# Selection of Optimum Drilling Process Variables Using Grey Relational Analysis Approach

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**Abstract -** *Productivity in particular process is depending on the process parameters at which operation is running. Therefore, selection of optimum process conditions is crucial particularly in multi objective interest. Al 6082 material is a light weight material widely used in aerospace application. GRA is one of the promising multi-objective techniques with a simple scientific methodology to select the cutting conditions.*

*Therefore, in the present work, an attempt was made to improve the drilling process performance during CNC drilling of Al 6082 material using Grey Relational Analysis (GRA) approach. In drilling process, spindle speed and feed rate, coolant type were selected as controllable process parameters and cutting temperature and surface roughness were considered as performance evaluation characteristics. Grey relational analysis (GRA) optimization technique was applied to select the optimum cutting parameters. The optimum drilling process parameters identified using GRA areas spindle speed 1500rpm, feed rate 0.1mm/rev and MQL condition combination respectively during drilling of Al 6082 material using tungsten carbide drill bit.*

**Key Words:** *Drilling Process; Al 6082 material; Cutting Temperature; Surface Roughness (Ra); Material Removal Rate (MRR); Grey Relational Analysis (GRA).*

## 1. INTRODUCTION

Drilling is one of the most efficient and usual actions that are usually ascertained metal processing companies or in other manufacturing industries. It is an effective method for producing holes of ordained diameter and roundness of the hole on the surface. Computer Numerical Controlled (CNC) drilling machines are rapidly replacing the older production drilling machines due to their ease of setting, operation, repeatability and accuracy. The part may be designed and the tool paths can programmed by the CAD/CAM process or manually by the programmer and the resulting file is uploaded to the machine. Once set, the machine will continue to turn out parts under the occasional supervision of an operator. The design of the drilled holes serve for fasteners such as rivets, bolts and nuts.

Akhil K.T et al. [1] illustrated optimization of drilling characteristics using grey relational analysis (GRA) in glass fiber reinforced polymer (GFRP).The cutting speed is the most significant process parameter which influences the delamination factor and surface roughness. Cutting Speed has highest contribution on the multiple performance characteristic followed by feed rate as obtained from analysis.

Hemant.S et al. [2] inspected the modeling of temperature distribution in drilling of titanium. The temperature distributions in the tool and the work piece are simultaneously predicted for variation in cutting speed and feed rate. In both the cases, increase in cutting speed and feed rate results in significant increase in temperature.

Balaji et al. [3] examined optimization of cutting parameters in drilling of AISI 304 stainless steel using taguchi and ANOVA. This work deals with the effect of cutting parameters namely cutting speed, feed rate and helix angle on the tool life and observed that Vibration of drill bit is found to be increased along with the progression of the tool wear and also the result showed that Helix angle is found to be significant on surface roughness followed by acceleration of drill vibration velocity.

Suman Chatterjee et al. [4] investigated Simulation and optimization of machining parameters in drilling of titanium alloys. The response surface methodology is adopted to take experimental readings. Various drilling parameters such as spindle speed, feed rate and drill bit diameter on performance characteristics such as thrust force, torque and circularity at entry and exit of the holes in drilling of titanium alloy using coated drill bit were analyzed. Thus, the Author concluded that the proposed simulation model can be used for machinability analysis of drilling of titanium alloys so as to save experimental time, cost and resources.

Abdelhafeeza et al. [5] studied the burr formation and hole quality when drilling titanium and aluminium alloys. Chemical vapour deposited (CVD) diamond coated carbide drills were used for the aluminium work pieces while uncoated carbide tools were employed for the titanium material. An experimental design based on response surface methodology was implemented. The author concluded that cutting speed was found to be significant when drilling Ti-6Al-4V.

Gaurav Chaudhary et al. [6] demonstrated the Optimization of drilling parameters of hybrid metal matrix composites using response surface methodology by using input response as speed, feed and point angle and the output response parameters considered are MRR, oversize and surface roughness. It is found that the feed rate is the most significant machining parameter used to predict the surface roughness. And also obtain the optimum condition for the output response.

Ramazan Cakıroglu et al. [7] inspected optimization of cutting parameters on drill bit temperature in drilling by taguchi method. Here the factors consider as input are cutting speed, feed rate and cutting tool. The result found that the drill bit temperature increases with increase in cutting speed and temperature decreases with increases in feed rate. But the most significant factor in affecting the drill bit temperature was the feed rate.

In any production line, processing cost and productivity significantly depend on the selection of process parameters. If it is a production line with machining work stations then machining cost and productivity largely depend on the performing machining operation at optimum cutting conditions. In machining work stations, optimum cutting conditions are required for simultaneous improvement of different performance characteristics including tool wear, surface roughness, cutting force, surface integrity, etc. Grey relational analysis is one of the promising multi-objective metaheuristic technique with a simple scientific methodology to select the cutting conditions for multi-objective optimization problems.

