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OPTIMIZATION OF MATERIAL REMOVAL RATE AND SURFACE ROUGHNESS USING TAGUCHI BASED MULTI-CRITERIA DECISION MAKING (MCDM) TECHNIQUE FOR TURNING OF AL-6082

Mihir Solanki[1]
Aakarsh Jain

Keywords:

Turning; Material removal rate; Surface roughness; ANOVA; TOPSIS; Grey relation analysis.

A B S T R A C T

The current work discusses the experimental investigation for the optimization of cutting parameters for turning process. The effect of process parameters-cutting speed, feed rate and depth of cut investigated against the response variables-Material Removal Rate (MRR) and Surface Roughness (R_a) for aluminium-6082 material. Each experiment is performed for two replications to minimize error and contribution of noise factors. Signal to Noise ratio (SNR) and mean values are computed to identify optimum levels of process parameters. Analysis of Variance (ANOVA) and F-test performed at 95% confidence interval. Regression analysis shows the high level of correlation for MRR and moderate correlation for R_a. TOPSIS and GRA are used to evaluate the effectiveness of the optimization process during turning operation for AL-6082.

1. INTRODUCTION

Globalization leads to integration and involvement between- people, organization and governments across the national boundaries. It brings the sharing of goods, technology, information, and employment across the national borders. This has created fierce competition in manufacturing industries (Ulsoy & Koren, 1993). Machining is the most vital and inevitable process among all the manufacturing processes, specifically for achieving the preferred shape, dimension and accuracy (Majumder & Saha, 2018). Machining operations consists of several operations, viz. Turning, Facing, Knurling, Boring, Milling, Drilling, Honing, Hobbing, Grinding, Sawing, Broaching, Shaping and Slotting (Lan, 2010; Gok, 2015). Among all these operations, turning is the most widely used primary operation in the machining industry. Turning is a process in which, the diameter of a cylindrical work piece is reduced through the removal of excess material (Koyee & Heisel, 2014). Turning operation is considered as a fundamental and important process in engineering industries, to obtain the desired size and circular geometry. Nowadays, advanced computer-based turning machines are available, which can perform entire machining work autonomously with the help of a program or code. For small industries of the developing country, the break-even point in terms of price for such machines is not justified by the utilization. In manufacturing industries, the machining process parameters are selected based on knowledge, skills of operator and standard handbooks. Many times, selected

Corresponding author: Mihir Solanki
Email: mihirsolanki@gcet.ac.in

process parameters are not optimal, which leads to an economic loss of production (Thakur et. al 2009). Maximum performance of the selected machine is obtained, if the selected parameters are optimum (Ribeiro et al., 2017). Material removal rate (MRR) is defined as a rate of removal of excess material (in cubic meter) in unit time (Deresse et. al, 2019). Surface roughness (R_a) is a measure of the profile or texture of the finished part (measured in microns) (Palanisamy et. al, 2018). In any machining operation, there is always a trade-off between Material Removal Rate (MRR) and surface finish, as the MRR increases- surface finish decreases (i.e. R_a increases). The variable which affects the MRR and R_a for turning operations are mentioned below.

a) Machine characteristics- Vibration, Machine error etc.
b) Work material characteristics – Chemical composition, Heat treatment, Mechanical properties etc.
c) Process parameters – Working conditions (wet/dry), speed, feed and depth of cut
d) Cutting tool parameters – Tool material, Coating of tool and coating method, cutting method (orthogonal/oblique) etc.

1.1 Problem definition

In machining process, as mentioned above, many parameters affect the response variable. Several parameters are out of control from the human capability such as ambient temperature, humidity, in built machine characteristics etc. Also, it is not possible to take into consideration all variables that affects the response variable due to constrained resources of manpower and cost of experiment. Henceforth, the selection of optimized process parameters with optimum working condition for the selected machine tool is essential (Gupta et. al, 2018). Selection of optimum process parameter is a complicated task. From the literature survey, it has been found that there are many case studies available for optimization of the turning process for various ferrous and non-ferrous alloys. Many of them are summarized in table 1. However, from the literature survey, authors did not find any study dealing with optimization of aluminium - 6082 for turning process. Hence, current study is dedicated to progress with aluminium- 6082.

1.2 Objective of the study

The current study aims at optimization of process parameters for turning operation of aluminium-6082 for MRR and R_a. MRR and R_a are considered as a contrast parameter and they have an inverse relation. The selected input parameters are cutting speed, feed rate, depth of cut and working condition. The specific objectives of the case are as follow.

a) To implement the design of experiment (DoE) practice for turning operation.
b) To identify the optimum value of process parameters for MRR and R_a.
c) To implement the practice of MCDM technique for optimization of conflicting response variables.
d) Identification of statistically significant process parameters for MRR and R_a value.

Table 1. Summary of related studies for turning and related processes

Work material	Cutting tool material	Parameter	Response variable	Technique	Process	Source
Titanium (Grade-2)	-	CS, FR, Approach angle and Nano-fluids	TW, Fc and R_a	RSM, TOPSIS and ANOVA	CNC-Turning	(Gupta et. al, 2018)
ASTM A588 mild steel	Carbide cutting tool insert	CS, FR, DC	Power, R_a	DOE, Hybrid MCDM	Turning	(Majumder and Saha, 2018)
Titanium alloy	-	CS, FR and approach angle	R_a	DOE, TOPSIS, AHP	CNC- Turning	(Bartoszuk and Gupta, 2018)
EN-353	TNMG 160404-08-12 with coating of TiCN	CS, FR, DC, NR	MRR, R_a, Power, Energy Efficiency	DOE, AHP, ANOVA	CNC-Turning	(Kumar et. al, 2017)
EN-25	CNMG 120404 – CVD coated	CS, DC, DC	Circularity and Cylindricality	DOE, TOPSIS, ANOVA	CNC-Turning	(Balasubramaniyan and Selvaraj, 2017)
CP-Ti grade 2	SNMG120408	CS, FR, DC	MRR, R_a, Fc, Tm	DOE, TOPSIS, ANOVA	Turning	(Khan and Maity, 2017)
EN25	CVD and PVD coated insert	CS, FR, DC	MRR, R_a, Micro hardness	DOE, TOPSIS	CNC-Turing	(Singaravel and Selvaraj, 2015)
15-5PH stainless steel	CNMG 120408-GM coated with TiAlN	CS, FR, DC	Fc, R_a	DOE, TOPSIS, GRA	CNC-Turning	(Palanisamy and Senthil, 2016)
Inconel-718	PVD coated CNMG 12 04 08-QM 1105	CS, FR, DC, HPCS	Fc, Ft, R_a, TW	DOE, TOPSIS	CNC-Turning	(Raykar and Dabade, 2016)

Table 1. Summary of related studies for turning and related processes (continued)

