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# Multi-Response Optimisation of End Milling Process Parameters

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## Abstract

*This paper presents a novel approach for the optimization of machining parameters of a CNC end milling process with multiple responses, based on Taguchi's orthogonal array (OA) and gray relational analysis (GRA). Experiments were conducted on BS L168 aluminum alloy test specimens with uncoated carbide solid end mills under dry cutting condition. The cutting process parameters considered: cutting speed (S), feed rate (F) and depth of cut (D) are optimized for betterment of the multiple responses such as: surface roughness ($R_a$), cutting tool tip temperature rise (T) and material removal rate (MRR). A grey relational grade (GRG) is determined from the grey relational analysis (GRA). Optimum levels of process parameters have been identified based on the values of grey relational grade and influence of each cutting process parameter is determined by ANOVA. To validate the test results, confirmation tests are performed. Experimental outcomes have proved that the output responses in end milling process can be enhanced efficiently through this approach.*

***Keywords:*** *GRA, ANOVA, MRR, End milling, Surface roughness, Tool tip temperature.*

## 1.0 Introduction

From the literature study it is understood that, Taguchi method has been extensively used by many researchers for parametric optimisation of metal cutting processes. Since, this method follows an orthogonal array of experimentation, which needs not only a minimum number of experimental runs but also less experimentation cost and less experimentation time. Due to involvement of huge number of performance futures and process variables, optimisation of end milling process has become a combinatorial task. To obtain the better quality of machining time and machined parts it is required to be evaluated the proper parametric combinations. In turn, for the evaluation of parametric combinations, 'mathematical functions or numerical models' are required to be developed[1]. The main advantage of Taguchi's philosophy[2-4] is that, this method predicts the optimum combination of machining process parameters within the specified discrete domain. But, it appears to be miserably fails when the issue of solving multi-objective optimisation problems. Hence, in order to eliminate this drawback, Taguchi based Grey relation analysis[4,5], Taguchi coupled TOPSIS[6] techniques were developed. And also Desirability function[7], Utility concept[8], MOORA[9] kind of techniques have been integrated with Taguchi's philosophy for solving the multi-response optimisation problems.17-4 PH SS test samples were machined by coated (AlTiN) carbide inserted cutting tools on a turning machine in cryogenic environment. The cryogenic medium used in their experimentation is liquid nitrogen. Feed rate, spindle speed and depth of cut are the cutting parameters considered. The output responses considered for optimisation are flank wear, average surface roughness and material removal rate. The techniques employed for optimisation of cutting process are

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Taguchi coupled TOPSIS and Taguchi based GRA. From the results they found that, T-GRA had given a better output compared to T-TOPSIS[10]. Multi-objective optimization using Taguchi based grey relational analysis for micro-milling of Al 7075 material with ball nose end mills has been done by Emel Kuram et al[11]. They expressed that, cutting force increases with the increase in feed rate, cutting speed and depth of cut. They also found that, radial cutting force is getting increasing with the increase of depth of cut while doing micro-milling on work samples. On the other hand, an increase in cutting force is leading to machine tool vibration, chattering problem etc. This diminishes the quality of end product especially its machined surface. The output response 'chatter index' has been evaluated using pre-processed signals in high speed machining. In order to rectify the signals recorded by using sensors contaminated by background noise an ensemble empirical mode decomposition technique has been used. Response surface methodology employed to develop the mathematical models and to estimate the dependency of performance characteristics on input parameters. Artificial neural network and multi-responsive genetic algorithm techniques have been used to predict optimal cutting zone. The optimal zone machining showed considerable improvement in productivity, by simultaneous increase in material removal rate and decrease in tool chatter[12-13]. Sivasakthivel et al[14] found that cutting temperature is getting increasing with the increase in cutting speed. And also it is observed that rise in temperature causes formation of build-up edge, which in turn increases the surface roughness. Another important observation is that, rise in cutting temperature not only leads to poor machining accuracy but also deformation in the work piece[15]. Tsao et.al[16] followed Grey relational analysis technique to do multi-response optimisation of end milling process parameters for machining of Al6061P-T651 alloy test specimens. There is an improvement in the surface finish from 0.44µm to 0.24µm has been achieved by this grey relational optimal combination. Further, GRA is an uncomplicated tool which does not require any complicated formulations for multi-response optimization. Hence it helps in obtaining the results in a short interval of time. So, it can be used for solving the multi-response optimisation problems more effectively. A series of milling experiments on AISI304 stainless steelwork pieces have been carried out. Then using desirability function and grey relational analysis, multi-objective optimisations were performed for evaluation of machining parameters simultaneously. The optimum combination of input parameters to minimise the surface roughness and to maximise material removal rate has been evaluated[17]. Multiple number of face milling experiments have been conducted on Al-2024 aluminium alloy to investigate the effect of different machining parameters. They aimed to achieve minimum surface roughness in minimum cutting time. Found that tool path strategy is showing significant effect on the performance characteristics of face milling. Taguchi based GRA technique has been employed to find the optimal machining parameters. Later conformation tests were conducted in order to verify the reliability of their study and analysis[18]. Experiments were conducted as per $L_9$ orthogonal array with three levels of input cutting factors. Taguchi method, GRA and principle component analysis techniques have been used[19] to optimise the cutting parameters. ANOM and ANOVA were employed to investigate the most influencing factor on the output responses[20]. Results of their study revealed that, depth of cut is the most significant cutting factor with maximum percentage of influence on the performance response Ra. Feed rate is showing moderate influence whereas cutting speed is showing lowest level of impact

