade (GRG) is obtained as:

GRG = 1/m ∑i=1 to m (GRCi)

Here m is the number of responses. The GRC and corresponding GRG for each experiment for milling operation are calculated. The higher value of GRG is near to the product quality for optimum process parameters. The highest grey relational grade is assigned an order of 1 and ranking is done in decreasing order.

IV. EXPERIMENTAL PLAN

The experimentation was carried out at CIHT, Jalandhar on CNC vertical milling center (DAEWOO ACE VC 510) having 15 kW power and maximum spindle speed of 10000 rpm. All experimental runs were carried out under wet condition. Maker of the tool selected for experimentation was TOTEM and tool was TOTEM FBK0500046 Standard Length 4 Flute carbide End Mill with Cutting Diameter 10 mm having high cutting speed and long tool life. Surface roughness after machining was measured using MITUTOYO SJ 301 roughness tester at DAVIET Jalandhar. Roughness measuring principle of tester was based on stylus method having 0.5 mm/sec measuring speed. MRR had calculated by weighing the sample before and after machining divided by the time taken to machine that sample.

Fig.4.1 End Milling on VMC

Table 4.1 Process parameters and their levels

S.No.	Factors	Level 1	Level 2	Level 3
1	Cutting Speed (V_c)(rpm)	3400	3700	4000
2	Feed (f) (mm/min)	600	750	900
3	Depth of Cut (a_p) (mm)	0.2	0.6	1

The experiments were carried out with controllable 3-level factors and two response variables. The literature survey and TOTEM catalogue identified the milling parameters and their levels for experiment. Based on Taguchi's design of experiment and orthogonal array L_9 (3^3) total 9 experiments were carried out. For each experimental run two trials were performed in order to get more accurate and precise results. Table 4.1 shows three controlled factors i.e. cutting speed (V_c) (rpm), feed (f) (mm/rev), depth of cut (a_p) (mm) with three levels for each factor.

V. EXPERIMENTAL RESULT AND ANALYSIS

All nine experimental runs are tabulated in Table 5.1 along with input parameters setting. For each run two trials were performed and respective Ra and MRR were calculated. Later their average was calculated and obtained values of surface roughness and material removal rate is listed in Table 5.1. In order to bring all obtained values of surface roughness and material removal rate in 0 to 1 range, normalization process (step 1) was carried out. The indication of the better performance for material removal rate is "higher the better" whereas it is "lower the better" for surface roughness. Thus to evaluate normalized values of surface roughness and material removal rate Eq. 2 and Eq. 1 is used respectively and are given in Table 5.2 along with their deviations.

Further, from computed deviations Grey Relational Coefficients are evaluated using Eq. 3 (step 2) for both surface roughness and material removal rate.

Grey Relation Grade (GRG) is average of grey relational coefficients of surface roughness and material removal rate as given in Eq. 4 (step 3) which is further ranked in decreasing order to point out best input parameter combination yielding better performance characteristic as shown in Table 5.3.

Table 5.1 Taguchi L_9 Orthogonal Array for experimental runs and results

Run No.	V_c (rpm)	F (mm/min)	a_p (mm)	Ra (µm)	MRR (g/min)
1	3400	600	0.2	.24	3.042
2	3400	750	0.6	.21	5.88
3	3400	900	1.0	.475	13.025
4	3700	600	0.6	.34	5.18
5	3700	750	1	.285	10.93
6	3700	900	0.2	.42	9.067
7	4000	600	1	.26	8.817
8	4000	750	0.2	1.175	4.78
9	4000	900	0.6	.55	7.414

Table 5.2 Evaluation of Normalized value and Deviation value for Ra and MRR

Run no.	Ra (µm)	Normalized values for Ra	Deviation for Ra	MRR (g/min.)	Normalized values for MRR	Deviation for Ra
1	0.24	0.969	0.031	3.042	0	1
2	0.21	1	0	5.88	0.284	0.716
3	0.475	0.725	0.275	13.025	1	0
4	0.34	0.865	0.135	5.18	0.214	0.786
5	0.285	0.922	0.078	10.93	0.79	0.21
6	0.42	0.782	0.218	9.067	0.604	0.396
7	0.26	0.948	0.052	8.817	0.578	0.422
8	1.175	0	1	4.78	0.174	0.826
9	0.55	0.648	0.352	7.414	0.438	0.562

Table 5.3 Evaluation of Grey Relational Coefficient and Grade values along with rank