Work material	Cutting tool material	Parameter	Response variable	Technique	Process	Source
Inconel 800H	Cryogenically Treated Multilayer CVD-Coated Tool	CS, FR, DC	MRR, R_a, Micro-Hardness, Degree of Work Hardening	DOE, TOPSIS	CNC-Turning	(Palanisamy and Selvaraj, 2018)
Magnesium alloy AZ91D	PCD cutting inserts	CS, FR, DC	R_a and TW	RSM, TOPSIS, GRA, ANOVA	Turning	(Ramesh et. al, 2016)
EN8	Carbide tool	CS, FR, DC	MRR and R_a	DOE, SNR, TOPSIS	Turning	(Rao and Venkatasubbaiah, 2016)
Ductile iron	SNMG 120408 – QM GC1125 and PSBNR 2020 K12	CS, FR, DC	Cutting Force, R_a	DOE, Fuzzy TOPSIS, ANOVA, RSM	CNC-Turning	(Gok, 2015)
S45C Steel	MITSUBISHI NX2525	CS, FR, DC, NR	MRR, R_a, TW	DOE, Fuzzy TOPSIS	CNC-Turning	(Lan, 2010)
AISI O1 tool steel	-	CS, FR, DC, NR	MRR and R_a	DOE, TOPSIS, GRA	Turning	(Kataria and Kumar, 2014)
INCOLOY 800H	CVD coated tool	Cutting speed, Tool condition Feed and Depth of cut	MRR, R_a, micro hardness	Orthogonal array, TOPSIS, GRA	Cylindrical Turning	(Palanisamy and Selvaraj, 2019)
Glass fiber reinforced polymer	Carbide tool VNMG110408	CS, FR, DC	MRR, R_a	DOE, TOPSIS	Turning	(Parida and Routara, 2014)

CS=Cutting Speed, FR=Feed rate, TW=Tool wear, Fc= Cutting force, Ft=Thrust force, DC= Depth of cut, NR=Nose radius, Tm=machining temperature, SNR= Signal to noise ratio, AHP= Analytical hierarchy process, HPCS=High pressure coolant system

2. DESIGN METHODOLOGY

Number of techniques can be applied for the optimization of process parameters of turning process. Many case studies show, multiple techniques that can be integrated to optimize several goals; and it will be helpful to conclude meaningful analysis.

Initially DoE is employed to generate layout of experiment. Using concept of signal to noise ratio (SNR), optimum process parameters are identified for MRR and R_a. Weights have been assigned to MRR and R_a. TOPSIS and GRA methods are implemented to optimize the response variables.

2.1 Design of experiment

Experiments are performed by investigators to discover meaningful relation between response and input variable (Montgomery, 2017). Design of experiment (DoE), one factor at a time (OFAT) and Best-guess-approach (BGA) are used for the construction of the experiment. BGA approach is most conventional; it works based on trial and error method. However, it requires significant knowledge related to process, and if initial guess is incorrect, it may take longer time to identify correct combination (Anderson and McLean, 2018). OFAT consider variation of single factor, while keeping the other factors constant. This creates maximum number of experiments, resulting highest cost. The major disadvantage of OFAT is that it misses key interactions or combined effect of process parameters on response. DoE is a statistic-based method and it makes the effective and efficient utilization of data for meaningful conclusion. It also helps to identify statistically significant process parameters, which have maximum impact on response variable. DoE includes full factorial, fractional factorial and Taguchi's orthogonal array-methods for construction of experiment. Full factorial considers all variables, at all levels. Total experiments are computed as $factor^{level}$. Fractional factorial design includes 50% of runs, compared to full factorial design (Somashekara and Swamy, 2013). Taguchi's orthogonal array is a compact design, with least number of runs and delivers the same results as full factorial experiment (Solanki et. al, 2021).

2.2 Taguchi's orthogonal array

Taguchi suggested extremely fractionated factorial designs and orthogonal arrays (OA) along with some novel statistical methods to solve problems. Due to this, implementation of DoE technique got the momentum, especially in the field of science and technology; and fourth era of statistical design begun (Deresse et. al, 2020). OA are selected based on total number of factors, levels of factors, interaction requirement among the factors, cost of experiment and degree of freedom. Identification of the parameters is concluded by cause-and-effect study, flow-chart and brainstorming study. Degree of freedom is directly proportional to the levels of the factors. Thus "increase in the levels of the parameter will increase degree of freedom, which in turn will increase number of runs of the experiment." Figure 1 delineate most used OA at different levels.

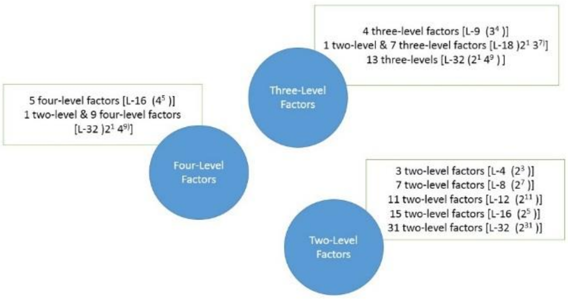


Figure 1. Commonly used orthogonal arrays

It is important to identify, common experimental conditions and equivalent experimental configurations (see table 2). Existing case study considers mixed level design.

Table 2. Experimental conditions and size of trial runs

Experimental condition	Number of experiments in full factorial design	Number of experiments in Taguchi's OA
4 three level factors	81	9
13 three level factors	1594323	32
5 four level factors	1024	16
3 two-level factors	8	4
7 two-level factors	128	8
11 two-level factors	2048	12
15 two-level factors	32768	16
31 two-level factors	2147483648	32

2.3 Multi Criteria Decision Method (MCDM)

The objective of MCDM is to convert multi criteria problem into single objective problem (Opricovic, 2004). MCDM is most widely used in manufacturing domain to identify optimum solution from finite number of alternatives. Each decision table (also referred as a decision matrix) in MCDM methods has four variables (Ananthakumar et. al, 2019). These variables are depicted below;

a) Alternatives: Term alternatives represent the different choices of action available for decision maker
b) Attributes: Attributes represents the criteria against which alternatives are assessed.
c) Decision weight: from the evaluator's perspective, all the criteria have different values as per the application. Weights are assigned to each criterion based on relative importance.
d) Decision matrix: Any MCDM problem can be expressed in a matrix form. Decision matrix is a measure of performance of alternatives with respect to the attributes.

TOPSIS is one of the MCDM methods used for solving multi criteria problem. The mathematics of this method is selecting the best alternative having the shortest distance from the positive ideal solution and farthest from the negative ideal solution (Nadda et. al, 2018).

2.4 Research gap

Based on the referred literature's summary, it is concluded that most of the research is dedicated to steel and its alloy, very few researches have reported for non-ferrous alloys. Optimization of process parameters for aluminium-6082 is probably not investigated, although it has applications in several areas. Also, in the optimization of turning operation, very few input parameters are considered.

3. EXPERIMENT DETAILS

3.1 Machine tool

The importance of turning center is to reduce the diameter of internal or external cylindrical part, which is either held rigidly or rotating. Turning center also used for many other operations viz. facing, drilling, boring, counter sinking, counter boring, knurling and so forth. Turning center refers to the workpiece held between the chuck and live center. Turning center is used to turn all the types of materials (soft to hard) with high degree of precision. Specifications of machine tool are mentioned in table 3.

Table 3. Technical specifications of the Machine tool

Machine tool	Kirloskar™ - Turn Master-40
Rotational speed of the spindle	50 – 2240 rpm
Longitudinal feed rate	0.5 – 1.75mm/sec
Transverse feed rate	0.0015-0.18mm/sec
Swing over bed	400mm
Total traverse length	1200mm
Drive	All gear train

3.2 Work material

6082 aluminium alloy is an alloy from the wrought aluminium-magnesium-silicon domain. Aluminium alloy 6082 is a medium to high strength alloy with outstanding corrosion resistance. With the introduction of this fresh alloy comparatively, aluminium 6061 is replaced by aluminium 6082 due to its higher strength, in many applications. The addition of enormous amount of manganese controls the grain structure which in turn results in a stronger alloy. Chemical composition for the 6082 aluminium alloy is mentioned in table 4. Typical applications of aluminium alloy 6082 are high stress applications, ore skips, trusses, beer barrels, bridges, milk churns, cranes and transport applications.