## 2.0 Material Testing and Specifications

Experiments were carried out on a AMS make CNC vertical milling machine tool, with dry machining conditions. The specifications of the machine tool are: maximum spindle speed-60000rpm; maximum feed rate-10m/min; basic power supply-18kVA, positional accuracy-0.015mm, repeatability ±0.005mm. BSL168 alloy test specimens of size 120mm × 80mm

Figure 1: Cutting tool tip temperature measurement

× 20mm were considered for this experimental study. HTC make industrial infrared non-contact digital thermometer has been used to measure the cutting tool tip temperature rise against each experimental run. Its temperature measuring range is –50ºC to +550ºC, accuracy is ±1ºC and its response time is <500ms. Averages of three readings of cutting tool tip temperature rise have been taken from three different positions on the cutter tip as shown in Figure 1. Surface roughness is measured with the help of Mitutoyo-surftest SJ-301 surface roughness tester (Figure 2) by taking average of three readings, taken at three different locations on the machined surface of the test specimen after making each milling slot. The chemical composition of the work piece material is confirmed by spectroscopy. Tungsten carbide solid end mills of 20mm diameter with two flutes (Figure 3) have been used for cutting process.

Figure 2: Carbide solid end mill with two flutes

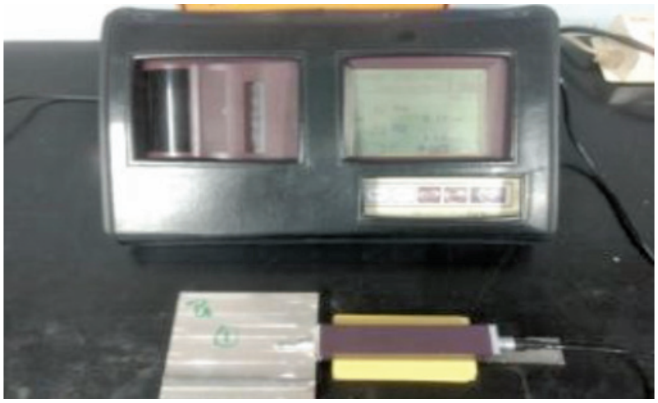

Figure 3: Surface roughness tester

## 3.0 Experimental Work

Since, Taguchi's method uses a special design of orthogonal arrays to cover the entire parameter space with minimum number of experiments. Experimentation has been carried out as per Taguchi's $L_9$ orthogonal array (OA) on BS L168 aluminium alloy test samples. Usually, this method of experimental procedure requires less number of experiments than the conventional experimentation approach[21]. The assigned levels of cutting process parameters are shown in Table 1, and were finalized based on the literature, cutting tool manuals and after conducting trial runs. The experimental results obtained from this experimentation procedure are depicted in Table 2.

**Table 1: Assignment of levels to the cutting factors**

| Cutting Parameters | Unit | Level 1 | Level 2 | Level 3 |
|---|---|---|---|---|
| Cutting speed (S) | rpm | 2000 | 3000 | 4000 |
| Feed rate (F) | mm/min | 200 | 400 | 600 |
| Depth of cut (D) | mm | 0.75 | 1.50 | 2.25 |

**Table 2: Allocation of machining parameters in $L_9$ OA and experimental results**

| Run | SRPM | Fmm/min | Dmm | $R_a$µm | TºC | MRRmm$^3$/sec |
|---|---|---|---|---|---|---|
| 1 | 2000 | 200 | 0.75 | 0.64 | 42.6 | 47.486 |
| 2 | 2000 | 400 | 1.50 | 0.76 | 58.7 | 193.126 |
| 3 | 2000 | 600 | 2.25 | 0.90 | 81.2 | 441.210 |
| 4 | 3000 | 200 | 1.50 | 0.52 | 53.5 | 95.414 |
| 5 | 3000 | 400 | 2.25 | 0.60 | 75.6 | 289.752 |
| 6 | 3000 | 600 | 0.75 | 0.92 | 59.2 | 147.404 |
| 7 | 4000 | 200 | 2.25 | 0.34 | 69.8 | 135.246 |
| 8 | 4000 | 400 | 0.75 | 0.67 | 52.7 | 96.723 |
| 9 | 4000 | 600 | 1.50 | 0.76 | 69.1 | 294.524 |

The material removal rate for the end milling operation has been calculated against each experimental run by the equation 1[22].

$$\mathrm{MRR} = \frac{W*D*L}{t}\ \mathrm{mm}^3/\mathrm{min} \qquad \text{... (1)}$$

Where, W is the width of milling cut in mm, D is the depth of cut in mm, and L is the length of end mill slot in mm and 't' is the time taken to form the cutting slot in min.