Run no.	Grey relational coefficient		Grey relational grade	Rank
	Ra (µm)	MRR (g/min.)		
1	0.943	0.333	0.638	5
2	1	0.397	0.698	4
3	0.645	1	0.822	1
4	0.787	0.389	0.588	7
5	0.865	0.704	0.784	2
6	0.696	0.558	0.627	6
7	0.905	0.542	0.723	3
8	0.330	0.377	0.359	9
9	0.586	0.471	0.528	8

VI. RESULT DISCUSSIONS

Table 5.3 shows the grey relational grade for each experimental run. Higher the grey relational grade better is the product quality. Therefore on the basis of GRG and their rank the factor effects can be estimated and optimal level for each controllable factor can also be determined. The mean of grey relational grade for each level of parameter is summarized and shown in Table 6.1. The higher value of GRG means comparability sequence has a stronger correlation to the reference sequence. By using Minitab 17 the Main Effect Plot graph for GRG for the level of processing parameters was plotted in Fig.6.1. Basically the larger the grey relational grade, the better is the multiple performance characteristics. In case of speed, as it increases from 3400 rpm to 4000 rpm but GRG goes down from 0.7193 to 0.6663 and further GRG reduces to 0.5320 as speed increases from 3700 rpm to 4000 rpm. In case of feed, GRG falls down from 0.6497 to 0.6090 and further slightly increases to 0.6590 as feed changes from

600 mm/min to 750 mm/min and 750 mm/min to 900 mm/min respectively. In case of depth of cut, as depth of cut changes from 0.20 mm to 0.6 mm GRG climbs up from 0.5367 to 0.6047 which further sharply shifts to 0.7763 as depth of cut increases from 0.6 mm to 1.0 mm. Therefore, from Fig.5.1 we can conclude that the optimal process parameters for multi-objective optimization are as follows: Cutting speed at level 1 (3400 rpm), feed at level 3 (900 mm/min) and depth of cut at level 3 (1 mm) i.e. v1-f3-d3.

Table 6.1 Response Table for GRG

Input Factors	Avg. GRG by factor level			Max-Min	Rank
	Level 1	Level 2	Level 3		
Cutting Speed (V_c)	0.71*	0.67	0.53	0.18	2
Feed (f)	0.65	0.61	0.66*	0.04	3
Depth of Cut (a_p)	0.54	0.60	0.78*	0.24	1

Total mean value of grey relational grade= 0.64

*Indicate optimum parameters levels

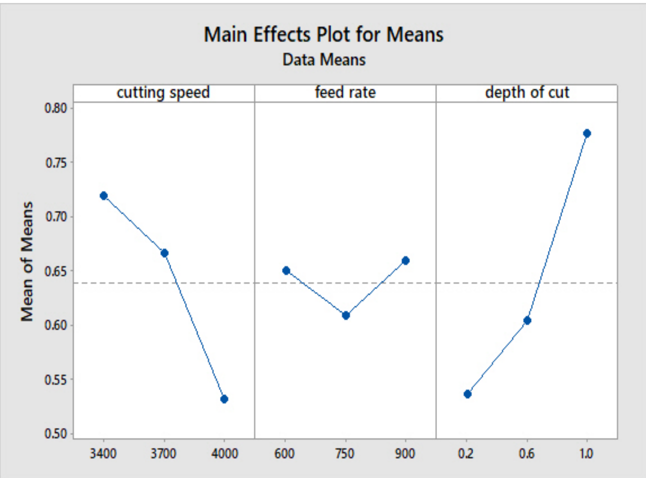

Fig.6.1 Main Effect Plot for Grey Relational Grade

Interaction plot for Grey Relational Grade was plotted using Minitab 17 as shown in Figure 6.2, 6.3 and 6.4. When the effect of one independent factor depends on the level of the other independent factor, we can use an interaction plot to visualize possible interactions. Parallel lines in an interaction plot indicate no interaction. The greater the difference in slope between the lines, the higher the degree of interaction.

Graph of interaction (Fig.6.2) between Depth of Cut and Feed Rate shows that there is positive interaction between the both as there is change in depth of cut along with Feed there is a change in GRG.

Graph of interaction (Fig.6.3) between Depth of Cut and Cutting speed shows that there is not much interaction between the both as line are not intersecting each other and sometimes parallel. This shows that these both factors are working independently.

Graph of interaction (Fig.6.4) between Feed Rate and Cutting speed shows that there is interaction between the both but no regular trend followed for GRG when one changes while keeping other constant.