To the author's best understanding, countable literature is available in CNC drilling of superalloys, ceramics and composite materials. However, the literature lacks on Al 6082 which have much application in the different fields. Yet again, tolerances limits of the drill hole are significantly depending on the surface roughness. Drilling a hole with meeting the stringent quality standards is a challenging task. To fulfil modern manufacturing obligations, conducting the drilling experiments at the optimum cutting conditions is preference. Nevertheless, deciding the optimum cutting conditions is a difficult job due to the involvement of many process parameters. Therefore, the main objective of the present work is to determine the optimum cutting conditions in CNC drilling of Al 6082 material using multi-objective optimization techniques. In this work, optimum CNC drilling process parameters were identified using grey relational analysis (GRA) to simultaneously reduce the surface roughness and cutting temperature.

## 2. EXPERIMENTAL WORK

In the present work, Taguchi $L_{27}$ orthogonal array (OA) design has been used to conduct experiments on Al 6082 material using CNC drilling machine. Each experiment was conducted three times and average was taken as final output values to get the accuracy in the data. Aluminum alloy 6082 is a "medium strength alloy with excellent corrosion resistance." Alloy 6082 is known as a structural alloy. In plate form, 6082 is the alloy most commonly used for machining. Figure 1 depicts the CNC drilling experimental set-up. The Taguchi $L_{27}$ OA design was employed to explore the analysis due to the necessity of minimum effort and low manufacturing cost. The surface roughness characteristics are measured using SJ 301 model Talysurf tester and the thermal image camera used to measure machining zone temperature. The process variables and their levels are shown in Table 1. As indicated in Table 2, $L_{27}$ Taguchi orthogonal array was chosen for the current study and attained outputs were recorded.

Figure 1. CNC drilling machine

**Table 1** Process variables and their levels

| Parameters | Levels | | |
|---|---|---|---|
| | -1 | 0 | 1 |
| Coolant Type | Wet | MQL | Dry |
| Feed Rate (mm/rev) | 0.05 | 0.075 | 0.1 |
| Cutting Speed (RPM) | 900 | 1200 | 1500 |

**Table 2** Average response values of different responses

| S.No. | Coolant Type | Feed Rate (mm/rev) | Cutting Speed (RPM) | Cutting Temperature (°C) | Surface Roughness (µm) |
|---|---|---|---|---|---|
| 1 | Wet | 0.05 | 900 | 35.8 | 0.707 |
| 2 | Wet | 0.05 | 1200 | 46.5 | 1.608 |
| 3 | Wet | 0.05 | 1500 | 53.3 | 2.854 |
| 4 | Wet | 0.075 | 900 | 35.2 | 1.140 |
| 5 | Wet | 0.075 | 1200 | 51.7 | 0.816 |
| 6 | Wet | 0.075 | 1500 | 57.9 | 1.299 |
| 7 | Wet | 0.1 | 900 | 35.9 | 1.190 |
| 8 | Wet | 0.1 | 1200 | 58.5 | 1.315 |
| 9 | Wet | 0.1 | 1500 | 61.2 | 2.236 |
| 10 | MQL | 0.05 | 900 | 36.4 | 2.087 |
| 11 | MQL | 0.05 | 1200 | 56.2 | 1.054 |
| 12 | MQL | 0.05 | 1500 | 62.4 | 1.374 |
| 13 | MQL | 0.075 | 900 | 37.1 | 1.597 |
| 14 | MQL | 0.075 | 1200 | 60.6 | 0.446 |
| 15 | MQL | 0.075 | 1500 | 66.2 | 1.150 |
| 16 | MQL | 0.1 | 900 | 36 | 0.912 |
| 17 | MQL | 0.1 | 1200 | 72.9 | 2.732 |

| | | | | | |
|---|---|---|---|---|---|
| 18 | MQL | 0.1 | 1500 | 64 | 0.311 |
| 19 | Dry | 0.05 | 900 | 36.8 | 1.113 |
| 20 | Dry | 0.05 | 1200 | 65 | 2.144 |
| 21 | Dry | 0.05 | 1500 | 68.2 | 2.731 |
| 22 | Dry | 0.075 | 900 | 37 | 1.576 |
| 23 | Dry | 0.075 | 1200 | 46 | 1.241 |
| 24 | Dry | 0.075 | 1500 | 71.4 | 0.586 |
| 25 | Dry | 0.1 | 900 | 36.2 | 1.038 |
| 26 | Dry | 0.1 | 1200 | 61 | 1.117 |
| 27 | Dry | 0.1 | 1500 | 64.6 | 0.339 |

## 3. RESULTS AND DISCUSSION

Selecting the right alternative among the more available choices is not an easy assignment. Therefore, a systematic and scientific methodology is required to solve such a difficult task. The researchers have shifted their concentration towards GRA because of easy understanding and simple methodology. In the present work, the relation between the process parameters and performance characteristics is unclear during drilling of Al 6082 material and selection of the right alternative which improves the laser performance is a difficult task. Hence, in the present work GRA was employed to identify the right choice a following steps to choose the right alternative among available alternatives.