## 4.0 Optimisation using GRA

### 4.1 Grey Relational Analysis

The relationship and influence between different cutting parameters of a multi-response optimisation problem is not only multifaceted but also not lucid. Hence, this kind of situation designated as grey, which denotes either uncertain or poor information. GRA analyses and resolves these types of uncertainty problems successfully among the multi-objectives in a given system of consideration. Then, it optimises the same with the help of GRG. Through this step a multi-objective optimisation problem will be converted to a single-objective problem. Now, this single objective problem is called as single relational grade. The scope of present work is to find the optimum combination of machining process parameters that concurrently minimises both surface roughness as well as cutting tool tip temperature rise, and at the same time to maximise MRR.

*Step 1: Grey relational generation*

'Optimal condition of various cutting parameters is determined by deploying grey relational analysis to obtain the best quality performance characteristics'[23-26]. Normalizing the results obtained from the experiments is the initial step to be followed in this procedure. This will be done according to the kind of performance characteristics taken into consideration in order to avoid different units involved and to reduce the uncertainty. Through 'Data Processing' procedure an array will be formed between '0' and '1'. For formation of this array 'appropriate values' will be derived from the 'original values'. In this process 'comparable data' will be derived by elimination of different units involved in the 'original data'. As the performance characteristic is required to be minimised, 'Lower-the-better' characteristic has been proposed for normalisation of the data to scale it into an acceptable range.

In this work, cutting tool tip temperature rise and surface roughness are the performance responses considered and are to be minimised for the process betterment. Hence, 'Lower-the-better' is the form we have chosen as an original sequence. And this original sequence can be normalised using the equation 2 as follows[27].

$$a_i^*(k) = \frac{\max(a_i^o(k)) - (a_i^o(k))}{max\left(a_i^o(k)\right) - min\left(a_i^o(k)\right)} \qquad \text{... (2)}$$

Material removal rate is the performance response has been considered and it is to be maximised for process betterment. Hence, 'Higher-the-better' is the form we have chosen as an original sequence. And this original sequence can be normalised using the equation-3 as follows[27].

$$a_i^*(k) = \frac{a_i^o(k) - min\left(a_i^o(k)\right)}{max\left(a_i^o(k)\right) - min\left(a_i^o(k)\right)} \qquad \text{... (3)}$$

Where, i=1,…, m; k=1,…, n., and 'm' is the number of experimental data and 'n' is the number of responses, $a_i^o(k)$ denotes the original sequence, $a_i^*(k)$ denotes the sequence after data processing, $max\ (a_i^o(k))$ denotes the largest value of $a_i^o(k)$, $min\ (a_i^o(k))$ denotes the smallest value of $a_i^o(k)$, and $'a'$ is the desired value[28].

If a defined target value for 'OA' exists, the normalization of actual sequence can be performed with the equation 4[27].

$$a_i^*(k) = 1 - \frac{\left|a_i^o(k) - OA\right|}{max\left[max\left(a_i^o(k)\right) - OA,\ OA - min\left(a_i^o(k)\right)\right]} \qquad \text{... (4)}$$

Where, $a_i^*(k)$ is the value after grey relational generation (normalized value), $max\ (a_i^o(k))$ and $min\ (a_i^o(k))$ are the largest and smallest values of $(a_i^o(k)$ for the $k^{th}$ response respectively, $k$ being '1' for surface roughness, '2' for cutting tool tip temperature rise and '3' for material removal rate.

*Step 2: Grey relational coefficient*

The level of correlation between the best result and actual experimental result can be found by grey relational coefficient ($\zeta_i(k)$). And it is calculated using the equation 5[27] shown below.

$$\zeta_i(k) = \frac{\Delta_{min} + \zeta\Delta_{max}}{\Delta_{0i}(k) + \zeta\Delta_{max}} \qquad \text{... (5)}$$

And $0 < \zeta_i(k) \leq 1$ ... (6)

Where, '$\Delta_{oi}(k)$' is the deviation sequence of the comparability sequence '$a_i^*(k)$' and reference sequence '$a_o^*(k)$'.

$$\Delta_{0i}(k) = \left\|a_0(k) - a_{ij}\right\| \qquad \text{... (7)}$$

$$\Delta_{min} = \min\left\|a_0(k) - a_{ij}\right\| \qquad \text{... (8)}$$

$$\Delta_{max} = \max\left\|a_0(k) - a_{ij}\right\| \qquad \text{... (9)}$$

Where, 'ζ' is the distinctive coefficient (ζ∈[0, 1]) and it is used to regulate the difference of the relational coefficient. In this work 'ζ' values was chosen as 0.5 and the grey relational coefficients are calculated using equation 5[27] against each experimental run and are depicted in Table 3.