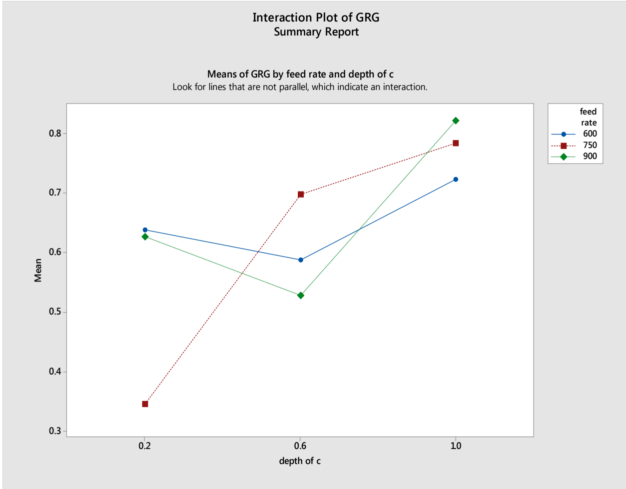

Fig.6.2.Interaction Plot of GRG between Depth of cut and Feedrate

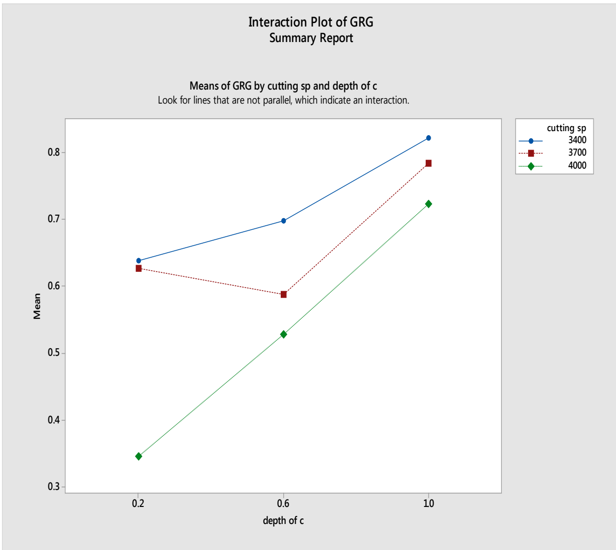

Fig.6.3.Interaction Plot of GRG between Depth of cut and Cutting speed

Table 6.2 shows comparison of initial experimental run with the optimum experimental run.

Table 6.2 Comparison of initial and optimum machining run

	Initial experiment	Optimum experiment
Setting level	V_{c3}, f_2, a_{p1}	V_{c1}, f_3, a_{p3}
Ra	1.175	0.475
MRR	4.78	13.025

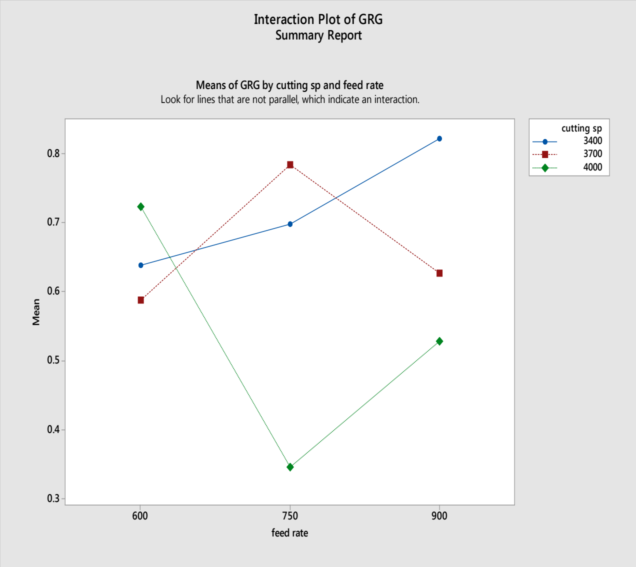

Figure 6.4.Interaction Plot of GRG between Feed Rate and Cutting speed

VII. CONCLUSION

In this study, the effects of cutting speed, feed and depth of cut on surface roughness and material removal rate during end milling of Stainless steel 304 were investigated using Taguchi's experimental design method combined with Grey relational analysis. The following conclusions can be made from performed experimental research:

Based on Grey Relational Grade analysis, the optimal process parameters for multi-objective optimization are as follows: Cutting speed at level 1 (3400 rpm), feed at level 3 (900 min/rev) and depth of cut at level 3 (1 mm) i.e. V_{c1}, f_3, a_{p3}.

The order of significance for the input factor are according to the rank calculated by GRG i.e. Depth of cut > Cutting speed > Feed Rate.

There is simultaneous significance decrease in Ra value and significance increase in MRR value.

It has been established that Taguchi based Grey Relational Analysis is an effective multi-objective optimization tool.

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