Table 4. Mechanical properties and chemical composition of Aluminium-6082

Hardness-Brinel	91 HB
Hardness, Vickers	95
Machinability	Good (40%)
Tensile strength, yield	250 Mpa
Tensile strength, Ultimate	290 Mpa
Modulus of Elasticity	70 Gpa
Bulk Modulus	45 Gpa
Elongation at break	6-12%
Density	2710 kg/m^3
Chemical Composition	Si: 0.7-1.3% Fe: 0.0-0.5% Cu: 0.0-0.1% Mn: 0.4-1.0% Mg: 0.6-1.2% Zn: 0.0-0.2% Ti: 0.0-0.1% Cr: 0.0-0.25% Al: Balance

Mpa= Mega Pascal, Gpa=Gigapascal, HB= Hardness-Brinell, %=Percentage, Kg=Kilogram, m^3=Cubic meter

3.3 Applied coolant and characteristics

Many different types of coolants are available for machining operations, and they can be categorized as synthetic oil, soluble oils, mineral oil and straight oil. Current study uses Enklo-68, as water soluble oil. Metal grinding and cutting operation generates heat. The purpose of coolant is to reduce heat generation and increase its dissipation. Enklo-68 is generally preferred cutting oil. Oil composition has a rich level of petroleum and emulsifiers. The emulsion formed with this oil and water at high dilution is very stable. It can be used for wide range of grinding and machining operation, also provides very good cooling, rust protection and lubrication properties. While making emulsion always add oil to water as it easily mixes with water. Total 15 liters of oil is used in this experiment, in which the blend of water is 1/3.

3.4 Process parameters selection for quality attribute

Team meeting is gathered to identify process parameters. Through brainstorming exercise, team identified number of factors, which may affect the quality characteristics of MRR and R_a. Using Ishikawa diagram, identified factors are categorized in to six categories. Figure 2 shows the outcome of brainstorming exercise.

The Ishikawa diagram is mainly used to analyze the product, process and problem dispersion. It is employed to correlate, end effect of an event with probable root causes (Solanki and Desai, 2015).

As an outcome of this exercise, team has identified controllable factors. The cutting tool used in turning operations is CNMG 12 04 04-QM 235 with CVD coating. The nomenclature for CNMG 12 04 04-QM 235 is depicted in table 5.

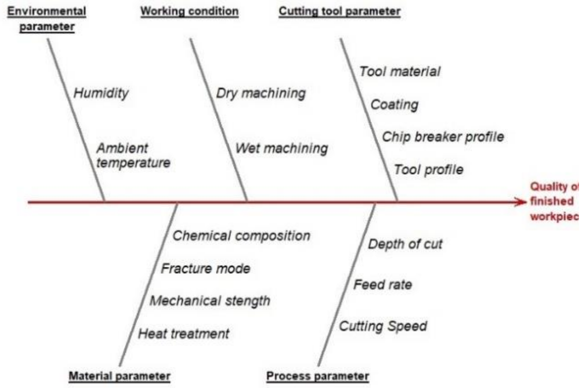
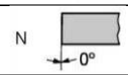
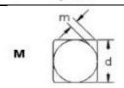


Figure 2. Ishikawa diagram for the quality of finished part during turning process

Table 5. Nomenclature of CVD coated CNMG 12 04 04-QM 235 tip

Index	Abbreviation	Explanation	
1	C	C- Shape Turning Insert	
2	N	Turning Insert with 0° clearance angle	
3	M	Turning insert tolerances (±0.002 to ±0.006)	
4	G	Turning insert with Cylindrical hole and Double-Sided Chip breaker	
5	12	Cutting edge length	12.90mm
6	04	Tool thickness	04.76mm
7	04	Nose radius	0.4mm
8	QM	Manufacturers designation for chip breaker	For medium turning process
9	235	Grade of tool	-

The team identified speed, feed rate and depth of cut as most significant parameters and decided to perform machining with wet condition. Before performing the experiment, it must be planned well. The careful planning is key for the successful application of DoE. In manufacturing industries, the machining process parameters are selected based on knowledge, skills of operator and standard handbooks. Many a times selected process parameters are not optimal, which leads to economic loss of production (Solanki et. al, 2020). Maximum performance of selected machine is obtained, if selected parameters are optimum. Team has conducted the primary test runs to identify range of process parameters. Table 6 represent the selected levels of process parameters.

Table 6. selected process parameters and levels

Speed (RPM)	180	450	710	1120
Feed (mm/sec)	0.18	0.25	0.32	0.40
Depth of Cut (mm)	0.2		0.6	
Tip	CVD coated CNMG 12 04 04-QM 235 insert			
Working condition	Anthromaxx-111 cutting oil (Wet)			

3.5 Selection of orthogonal array

Based on primary test runs, team had identified four levels for speed and feed rate, while two levels selected for depth of cut. This is the case of mixed level design. From Minitab statistical software, authors have identified number of options for the selection of OA. The details of available options for the selection of OA are mentioned in table 7. Authors have selected L16 OA with two factors at four level and one factor at two level. The details of experiment runs are mentioned in table 8. Table 9 represents physical description of the experiment, experimental setup and working conditions.

Table 7. Options for selection of orthogonal array with mixed level design

Runs	Level^Column	Level^Column
L8	4^1	2^2
L16	4^1	2^2
L16	***4^2***	***2^1***
L16	8^1	2^2
L18	2^1	3^2
L18	6^1	3^2
L32	2^1	4^2
L36	2^1	3^2
L36	2^2	3^1

Table 8. L_{16} orthogonal array

Sr. No.	Speed (rpm)	Feed (mm/sec)	Depth of cut (mm)
1	180	0.18	0.2
2	180	0.25	0.2
3	180	0.32	0.6
4	180	0.4	0.6
5	450	0.18	0.2
6	450	0.25	0.2
7	450	0.32	0.6
8	450	0.4	0.6
9	710	0.18	0.6
10	710	0.25	0.6
11	710	0.32	0.2
12	710	0.4	0.2
13	1120	0.18	0.6
14	1120	0.25	0.6
15	1120	0.32	0.2
16	1120	0.4	0.2

Table 9. Summary of experimental set-up

Work piece material	Aluminium-6082 (bar length 625mm, diameter 63mm, chuck holding length 27mm and effective length for turning 598mm)
Response variable	Material removal rate (MRR) and Surface roughness (R_a)
Control variables and levels	Cutting speed (180, 450, 710 and 1120 rpm), Feed rate (0.18, 0.25, 0.32 and 0.40mm/sec) and Depth of cut (0.2 and 0.6mm)
Tool material	CNMG 12 04 04-QM 235
Machine tool	Kirloskar™ - Lathe machine
Methodology	Taguchi's Orthogonal array, ANOVA, Regression analysis, TOPSIS and GRA
Selected orthogonal array	L-16 (with mixed level design)
Objective function	"Small-the-better" for R_a
	"larger-the-better" for MRR

3.6 Performance of experiment and data Collection

To perform the experiment, team has divided the entire length of the bar in to 16 parts. Each test run is performed on a specific length of 30mm.

Surface roughness is measured with the help of sophisticated surface texture measuring instrument SV-2100 of Mitutoyo Corporation. Measurement conditions are selected as, sample length of 25mm; total number of 16 samples and pitch of 1.0μm with filter setting of Gaussian element and speed of stylus movement is 0.5 mm/second.

Before performing the experiment, team has decided to perform Gage R&R study for the accuracy of surface measurement instrument. For performing Gage R&R test, team selected two operator and R_a value is computed for two repetition. Total five samples are tested to identify differences among operator and measurement system. The results of Gage R&R study are depicted in figure 3. It shows the variation among measurement is 1.9%, which is less than the prescribed limit of 10%. Henceforth, measurement system is accurate.