### *Step 3: Grey relational grade*

The grey relational grade is computed by finding the average of the grey relational coefficient corresponding to each performance characteristics. This degree is being approximated using equation 10, mentioned below.

$$\alpha_i = \frac{1}{n}\sum_{k=1}^{n}\zeta_i(k) \quad \text{... (10)}$$

Where, $\alpha_i$ is the required grey relational grade for $i^{th}$ experiment and 'n' is number of performance characteristics taken into consideration for the study. If the grey relational grade is having a greater value, it means that the concerned parametric combination will give the response closer to the optimum value. GRG depicts the overall quality index, transformed to single response. The values of GRG, determines the ranking of experimental runs and to obtain near-optimal set of variables.

### *Step 4: Grey relational ordering*

Grey relational grades were calculated using equation-10, and the calculated grey relational order was figured out in Table 3 as per $L_9$ orthogonal array design of experiments. An order of '1' is allotted to greatest grey relational grade. From Table 4, we can see that the control parameter's setting of seventh experiment had the greatest grey relational grade and hence it indicates that, seventh experiment has the optimal end milling parameters setting to obtain minimum surface roughness, minimum cutting tool tip temperature rise and maximum material removal rate concurrently among the conducted nine number of experimental runs as per $L_9$ orthogonal array. Higher the GRG better is the product quality. Therefore, on the basis of GRG, factor effect can be estimated and also optimal levels for each controllable factor can be determined.

The mean of the GRG for each level of parameter is summarized and shown in Table 4. In addition to that, the total mean of the GRG (0.5156) for all the nine experiments has been calculated and it is listed in the Table 4. Figure 4 illustrates the main effects plot for GRG of various levels of cutting parameters considered. If larger is the GRG, better is the multiple performance characteristics. However, relative importance among the input parameters for multi-objective characteristics still need to be identified, so that the optimal combinations of the process control parameter levels can be determined more accurately[29]. Bigger delta reverence demonstrates the higher centrality of the parameter in controlling the response. In the response table (Table 4) it can be seen that feed rate has been assigned with a rank of ONE, which means that it is the most significant parameter in controlling the response followed by cutting speed and depth of cut.

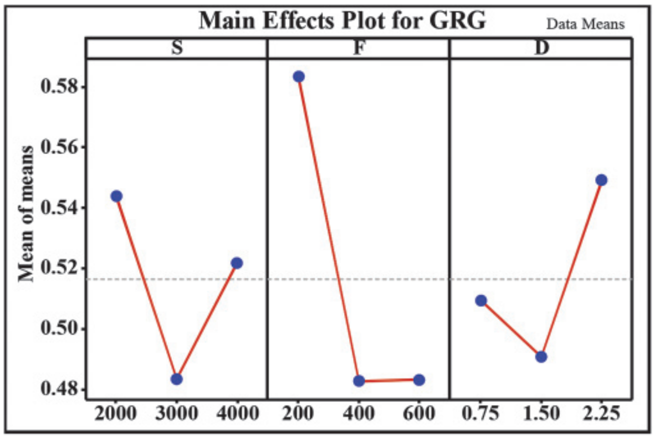


Figure 4: Main effects plot for grey relational grade

**Table 3: Normalized values, grey relational coefficients and grey relational grades of responses**

| Normalized values of responses | | | Deviation Sequence | | | Grey Relational Coefficients | | | GRG | Rank |
|---|---|---|---|---|---|---|---|---|---|---|
| Raμm | T°C | MRR mm³/sec | Ra μm | T°C | MRR mm³/sec | Ra μm | T°C | MRR mm³/sec | GRG | Grade |
| 0.483 | 1.000 | 0.000 | 0.517 | 0.000 | 1.000 | 0.492 | 1.000 | 0.333 | 0.608 | 2 |
| 0.276 | 0.583 | 0.411 | 0.724 | 0.417 | 0.589 | 0.408 | 0.545 | 0.459 | 0.471 | 8 |
| 0.034 | 0.000 | 1.000 | 0.966 | 1.000 | 0.000 | 0.341 | 0.333 | 1.000 | 0.558 | 3 |
| 0.690 | 0.718 | 0.166 | 0.310 | 0.282 | 0.834 | 0.617 | 0.639 | 0.375 | 0.544 | 4 |
| 0.552 | 0.145 | 0.761 | 0.448 | 0.855 | 0.239 | 0.527 | 0.369 | 0.676 | 0.524 | 5 |
| 0.000 | 0.570 | 0.305 | 1.000 | 0.430 | 0.695 | 0.333 | 0.538 | 0.418 | 0.430 | 9 |
| 1.000 | 0.295 | 0.348 | 0.000 | 0.705 | 0.652 | 1.000 | 0.415 | 0.434 | 0.616 | 1 |
| 0.431 | 0.738 | 0.184 | 0.569 | 0.262 | 0.816 | 0.468 | 0.656 | 0.380 | 0.501 | 7 |
| 0.276 | 0.313 | 0.805 | 0.724 | 0.687 | 0.195 | 0.408 | 0.421 | 0.719 | 0.516 | 6 |