### *Step1: Normalization of experimental data*

As the raw data cannot be compared because of different ranges of data and units. For, comparison purpose data processing is required (i.e., normalizing the data between 0 and 1). Normalization is a process of converting the original sequence into a compatible sequence. Experimental data is normalized as $D_p{}^*(q)$ ($0 \le D_p{}^*(q) \le 1$) by the following formulae. Equation (2) is used for the larger-the-better quality characteristic and equation (1) is used for the smaller the better quality characteristic. In the current study, to improve the productivity, cutting temperature and surface roughness were chosen for smaller-the-better characteristics. The calculated normalized values are tabulated in the Table 3.

Smaller - the - better

$$D_p{}^*(q) = \frac{Max\ D_p(q) - D_p(q)}{Max\ D_p(q) - Min\ D_p(q)} \text{--------------------------(1)}$$

Larger - the - better

$$D_p{}^*(q) = \frac{D_p(q) - Min\ D_p(q)}{Max\ D_p(q) - Min\ D_p(q)} \text{---------(2)}$$

Where

$D_p{}^*(q)$= Sequence after data processing

$D_p(q)$= Original sequence

$Max\ D_p(q)$= Maximum value of entity p

$Min\ D_p(q)$ = Minimum value of entity p

p= Number of characteristics (1, 2, 3, 4)

q = Number of experimental runs (1, 2,….., 9)

**Table 3** Normalized values

| S.No. | Coolant Type (mm) | Feed Rate (mm/rev) | Cutting Speed (RPM) | Cutting Temperature (ºC) | Surface Roughness (µm) |
|---|---|---|---|---|---|
| 1 | wet | 0.05 | 900 | 0.0232 | 0.3705 |
| 2 | wet | 0.05 | 1200 | 0.3824 | 0.7412 |
| 3 | wet | 0.05 | 1500 | 0.5699 | 1 |
| 4 | wet | 0.075 | 900 | 0 | 0.586 |
| 5 | wet | 0.075 | 1200 | 0.528 | 0.4352 |
| 6 | wet | 0.075 | 1500 | 0.6836 | 0.6449 |
| 7 | wet | 0.1 | 900 | 0.027 | 0.6054 |
| 8 | wet | 0.1 | 1200 | 0.6977 | 0.6504 |
| 9 | wet | 0.1 | 1500 | 0.7597 | 0.8899 |
| 10 | MQL | 0.05 | 900 | 0.046 | 0.8588 |
| 11 | MQL | 0.05 | 1200 | 0.6426 | 0.5506 |
| 12 | MQL | 0.05 | 1500 | 0.7864 | 0.6702 |
| 13 | MQL | 0.075 | 900 | 0.0722 | 0.7381 |
| 14 | MQL | 0.075 | 1200 | 0.7462 | 0.1626 |
| 15 | MQL | 0.075 | 1500 | 0.8676 | 0.5899 |
| 16 | MQL | 0.1 | 900 | 0.0309 | 0.4853 |
| 17 | MQL | 0.1 | 1200 | 0.8212 | 0 |
| 18 | MQL | 0.1 | 1500 | 1 | 0.9803 |
| 19 | Dry | 0.05 | 900 | 0.0611 | 0.5752 |
| 20 | Dry | 0.05 | 1200 | 0.8425 | 0.871 |
| 21 | Dry | 0.05 | 1500 | 0.9085 | 0.9801 |
| 22 | Dry | 0.075 | 900 | 0.0685 | 0.7321 |
| 23 | Dry | 0.075 | 1200 | 0.3676 | 0.6243 |
| 24 | Dry | 0.075 | 1500 | 0.9714 | 0.2858 |
| 25 | Dry | 0.1 | 900 | 0.0385 | 0.5437 |
| 26 | Dry | 0.1 | 1200 | 0.7552 | 0.5768 |
| 27 | Dry | 0.1 | 1500 | 0.834 | 0.0389 |

### *Step 2: Calculation of grey relational coefficient (GRC)*

The purpose of calculating the Grey relational coefficient is to know the relation between the desirable and real experimental data. The grey relation coefficients $\varepsilon_p(q)$ for the all turning performances are calculated using equation (4) and listed in the Table 4.

$$\varepsilon_p(q) = \frac{\Delta_{Min} + \zeta \Delta_{Max}}{\Delta_{op}(q) + \zeta \Delta_{Max}} \text{---------------------------------- (3)}$$