4 EXPERIMENTAL OBSERVATION AND ANALYSIS

4.1 Experiment results

Authors conducted experiments to identify effect of process parameters (i.e. WS, FR and DOC) on the "output response variable" (i.e. MRR and R_a). Table 10 and 11 shows the outcome results from the experiments. This study is performed with L_{16} OA, i.e., sixteen experiments are performed.

The experimental process is carried out for two iteration to minimize chances of error due to inherent characteristics of machine, from operator side, from metrology side and to avoid effect of environmental constraints. MRR is calculated using equation 1 and its values are mentioned in table 10, SNR and mean values for MRR are computed using equation 2 and 4 respectively. R_a value is measured using surface roughness tester. R_a value for all 16 experiments is mentioned in table 11. SNR and mean values for R_a are computed using equation 3 and 4, respectively.

$$MRR = \left(\frac{\frac{W_b - W_a}{T}}{\rho}\right) \times 1000 \quad (1)$$

$$SNR = -10 \times \log\left[\sum_{i=1}^{n}\left(\frac{1/Y^2}{n}\right)\right] \quad (2)$$

$$SNR = -10 \times \log\left[\sum_{i=1}^{n}\frac{Y^2}{n}\right] \quad (3)$$

$$Mean = \frac{\sum_{i=1}^{n} Y}{n} \quad (4)$$

W_b= Weight of aluminium bar before turning operation
W_a= Weight of aluminium bar after turning operation
T = Machining time (seconds)
ρ = Density of work material
N = Total number of runs in experiment
Y_i = Result of i^{th} run

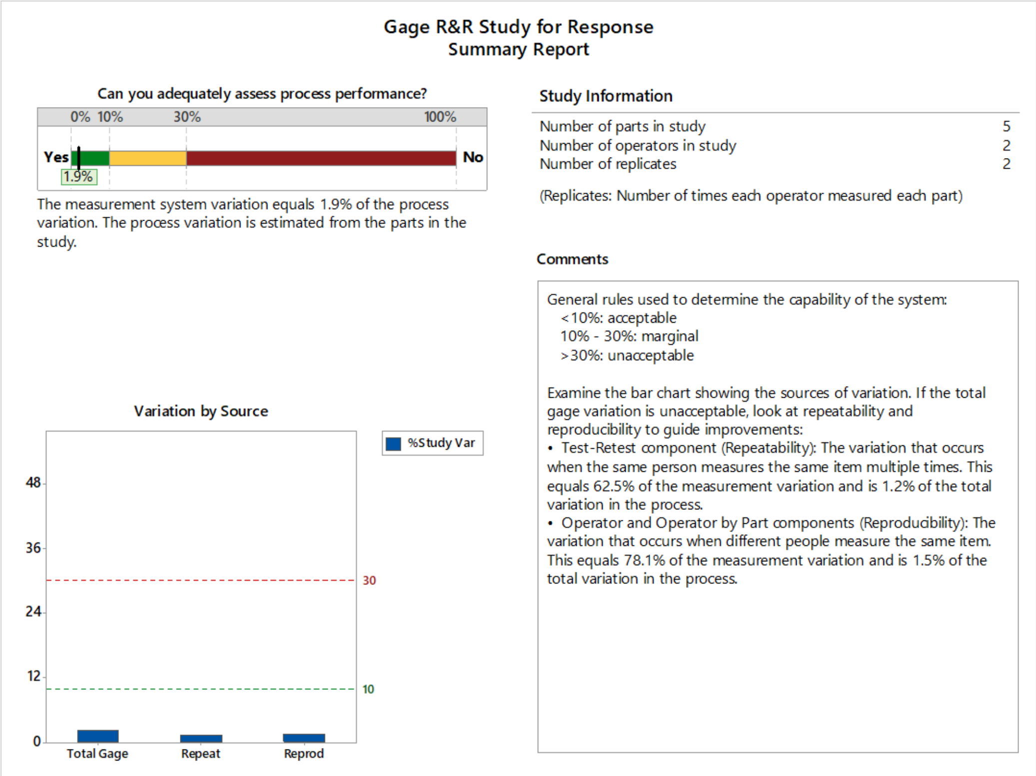


Figure 3. Summary report of Gage R&R study for surface texture measuring instrument

Table 10. Experimental results for MRR

Sr. No.	Run Order	Speed (rpm)	Feed (mm/sec)	Depth of cut (mm)	MRR for Iteration-1 (mm^3)	MRR for Iteration-2 (mm^3)	S/N Ratio for MRR (db)	Mean (mm)
1	8	180	0.18	0.2	0.43	0.48	-6.8791	0.455
2	11	180	0.25	0.2	0.60	0.63	-4.2302	0.615
3	3	180	0.32	0.6	2.28	2.35	7.2880	2.315
4	13	180	0.4	0.6	2.85	3.10	9.4467	2.975
5	7	450	0.18	0.2	0.42	0.65	-6.0400	0.535
6	2	450	0.25	0.2	0.60	0.75	-3.5751	0.675
7	10	450	0.32	0.6	2.60	2.90	8.7479	2.750
8	15	450	0.4	0.6	3.10	3.38	10.1866	3.240
9	6	710	0.18	0.6	1.35	1.42	2.8206	1.385
10	1	710	0.25	0.6	1.90	2.21	6.1820	2.055
11	14	710	0.32	0.2	0.95	1.05	-0.0326	1.000
12	16	710	0.4	0.2	1.23	1.10	1.2859	1.165
13	9	1120	0.18	0.6	1.45	1.62	3.6822	1.535
14	5	1120	0.25	0.6	1.85	1.99	5.6487	1.920
15	12	1120	0.32	0.2	0.80	0.68	-2.7011	0.740
16	4	1120	0.4	0.2	1.10	1.30	1.4930	1.200

Table 11. Experimental results for R_a

Sr No.	Run Order	Speed (rpm)	Feed (mm/sec)	Depth of cut (mm)	Surface roughness for Iteration-1 (µm)	Surface roughness for Iteration-2 (µm)	S/N Ratio for MRR (db)	Mean (mm)
1	8	180	0.18	0.2	0.95	0.96	0.4455	0.955
2	11	180	0.25	0.2	1.38	1.40	-2.8605	1.390
3	3	180	0.32	0.6	1.65	1.68	-4.4286	1.665
4	13	180	0.4	0.6	3.99	3.63	-11.6282	3.810
5	7	450	0.18	0.2	1.35	2.00	-4.6408	1.675
6	2	450	0.25	0.2	1.74	1.73	-4.7860	1.735
7	10	450	0.32	0.6	2.77	1.83	-7.4122	2.300
8	15	450	0.4	0.6	4.53	3.93	-12.5486	4.230
9	6	710	0.18	0.6	1.12	1.09	-0.8680	1.105
10	1	710	0.25	0.6	1.39	1.39	-2.8603	1.390
11	14	710	0.32	0.2	2.00	2.05	-6.1292	2.025
12	16	710	0.4	0.2	4.05	3.86	-11.9454	3.955
13	9	1120	0.18	0.6	1.41	1.23	-2.4316	1.320
14	5	1120	0.25	0.6	1.67	1.59	-4.2464	1.630
15	12	1120	0.32	0.2	2.20	2.22	-6.8879	2.210
16	4	1120	0.4	0.2	4.07	3.88	-11.9892	3.975

4.2 Analysis of results

A) Analysis of the signal to noise ratio and mean value

Material removal rate (MRR) and surface roughness (R_a) values are measured for all the combination of the input control factors. The behavior characteristic of MRR is "higher the better", i.e. higher value of MRR is good as it reduces the machining time. The behavior characteristic of the R_a is "smaller the better", i.e. lower value of roughness indicates better surface finish. Table 12 shows the value of SNR and mean for MRR. Table 13 shows the value of SNR and mean for R_a. At the end of experiment the average value of MRR and R_a is computed as 1.535mm and 2.210µm.