**Table 4: Response table for means of GRG**

| Levels and Parameters | Level-1 | Level-2 | Level-3 | Delta (max-min) | Rank |
|---|---|---|---|---|---|
| A. Cutting Speed (S) | 0.5440* | 0.4836 | 0.5219 | 0.0604 | 2 |
| B. Feed rate (F) | 0.5834* | 0.4829 | 0.4833 | 0.1005 | 1 |
| C. DoC (D) | 0.5094 | 0.4909 | 0.5492* | 0.0583 | 3 |

Total Mean Value of the Grey Relational Grade = 0.5165
* Indicates optimum levels

A main effects plot (Figure 4) illustrates the effect of input process parameters on GRG. The peak value of each plot represents the optimal result for GRG i.e. X1 (cutting speed at 2000 rpm), Y1 (feed rate at 200mm/min) and Z3 (depth of cut at 2.25mm), and the same was observed from the response table for the GRGs shown in Table 5. To achieve minimum surface roughness, minimum cutting tool tip temperature rise and maximum material removal rate concurrently, this combination of parameter levels of cutting factors can be used.

Unlike main effects plots, an interaction effects plot displays the interaction effect of independent variables on the dependent variables. Generally interaction effect occurs, when there is an interaction between the independent cutting parameters that will affect the dependent responses. In the interaction plots, non-parallelism of lines denotes significant interaction[30-31]. From Figure 5, it can be seen that the combinations of 'cutting speed and feed rate', 'cutting speed and depth of cut' and 'depth of cut and feed rate' have significant interaction effects compared to other combinations.