Where $\Delta_{op}(q)$ indicates the absolute difference between current data sequence value (($D_p{}^*(q)$) and ideal value $D_p{}^o(q)$ and $\zeta$ is the distinguishing coefficient and it is used to alter the variation of the grey relational coefficients and if lower distinguishing coefficient higher will be the distinguishing ability. $\zeta$ is taken as 0.5 by taking into account of all the process variables are equally weighing (Sarikaya and Gullu, 2015). Equation (5), (6) and (7) are used to compute the values of $\Delta_{op}(q)$, $\Delta_{Min}$, $\Delta_{Max}$ .

$$\Delta_{op}(q) = \left| D_p{}^o(q) - D_p{}^*(q) \right| \text{------------------------(4)}$$

$$\Delta_{Min} = \min_p \min_q \Delta_{op}(q) \text{----------------------------(5)}$$

$$\Delta_{Max} = \max_p \max_q \Delta_{op}(q) \text{--------------------------(6)}$$

**Table 4** Performance characteristics GRC, GRG and its orders.

| Exp. No. | Grey relational coefficient (GRC) | | Grey relational grade (GRG) | Orders |
|---|---|---|---|---|
| | Cutting Temperature | Surface Roughness | | |
| | Ideal sequence | | | |
| | **1.0000** | **0.4427** | | |
| 1 | 0.3386 | 0.6589 | 0.3906 | 27 |
| 2 | 0.4474 | 1 | 0.5532 | 13 |
| 3 | 0.5376 | 0.547 | 0.7688 | 4 |
| 4 | 0.3333 | 0.4696 | 0.4402 | 21 |
| 5 | 0.5144 | 0.5847 | 0.492 | 19 |
| 6 | 0.6124 | 0.5589 | 0.5986 | 10 |
| 7 | 0.3395 | 0.5885 | 0.4492 | 20 |
| 8 | 0.6232 | 0.8196 | 0.6059 | 9 |
| 9 | 0.6754 | 0.7798 | 0.7475 | 5 |
| 10 | 0.3439 | 0.5267 | 0.5618 | 11 |
| 11 | 0.5832 | 0.6026 | 0.5549 | 12 |
| 12 | 0.7007 | 0.6562 | 0.6516 | 8 |
| 13 | 0.3502 | 0.3739 | 0.5032 | 17 |
| 14 | 0.6633 | 0.5494 | 0.5186 | 16 |
| 15 | 0.7906 | 0.4928 | 0.67 | 7 |
| 16 | 0.3403 | 0.3333 | 0.4166 | 25 |
| 17 | 0.7365 | 0.9621 | 0.5349 | 15 |
| 18 | 1 | 0.5407 | 0.981 | 1 |
| 19 | 0.3475 | 0.7949 | 0.4441 | 24 |
| 20 | 0.7604 | 0.9618 | 0.7776 | 3 |
| 21 | 0.8453 | 0.6511 | 0.9035 | 2 |
| 22 | 0.3493 | 0.571 | 0.5002 | 18 |
| 23 | 0.4415 | 0.4118 | 0.5062 | 16 |
| 24 | 0.946 | 0.5229 | 0.6789 | 6 |
| 25 | 0.3421 | 0.5416 | 0.4325 | 23 |
| 26 | 0.6713 | 0.3422 | 0.6065 | 22 |
| 27 | 0.7507 | 0.4427 | 0.5465 | 14 |

***Step 3: Calculation of Grey relational grade (GRG)***

Grey relational grade is useful in evaluating the multiple performance characteristics. Average of all obtained grey relational coefficient gives the grey relation grade. Equation (7) is used to compute the grey relation grade $(\gamma_p(q))$ and obtained results and grey relational grade ranks were tabulated in Table 4.

$$\gamma_p(q) = \frac{1}{N}\sum_{i=0}^{N} \varepsilon_p(q) \text{-------------------------------------}(7)$$

Where N = No. of performance characteristics.

The larger grey relational grade represents how closer the corresponding experimental response to the ideal value. From the Table 4, 18th experiment with spindle speed 1500RPM, feed rate 0.1mm/rev and MQL condition combination has the highest grade among all the orthogonal experiments. Therefore, spindle speed 1500RPM, feed rate 0.1mm/rev and MQL condition combination has identified as the optimum cutting condition using GRA Technique.

## 4. CONCLUSIONS

- Grey Relational Analysis (GRA) method involved simple mathematical equation and can be applied to multi response optimization problems effectively.

- The optimum combination of drilling process parameters was determined as spindle speed 1500RPM, feed rate 0.1mm/rev and MQL condition combination during drilling of Al 6082 material using tungsten carbide drill bit.

- MQL cooling consumes less coolant over wet cooling condition therefore coolant cost involved in MQL is low compared to wet cooling method.

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