Table 12. Response table of MRR for SNR and mean

SNR response				Mean response		
Levels	Cutting Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)	Cutting Speed (rpm)	Feed Rate (mm/rev)	Depth of Cut (mm)
	A	B	C	A	B	C
Level-1	1.406	-1.604	-2.585	1.5900	0.9775	0.7981
Level-2	**2.564**	1.006	**6.750**	**1.8000**	1.3162	**2.2719**
Level-3	2.330	3.326		1.4012	1.7012	
Level-4	2.031	**5.603**		1.3488	**2.1450**	
Delta	1.158	7.207	9.335	0.4512	1.1675	
Rank	3	2	1	3		

Note: Bold value indicates optimum level, "larger-the-better" analysis conducted.

Analysis of the end effect of the process parameters (CS, FR and DOC) on response variable (MRR and R_a is performed with "SNR response table" and "mean response table".These values show the optimal level of process parameters for maximizing MRR and minimizing R_a. The level values mentioned in table 12 and 13 are also presented in the graphical form in figure 4(a) & (b) and figure 5 (a) & (b) for MRR and R_a respectively. Optimal values of control factors can also be determined from these graphs to maximize MRR. The best level factor for MRR is computed based on the highest value of SNR and mean. To maximize MRR specified levels of factors are, Cutting speed (Level-3, SNR 2.564 dB), Feed rate (Level-4, SNR 5.603 dB) and depth of cut (Level-2, SNR 6.750 dB). In other words, maximum MRR is obtained at chuck speed of 710 rpm, feed rate of tool 0.40mm/rev and depth of cut 0.6mm. Likewise, to minimize R_a specified levels of factors are, cutting speed (Level-1, SNR -4.618 dB), feed rate (Level-1, SNR -1.874dB) and depth of cut (Level-2, SNR -5.809), i.e. cutting speed 180rpm, feed rate 0.18mm/rev and depth of cut 0.6mm.

B) ANOVA

Analysis of variance (ANOVA) is used to determine statistical significance of control factors on response variable (Bhatt et. al, 2021, Solanki and Desai, 2020). ANOVA is employed here to identify control factors, which have a highest impact on MRR and R_a. Table 14 and 15 depict ANOVA for MRR and R_a respectively. The ANOVA is conducted with 95% (i.e. α=0.05) confidence interval. Cutting speed has DOF (3), Adj SS (0.5033), Adj MS (0.16777), F-value (6.66) and P-value (0.014). As the P-value (0.014) < 0.05, Cutting speed is statistically significant for MRR. Likewise, for feed rate

– DOF (3), Adj SS (3.0336), Adj MS (1.01120), F-value (40.15) and P-value (0.000). For depth of cut, P-Value (0.000). Feed rate and depth of cut, both are statistically significant for MRR, as P-value <0.05. For R_a value, cutting speed has P-value (0.000), feed rate has P-value (0.000) and depth of cut has P-value (0.283). Cutting speed and feed rate are statistically significant for R_a value as they have P-value<0.05. Since depth of cut has P-value > 0.05, it is not statistically significant.

Table 13. Response table of SNR and mean for R_a

	SNR response			Mean response		
Levels	**Cutting Speed (rpm)**	**Feed Rate (mm/rev)**	**Depth of Cut (mm)**	**Cutting Speed (rpm)**	**Feed Rate (mm/rev)**	**Depth of Cut (mm)**
Level-1	**-4.618**	**-1.874**	-6.099	**1.954**	**1.263**	2.239
Level-2	-7.347	-3.688	**-5.809**	2.485	1.536	**2.181**
Level-3	-5.451	-6.214		2.119	2..050	
Level-4	-6.389	-12.028		2.284	3.993	
Delta	2.729	10.154	0.296	0.531	2.730	0.058
Rank	2	1	3	2	1	3

Note: Bold value indicates optimum level, "smaller the better" analysis conducted.

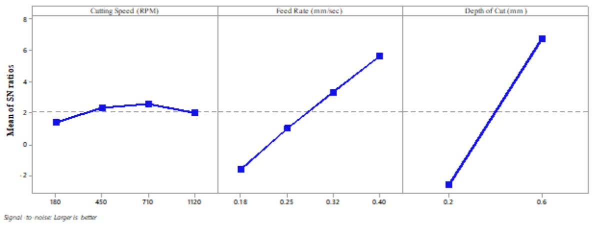


Figure 4 (a) SNR plot for MRR

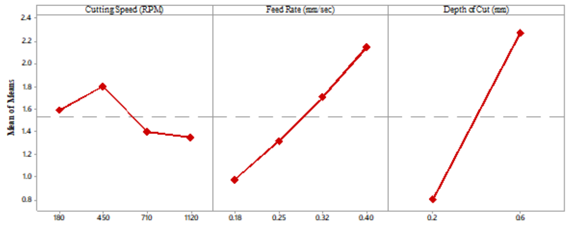


Figure 4 (b) Mean plot for MRR

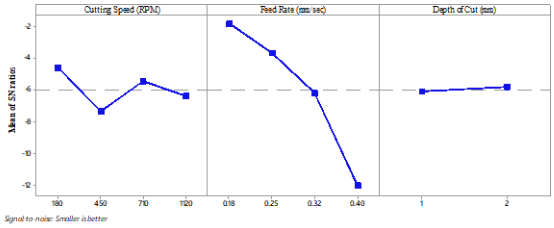


Figure 5 (a) SNR plot for R_a

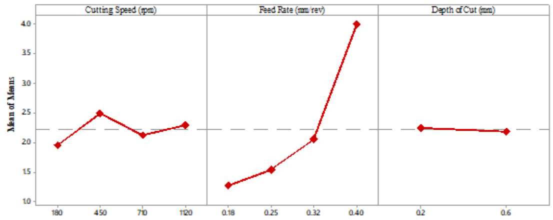


Figure 5 (b) Mean plot for R_a

C. Regression analysis

Regression analysis is used for the purpose of modeling and analysis. It is used to establish a relationship between a dependent variable and number of independent variables. In this case study, MRR and R_a are dependent variables, whereas, cutting speed (CS), feed rate (FR) and depth of cut (DOC) are independent variables. To obtain predictive analysis of MRR and R_a, linear regression model is used. The predictive equations for MRR and R_a, obtained from linear regression model are mention in equation 5 and 6 respectively.

$$MRR_1 = -1.248 - 0.000363CS + 5.32FR + 3.68DOC \quad (5)$$

$$R_{a1} = -1.299 + 0.00019CS + 12.09FR - 0.058DOC \quad (6)$$

Here, MRR_1 and R_{a1} shows the predictive equations for MRR and R_a. For MRR, R-sq (96.34%), R-sq(adj) (95.43%) and R-sq(pred) (93.74). similarly, for R_a, R-sq (82.81%), R-sq(adj) (78.52%) and R-sq(pred) (70.72). Thus, Values of R-sq, R-sq(adj) and R-sq (pred) are nearer to each other, model predicts relatively accurate outcome. Normal probability plot for MRR and R_a are plotted in figure 6(a) and (b). Actual versus predicted graphs for MRR and R_a is shown in figure 7(a) and (b).