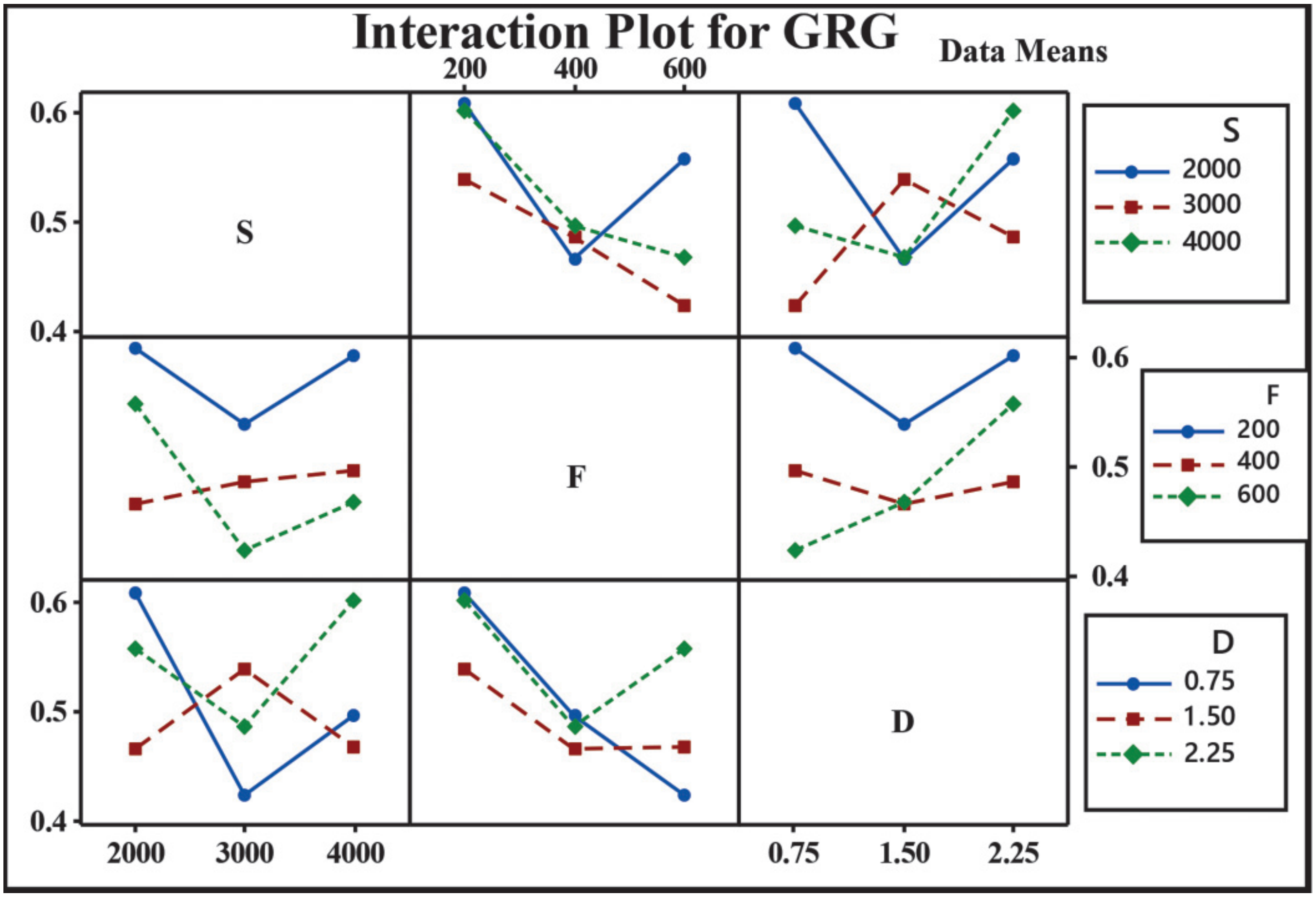


Figure 5: Interaction plots for Grey relational grade

## 4.2 Analysis of Surface Roughness

The measured experimental values of surface roughness, cutting tool tip temperature rise and material removal rate are listed in Table 2. Highest value of surface roughness (0.92μm) was obtained in the sixth experimental run (i.e at S: 3000rpm, F: 600mm/min and D: 0.75mm) and least value (0.34μm) of the same was found in the seventh experimental run (i.e at S: 4000rpm, F: 200mm/min and D: 2.25mm). From the main effects plots (Figure 6) it is implicit that, surface roughness decreases with the increase of cutting speed as well as depth of cut. But the slope of mean surface roughness vs DOC plot is somewhat less compared to slope of mean surface roughness vs cutting speed. It means that the influence of DOC is not that much significant as such of cutting speed. Whereas, the main effects plot of surface roughness vs feed rate is showing sharply increasing slope. It means that, feed rate is having more influence on surface roughness and hence the same is increasing significantly with the increase of feed rate.

The decrease in surface roughness with the increase of either cutting speed or depth of cut might be due to decreased chatter vibrations within the selected range of these process parameters. The drastic increase in surface roughness with the increase of feed rate is due to continuous chip formation and also development of more contacts area between work piece and cutting tool. Obviously, this will cause for more friction and wear, which in turn leads to deterioration of surface quality.

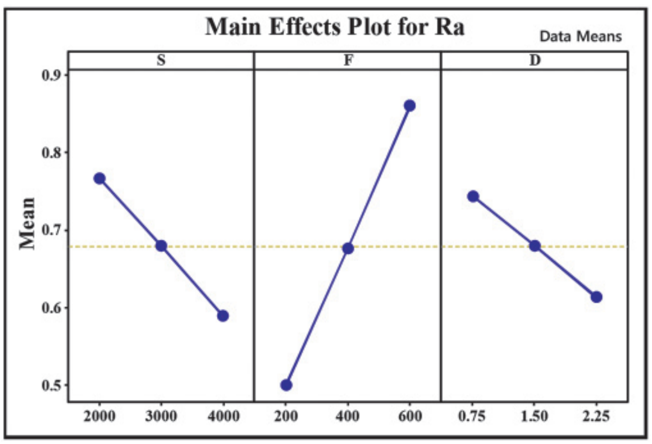


Figure 6: Main effects plot for average surface roughness

## 4.3 Analysis of Cutting Tool Tip Temperature Rise

From the result in Table 2, it is implicit that, highest value of cutting tool tip temperature (81.2ºC) was found at the combination of input cutting process parameters (S: 2000rpm, F: 600mm/min and D: 2.25mm). Whereas least value of cutting tool tip temperature (42.6ºC) was attained at the combination of input factors (S: 2000rpm, F: 200mm/min and D: 0.75mm). From the main effects plot (Figure 7) it is perceived that cutting tool tip temperature is increasing with the increase of cutting speed, feed rate and depth of cut as well. But the rate of increase of cutting tool tip temperature is sluggish w.r.t. cutting speed, intermediate w.r.t. feed rate and it is drastic w.r.t. depth of cut as revealed from the main effects plot.

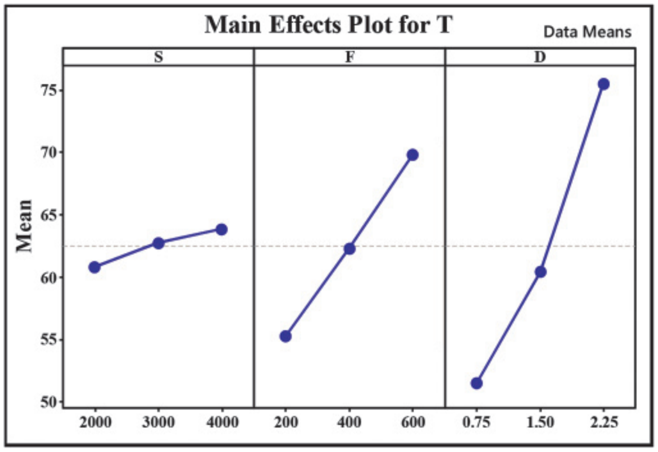


Figure 7: Main effects plot for cutting tool tip temperature rise

The increase in cutting temperature with the increase of cutting speed, feed rate and depth of cut might be due to increase in friction force and strain rate in the primary and secondary deformation zones. This increases in cutting temperature at cutting zone in turn obviously increases the temperature on the cutting tool tip.