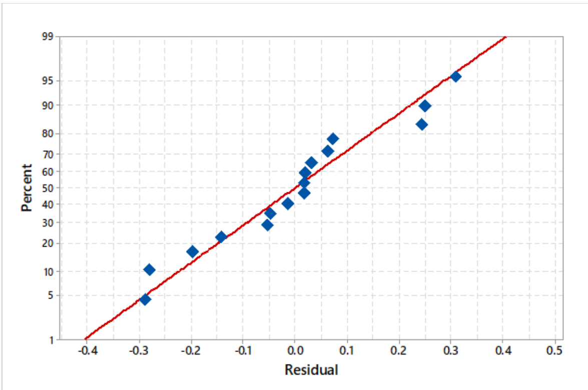


Figure 6(a). Normal probability plot for MRR

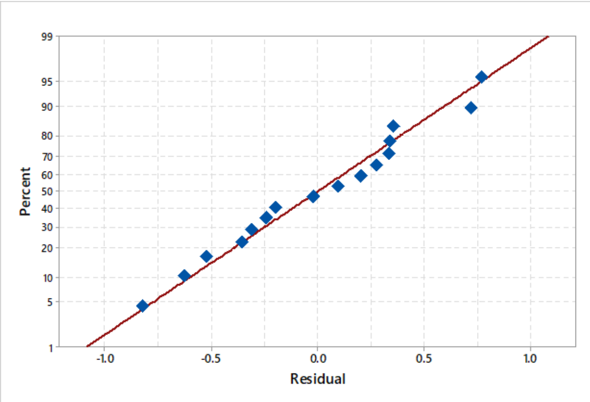


Figure 6(b). Normal probability plot for R_a

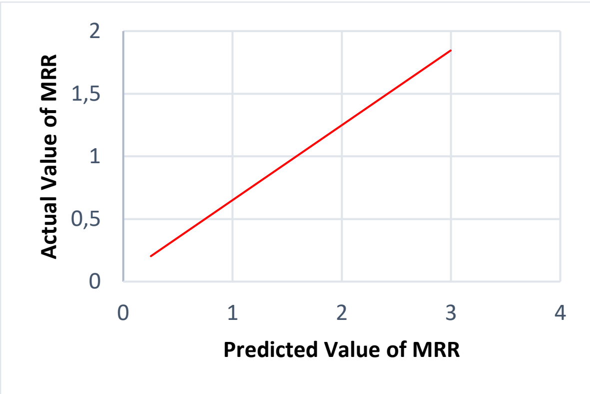


Figure 7(a). Actual and predicted value plot using linear regression for MRR

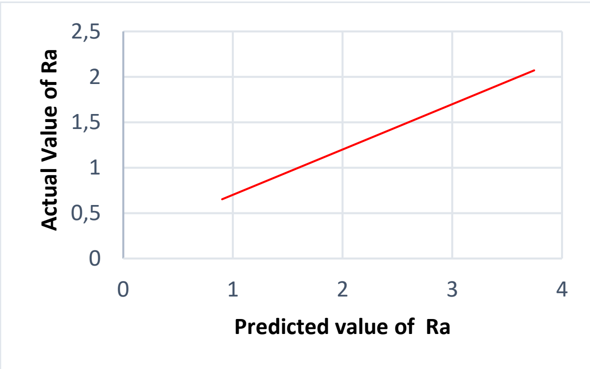


Figure 7(b). Actual and predicted value plot using linear regression for R_a

Table 14. ANOVA for MRR

Source	DOF	Adj SS	Adj MS	F-Value	P-Value
	A	B	C		
Cutting Speed	3	0.5033	0.1677	6.66	***0.014***
Feed rate	3	3.0336	1.0112	40.15	***0.000***
Depth of cut	1	8.6878	8.6877	344.93	***0.000***
Error	8	0.2015	0.02519		
Total	15	12.4262			

Table 15. ANOVA for R_a

Source	DOF	Adj SS	Adj MS	F-Value	P-Value
	A	B	C		
Cutting Speed	3	0.620	0.206	20.26	***0.000***
Feed rate	3	18.21	6.072	595.10	***0.000***
Depth of cut	1	0.135	0.012	1.32	0.283
Error	8	0.081	0.010		
Total	15	18.93			

D. Confidence interval estimation and conformance experiment

With Taguchi optimization technique, it is essential to conduct conformance experiment for optimized levels of control input parameters. For the estimation of optimum MRR and R_a, equation 7 and 8 are used.

$$MRR_{opt} = (A_2 - T_{MRR}) + (B_4 - T_{MRR}) + (C_2 - T_{MRR}) + T_{MRR} \quad (7)$$

$$R_{a\,opt} = (A_1 - T_{Ra}) + (B_1 - T_{Ra}) + (C_2 - T_{Ra}) + T_{Ra} \quad (8)$$

Here, (A_2, B_4, C_2) and (A_1, B_1, C_2) represents the optimum value of process parameters (i.e. (cutting speed, feed rate, depth of cut)), which are identified from table 12 and 13 for MRR and R_a respectively. T_{MRR} and T_{Ra} are the mean of all the MRR and R_a values obtained from the experiment (see table 12 and 13). From the calculations, it is estimated that T_{MRR}= 1.53499 mm and T_{Ra} = 2.0054 µm. As a result of calculations, Values of MRR_{opt} and R_{aopt} are estimated 3.14692 mm and 1.3872 µm. To identify accuracy of the optimized result confidence interval is estimated using following formula mentioned in equation 9.

$$CI_{MRR,Ra} = \sqrt{F_{\alpha,1,f_e} \times v_e \times \left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \quad (9)$$

Where, $n_{eff} = \frac{N}{1+T_{dof}}$

In equation 9, $F_{\alpha,1,f_e}$ is the F ratio at 95% confidence interval, f_e is the degree of freedom for error and α is the significance level (α=0.05). v_e referred to error of variance, R is the total replicates performed for confirmation experiment, n_{eff} are the effective number of replications. N is the total number of experiments and T_{dof} is the total degree of freedom for all the main variables. For MRR and R_a, f_e (8) (see table 14 and 15), $F_{0.05,1,8}$ = 5.32 (from F-table), $v_{e_{MRR}}$ (0.02519) (see table 14), $v_{e_{Ra}}$(0.01020) (see table 15) and R (3) (i.e. number of confirmation experiment are three). N (16*2=32) (i.e. Total sixteen experiments with two replicates) and total degree of freedom associated in the estimated mean (T_{dof}=7). For R_a, v_e (0.01020) (see, table 15)

$$n_{eff} = \frac{32}{1+7} = 4$$

$$CI_{MRR} = \sqrt{5.32 \times 0.02519 \times \left[\frac{1}{4}+\frac{1}{3}\right]} = 0.2796 \quad (10)$$

$$CI_{R_a} = \sqrt{5.32 \times 0.01020 \times \left[\frac{1}{4}+\frac{1}{3}\right]} = 0.1799 \quad (11)$$

Using equation 10 and 11, computed value of confidence interval for MRR and R_a is ± 0.1398 and ±0.0899, respectively. The estimated average optimal MRR and R_a value with 95% confidence interval is;

$MRR_{opt} - CI_{MRR} < MRR_{exp} < MRR_{opt} + CI_{MRR}$

$[3.14692-0.1398] < MRR_{exp} < [3.14692+0.1398]$

$3.00712 < MRR_{exp} < 3.28672$

$R_{aopt} - CI_{Ra} < R_{aopt} < R_{aopt} - CI_{Ra}$

$[1.3872-0.0899] < R_{aopt} < [1.3872+0.0899]$

$1.2973 < R_{aopt} < 1.4771$

E. Confirmation experiment

The last step in design of experiment is confirmation test (Dvivedi and Kumar, 2007). Total, three confirmation tests are carried out at the optimum levels of process parameters. For MRR, optimum settings (A_4, B_2, C_2) selected. The average response for turning process with three repetitions is computed as 3.2220 mm, which is within the limits of the confidence interval of the predicted optimal MRR. Likewise, For R_a, optimum process parameter settings (A_1, B_1, C_2) selected. The mean response for turning process with three repetitions is computed as 1.4238 µm, which is within the limits of the confidence interval. Hence, computed optimal process parameters are verified.