## 4.4 Analysis of Material Removal Rate

From the result in Table 2, it is implicit that, the highest value of material removal rate (441.21mm$^3$/min)) was found at the combination of cutting process control parameters (S: 2000rpm, F: 600mm/min and D: 2.25mm). Whereas least value

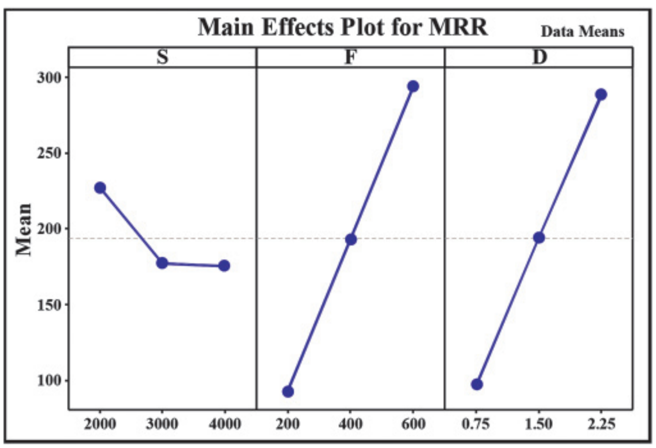


Figure 8. Main effects plot for material removal rate

of material removal rate (47.486mm$^3$/min) was achieved at the input parameters combination (S: 2000rpm, F: 200mm/min and D: 0.75mm). Among the chosen operating parameters the maximum S/N ratio is seen for feed rate. This indicates that feed rate is the most predominant factor in MRR followed by depth of cut and the cutting speed. Figure 8 shows the main effect plot of mean of S/N ratio on for MRR as response. It is observed that the material removal rate is drastically increasing with the increase of feed rate and depth of cut as well. But it decreases sharply up to some extent (from 2000rpm to 300rpm) and after that it decreases gradually with the increase of cutting speed (from 3000rpm to 4000rpm).

The higher feed rate promotes the radial movement of the cutting tool along the cutting direction; resulting shifting of cutter to new position at faster rate thereby increases of MRR. Higher DOC creates higher axial thrust force between work piece and the cutting tool and hence scoops out more and more material in unit time. The effect of both feed rate and depth of cut is more as compared to variation in cutting speed.

### 4.5 Analysis of Variance Outcomes for GRG

The purpose of ANOVA is to investigate, which machining process parameter is significantly affecting the performance characteristics. 'This is consummated by separating the total variability of the grey relational grades, which is measured by the sum of squared deviations from the total mean of the GRG, into contributions by each machining parameter and the error'[32]. The total sum of the squared deviations $SS_T$ from the total mean of the grey relational grade is calculated by equation 11.

$$SS_T = \sum_{j=1}^{P}(\gamma_j - \gamma_m)^2 \quad \text{... (11)}$$

Where, 'p' is the number of experiments conducted from the OA, and $\gamma_j$ is the mean grey relational grade for $j^{th}$ experiment.

The total sum of squared deviations '$SS_T$' is disintegrated in to two sources: the sum of the squared deviations '$SS_d$' due to each machining parameter and the sum of squared error '$SS_e$'. The percentage contribution of each of the machining parameter in the total sum of squared deviations '$SS_T$' can be used to evaluate the importance of machining parameter change on the performance characteristic. In addition, the Fisher's F-test can also be used to determine which machining parameter has a significant effect on the performance characteristic. Usually, the change of machining parameters has a significant effect on the performance characteristic when F-value is large. Percentage contribution of each machining parameter on multi-objective optimization was assessed using ANOVA. Results of analysis of variance for grey relational grade indicated that feed rate is the most substantial machining parameter affecting the multi-performance characteristics with 45.71% followed by depth of cut (7.21%) and cutting speed (2.21%). Then, coming to interactive effect of cutting factors, feed rate multiplied by depth of cut (F*D) is having significant influence with 42.65% on multi-performance characteristics.

## 5.0 Confirmation Experiments

By grey relational analysis the optimal combination of process parameters is identified to improve the milling characteristics. The final stage of grey relational analysis is to verify the obtained optimum condition for multi-objective quality characteristics through conformation experiments. The equation for confirmation experiments can be expressed as below with equation-12[33].

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{n}(\gamma_i - \gamma_m) \quad \text{... (12)}$$

Where, $\gamma_{predicted}$ is the grey relational grade for predicting the optimal end milling input factor. $\gamma_m$ is the total mean of the grey relational grade, $\gamma_i$ is the mean of grey relational

**Table 5: ANOVA for grey relational grade (Multiple response characteristics)**

| Source | DF | Seq SS | Contribution | Adj SS | Adj MS | F-Value | P-Value |
|---|---|---|---|---|---|---|---|
| Regression | 6 | 0.032514 | 98.91% | 0.032514 | 0.005419 | 30.22 | 0.032 |
| S | 1 | 0.000727 | 2.21% | 0.001111 | 0.001111 | 6.20 | 0.131 |
| F | 1 | 0.015025 | 45.71% | 0.000165 | 0.000165 | 0.92 | 0.439 |
| D | 1 | 0.002369 | 7.21% | 0.011065 | 0.011065 | 61.71 | 0.016 |
| S*F | 1 | 0.000247 | 0.75% | 0.008648 | 0.008648 | 48.23 | 0.020 |
| S*D | 1 | 0.000124 | 0.38% | 0.007613 | 0.007613 | 42.46 | 0.023 |
| F*D | 1 | 0.014021 | 42.65% | 0.014021 | 0.014021 | 78.19 | 0.013 |
| Error | 2 | 0.000359 | 1.09% | 0.000359 | 0.000179 | | |
| Total | 8 | 0.032872 | 100.00% | | | | |

**Table 6: Comparison between initial and optimal process parameters**

| Levels | Initial machining parameters | Optimal machining parameters | |
|---|---|---|---|
| | | Predicted | Experimental |
| Setting Level | X1Y1Z1 | X1Y1Z3 | X1Y1Z3 |
| Surface roughness | 0.64 | | 0.44 |
| Cutting tool tip temperature | 42.6 | | 40.2 |
| Material removal rate | 47.486 | | 149.870 |
| Grey relational grade | 0.6080 | 0.6436 | 0.7156 |

Improvement in grey relational grade = 0.1017

grade at optimum level of significant factors A, B and C., 'n' is the number of significant milling parameters (S, F and D) affect the quality characteristics. Calculation of grey relational grade for predicting the optimal end milling process parameters is as follows:

$$\gamma_{predicted} = \gamma_m + \sum_{i=1}^{3}(\gamma_i - \gamma_m)$$

= 0.5165 + (0.5440 – 0.5165) + (0.5834 – 0.5165) + (0.5492-0.5165) = 0.6436

The optimum combination for input control parameters is X1Y1Z3 and calculated grey relational grade by equation 12 is 0.6436.

Based on equation 12, the estimated grey relational grade using optimal machining parameters can then be obtained. Table 6 shows the results of confirmation experiment using optimal machining parameters. The surface roughness ($R_a$) is improved from 0.64µm to 0.44µm, cutting tool tip temperature reduced from 42.6°C to 40.2°Cand the material removal rate is greatly increased from 47.486 $mm^3$/sec to 149.87$mm^3$/sec. It can be noted that, the experimental value of surface roughness, cutting tool tip temperature rise and material removal rate are considerably enhanced by grey relational analysis.

## 6.0 Conclusions

A vertical CNC milling centre has been considered for machining of BS L168 alloy test specimens. It is one of the most important aluminium alloy used for fighter aircraft structural detail components. To obtain high-quality machining, multi-response decision model has been developed with cutting speed, feed rate and depth of cut as process control parameters. Cutting tool tip temperature rise, surface roughness and material removal rate are considered as the process performance characteristics. Taguchi's orthogonal array design coupled with grey relational analysis is considered for the process optimization. Following are the main conclusions drawn from this study.

1. The grey relational analysis of the experimental results of surface roughness, cutting tool tip temperature rise and material removal rate can convert optimization of the multiple performance characteristics in to optimization of a single performance characteristic called grey relational grade.
2. It has been found that, the optimal cutting parameters for machining process lies at 2000rpm of cutting speed, 200mm/min of feed rate and 2.25mm of depth of cut. Further it has been observed that, there is a 215.61% increase in material removal rate, 31.25% improvement in surface finish and 5.64% reduction in cutting tool tip temperature rise simultaneously. This encourages applying Taguchi based Grey Relational Analysis (T-GRA) concept for optimizing the multi-response processing with multiple input cutting process parameters.
3. Analysis of variance for grey relational grade shows that, the feed rate is the most significant machining parameter with 45.71% influence, followed by depth of cut, and cutting speed is having least influence on the multi-performance characteristics. The value of multi-performance characteristics obtained from confirmation experiments is with more than 95% confidence level.
4. The best multi-performance characteristics was obtained with carbide solid end mills on BS L168 alloy with the low level of cutting speed 2000rpm, low level of feed rate 200mm/min and high level of depth of cut 2.25mm with the estimated multi-performance characteristics at grey relational grade: 0.6436. The experimental value of grey relational grade for the said combination of parameters is 0.7156.
5. The grey relational grade (0.7156) reached through the confirmation test is 16.23% higher over the highest grey relational grade value (0.6160) in the experimental matrix, represents the optimum condition.

This work can be aimed to extend with hard-to-machine aerospace materials, such as Titanium, Nimonic alloys, Steel and Composites as work piece material in future. More process responses can be considered, such as tool wear, chatter vibration, cutting force, surface waviness or flatness and power consumption by the machine tool etc.

## 6.0 References


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