5. APPLICATION OF MULTI-CRITERIA DECISION MAKING (MCDM) TECHNIQUE

5.1 TOPSIS

TOPSIS is one of the MCDM method used for solving conflicting criteria problems. The concept of TOPSIS method is identification of the best alternative solution, which has shortest distance from the best positive ideal solution and farthest distance from the negative ideal solution (Nguyen et. al, 2018). Criteria are categorized as cost and benefit. Cost criteria are "smaller-the-better" (e.g. R_a), benefit criteria are "larger-the-better" (e.g. MRR). The steps for TOPSIS are as follow.

Step-1: Formulation of decision matrix

The first step in TOPSIS method is the formulation of decision matrix and identification of cost and benefit attributes. In present case study, material removal rate (MRR) is considered as a benefit criterion, which indicates higher value is preferable. Surface roughness (R_a) of aluminium-6082 is considered as a cost criterion that indicates lower value of surface roughness is preferable. Assume that P alternatives must be evaluated against Q criteria then the decision matrix (D) has an order of P×Q. (i.e. $D_{16\times2}$)

$$D_{P\times Q} = \begin{bmatrix} x_{11} & x_{12} & \cdots & \cdots & x_{1j} & \cdots & \cdots & \cdots & x_{1Q} \\ x_{21} & x_{22} & \cdots & \cdots & x_{2j} & \cdots & \cdots & \cdots & x_{2Q} \\ \vdots & \vdots & & & \vdots & & & & \vdots \\ x_{i1} & x_{i2} & \cdots & \cdots & x_{ij} & \cdots & \cdots & \cdots & x_{iQ} \\ \vdots & \vdots & & & \vdots & & & & \vdots \\ x_{P1} & x_{P2} & \cdots & \cdots & \cdots & \cdots & \cdots & \cdots & x_{PQ} \end{bmatrix}$$

Where, X_{ij} (i=1, 2…P and j= 1, 2...Q) represents value of i^{th} alternative against j^{th} criterion. For existing case study, the average value of MRR and R_a is taken for the TOPSIS study and the decision matrix appears as shown below.

$$D = \begin{bmatrix} 0.455 & 0.955 \\ 0.615 & 1.390 \\ 2.315 & 1.665 \\ 2.975 & 3.810 \\ 0.535 & 1.675 \\ 0.675 & 1.735 \\ 2.750 & 2.300 \\ 3.240 & 4.230 \\ 1.385 & 1.105 \\ 2.055 & 1.390 \\ 1.000 & 2.025 \\ 1.165 & 3.955 \\ 1.535 & 1.320 \\ 1.920 & 1.630 \\ 0.740 & 2.210 \\ 1.200 & 3.975 \end{bmatrix}$$

Step-2: Normalised Matrix

The measuring unit for different property are different. Hence, it is necessary to bring all the data in standard normalised form using equation 12.

$$N_{ij} = \frac{x_{ij}}{\sqrt{\sum x_{ij}^2}} \qquad (12)$$

$$N = \begin{bmatrix} 0.0185 & 0.0269 \\ 0.0250 & 0.0393 \\ 0.0943 & 0.0471 \\ 0.1211 & 0.1077 \\ 0.0218 & 0.0474 \\ 0.0275 & 0.0491 \\ 0.1120 & 0.0650 \\ 0.1319 & 0.1196 \\ 0.0564 & 0.0312 \\ 0.0837 & 0.0393 \\ 0.0407 & 0.0573 \\ 0.0474 & 0.1118 \\ 0.0625 & 0.0373 \\ 0.0782 & 0.0461 \\ 0.0301 & 0.0625 \\ 0.0489 & 0.1124 \end{bmatrix}$$

Step: 3 Weighted normalised Matrix

Weighted normalised matrix (W_{ij}) is computed by multiplication of respective column of normalised matrix with associated weight of criterion. The associated weights of criterion are taken as 0.67 for MRR and 0.33 for R_a.

$$W = \begin{bmatrix} 0.0124 & 0.0089 \\ 0.0268 & 0.0130 \\ 0.0632 & 0.0155 \\ 0.0812 & 0.0356 \\ 0.0146 & 0.0156 \\ 0.0184 & 0.0162 \\ 0.0750 & 0.0215 \\ 0.0884 & 0.0395 \\ 0.0378 & 0.0103 \\ 0.0561 & 0.0130 \\ 0.0273 & 0.0189 \\ 0.0318 & 0.0369 \\ 0.0419 & 0.0123 \\ 0.0524 & 0.0152 \\ 0.0202 & 0.0206 \\ 0.0327 & 0.0371 \end{bmatrix}$$

Step 4: Calculation of positive and negative ideal points

The positive (Ψ) and negative (λ) ideal reference points are determined from normalised weighted matrix using following relation.

$$\Psi = (d_1^+, d_2^+ \dots . d_N^+)$$
$$\lambda = (d_1^-, d_2^- \dots . d_N^-)$$

Where,
d_i^+= Maximum value from jth column, if it is benefit criterion and minimum value from jth column, if it is cost criterion

$$d_i^+ = (0.0884{,}0.0089)$$

d_i^-= Minimum value from jth column, if it is benefit criterion or maximum value from j^{th} column, if it is cost criterion

$$d_i^- = (0.0124{,}0.0395)$$

Step 5: Calculation of Euclidian distance

The Euclidian distance of all the alternatives from the positive and negative ideal solution computed using following relation.

$si+=j=1N(Wij-di+)2$ and
$si-=j=1N(Wij-di-)2$ for i=1,2, 3…M.
Si+ is positive ideal and Si- is negative ideal solution.

Step 6: separation measure

The separation measure from Euclidian distance, can be computed using following relation.

$$s = \frac{s_i^-}{s_i^- + s_i^+}$$

Based on the separation measure, best alternative with highest value is selected. In current case study, alternative 7 ((i.e., CS (450rpm), FR (0.32mm/rev) and DOC (0.6mm)) is optimum. Table 16 depict Euclidian distance, separation measure and ranking alternative.

Table 16. Euclidian distance, separation measure and ranking of alternative

Alternative (Run Order)	s_i^+	s_i^-	s	Rank
A-1	0.9738	0.5690	0.3688	9
A-2	0.9583	0.5348	0.3582	10
A-3	0.4903	0.7030	0.5891	04
A-4	0.4818	0.8258	0.6315	02
A-5	0.9684	0.5053	0.3429	12
A-6	0.9529	0.4990	0.3437	11
A-7	***0.3142***	***0.8140***	***0.7215***	***01***
A-8	0.5690	0.9738	0.6312	03
A-9	0.8120	0.5813	0.4172	08
A-10	0.5948	0.6558	0.5244	05
A-11	0.9051	0.4679	0.3408	13
A-12	0.9959	0.1324	0.1173	16
A-13	0.7710	0.4778	0.4284	07
A-14	0.6472	0.6073	0.4841	06
A-15	0.9510	0.4368	0.3148	14
A-16	0.9919	0.1361	0.1207	15

5.2 GREY Relation analysis (GRA)

Grey relation analysis functions on the normalisation of data between zero and one. This process is referred as Grey relation generation. Based on normalisation process, grey relation coefficient is computed to represent a correlation between actual and desired data. The overall grey relation grade is calculated by averaging the grey relation coefficient. This process converts multi-objective optimization problem into a single response function with stated aim of maximization of grey relation grade (Esme et. al, 2009).

Step-1: Normalization of data

Normalization process converts all the data values between zero and one. For a data set have a characteristic of "higher-the-better" (i.e. MRR) can be normalized by equation 13.

$$x_i(k) = \frac{y_i(k) - min\ y_i(k)}{max\ y_i(k) - min\ y_i(k)} \qquad (13)$$

For a data set have a characteristic of "smaller-the-better" (i.e. R_a) can be normalized using equation 14.

$$x_i(k) = \frac{max\ y_i(k) - y_i(k)}{max\ y_i(k) - min\ y_i(k)} \quad (14)$$

Where, $x_i(k)$the value of alternative is after the grey relation generation, $y_i(k)$ is the kth response. $min\ y_i(k)$ and $max\ y_i(k)$ are the smallest and largest value of $y_i(k)$ for kth response. An ideal sequence is $x_0(k)\ (k = 1,2,3, \ldots 16)$. Table 17 shows grey normalized matrix.

Table 17. Grey normalized matrix

MRR	R_a
1.000	0.0000
0.9425	0.1341
0.3321	0.2180
0.0952	0.8720
0.9713	0.2210
0.9210	0.2393
0.1759	0.4116
0.0000	1.0000
0.6661	0.0473
0.4255	0.1341
0.8043	0.3277
0.7451	0.9162
0.6122	0.1128
0.4740	0.2073
0.8977	0.3841
0.7325	0.9223

Step-2: Grey relation coefficient

The grey relation coefficient indicates relationship between all selected alternatives. The grey relation coefficient $\xi_i(k)$ can be computed using following equation 15.

$$\xi_i(k) = \frac{\Delta_{min} - \gamma\Delta_{max}}{\Delta_{0i}(k) + \gamma\Delta_{max}} \ (15)$$

Where, $\Delta_{0i}(k)$ is subtraction of the absolute value of $x_i(k)$and$x_0(k)$, $\Delta_{0i}(k) = \|x_i(k) - x_0(k)\|$, γ is the distinguish coefficient ($\gamma = 0.5$), $\Delta_{min} = \forall_j^{min} \in i\forall k^{min}\|x_0(k) - x_i(k)\|$= smallest value of $\Delta_{0i}(k)$ and $\Delta_{max} = \forall_j^{max} \in i\forall k^{max}\|x_0(k) - x_i(k)\|$ = largest value of $\Delta_{0i}(k)$. Table 18 shows grey relation coefficient matrix.

Table18. Grey relation coefficient matrix

MRR	R_a
0.3333	1.0000
0.3466	0.7885
0.6009	0.6964
0.8401	0.3644
0.3398	0.6934
0.3519	0.6763
0.7397	0.5485
1.0000	0.3333
0.4288	0.9136

Table18. Grey relation coefficient matrix (continued)

MRR	R_a
0.5403	0.7885
0.3833	0.6041
0.4016	0.3531
0.4496	0.8159
0.5134	0.7069
0.3577	0.5655
0.4057	0.3515

Step-3: Grey relation grade

Before computing grey relation grade, grey relation coefficient values are multiplied with respective weights (i.e. MRR (0.67) and R_a (0.33)). Grey relation grade can be computed using following relation,

$$\epsilon_i = \frac{1}{n}\sum_{i=1}^{n} \xi_i(k) \quad (16)$$

Where, n is the total number of the process responses, higher value of grey relation grade indicates the strong correlation between reference sequence $x_0(k)$ and given sequence $x_i(k)$. Henceforth, higher grey relation grade indicates given alternative is closer to optimal. Table 19 shows the grey relation grade and ranking of alternative based on GRA.

Table 19. Grey relation grade and ranking of alternative

Alterative	Grey relation grade	Rank
A-1	0.2767	09
A-2	0.2462	10
A-3	0.3162	04
A-4	0.3416	02
A-5	0.2283	12
A-6	0.2295	11
A-7	0.3383	03
A-8	0.3900	01
A-9	0.2944	06
A-10	0.3111	05
A-11	0.2281	13
A-12	0.1928	16
A-13	0.2852	08
A-14	0.2886	07
A-15	0.2132	14
A-16	01939	15

6. Concluding remarks

6.1 Significance of the case study

This case study constitutes a great contribution in the field of turning process as it explores initial optimal working condition including CS, FR and DOC parameters to optimize MRR and R_a as quality characteristics. The study uses application of Taguchi's orthogonal array for the generation of trial runs. The selected process parameter combination also has significant effect on machining time, tool wear and associated cost. Thus, machining industries can get benefit through this study that details identification and optimization of process parameters for machining of aluminium-6082.

6.2 Conclusion

In the existing case study, design of experiment is used to plan the experiment. The turning of aluminium-6082 is done with CVD coated tool tip CNMG 12 04 04-QM 235 and Enklo-68 water soluble cutting oil as working conditions. Based on SNR and mean value, optimum cutting conditions are identified for MRR and R_a. Statistical significance of process parameters is decided with ANOVA. Confirmation test is carried out to verify selected optimum levels of process parameters. Taguchi method is integrated with TOPSIS and GRA to identify levels of factors for multi-criteria optimization of MRR and R_a. Based on this case study, following conclusions are drawn.

- Taguchi method is effective tool to optimize process parameters with limited number of trials.
- CVD coated carbide inserts with cutting oil Enklo-68 works very well with aluminium-6082 and is recommended for turning of aluminium-6082.
- The optimal levels of process parameters for MRR and R_a is observed at $A_2B_4C_2$ (i.e. cutting sped 450rpm, feed rate 0.4mm/sec and depth of cut 0.6mm) and $A_1B_1C_2$ (i.e. cutting sped 180rpm, feed rate 0.18mm/sec and depth of cut 0.6mm).
- As per the statistical analysis, depth of cut is most significant parameter for MRR, and feed rate is most significant parameter for R_a.
- Developed linear regression model shows very high correlation for MRR (0.96) between actual experimental results and predicted results. The correlation value for R_a is (0.82).
- TOPSIS and GRA methodology has been found effective for identification of optimal process parameter combination for best machining performance combination of MRR and R_a. TOPSIS suggests optimal setting as $A_2B_3C_2$ (i.e. cutting sped 450rpm, feed rate 0.32mm/sec and depth of cut 0.6mm). While, GRA suggests optimal process parameter setting as $A_2B_4C_2$ (i.e. cutting sped 450rpm, feed rate 0.40mm/sec and depth of cut 0.6mm).

6.3 Limitations and future work

Limitation of this study is that the experiment involved a few numbers of process parameters. In future, several more process parameters shall be considered. A further limitation is that the study involved gear drive turning center; however, in future work, a precise CNC machine tool can be used to compare current results with future results. Moreover, there are no studies reported related to the machining of Aluminium-6082, the selected range of process parameter (Cutting speed (180 to 1120 rpm), feed rate (0.18 to 0.40mm/sec), depth of cut (0.2 to 0.6mm)) would be not wide enough. Thus, the study should involve a wide range of process parameter to further optimized process parameters. Another limitation of existing case study is that statistical analysis shows the value of R-sq and R-sq(adj) for R_a is 82.81 and 78.52 respectively. It is better to have both the values above 95% and nearly the same. It is suggested to improve these values in extended analysis.

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Mihir Solanki
G.H. Patel College of Engineering & Technology,
Anand - Gujarat,
India
mihirsolanki@gcet.ac.in

Aakarsh Jain
G.H. Patel College of Engineering & Technology,
Anand - Gujarat,
India
akarshjain@gcet.ac.in