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Optimization of Cutting Parameters for Milling Process of (4032) Al-Alloy using Taguchi-Based Grey Relational Analysis

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Abstract

The objective of this work is to study the influence of end milling cutting process parameters, tool material and geometry on multi-response outputs for 4032 Al-alloy. This can be done by proposing an approach that combines Taguchi method with grey relational analysis. Three cutting parameters have been selected (spindle speed, feed rate and cut depth) with three levels for each parameter. Three tools with different materials and geometry have been also used to design the experimental tests and runs based on matrix L9. The end milling process with several output characteristics is solved using a grey relational analysis. The results of analysis of variance (ANOVA) showed that the major influencing parameters on multi-objective response were spindle speed and cutting tool with contribution percentage (52.75%, 24%), respectively. In addition, the optimum combination of end milling process parameters was then validated by performing confirmation tests to determine the improvement in multi-response outputs. The confirmation tests obtained a minimum (surface roughness and micro-hardness) and maximum metal removal rate with grey relational grade of 0.784 and improvement percentage of 2.3%.

Keywords: *Al-alloy 4032, end milling process, grey relational analysis, multi-objective optimization, Taguchi method.*

1. Introduction

There is an increase in the demand to produce complex 3D shapes with sharp edges, better surface quality (low surface roughness and hardness), maximum productivity and low-cost machining such as production cars, die sinking and many engineering industries. This has led to increase the demand to use the traditional cutting operations such as milling cutting operation rather than using the non-traditional operations.

The milling process is the one important part of the conventional machining process, which can machine fine, rough, unsymmetrical, slot and curved surfaces by movement of the work part against a rotating multi-flute cutting tool. The machines used in the milling process can be classified as either vertical or horizontal machines [2,6-8,11,16].

There are three main parameters (spindle speed, feed rate, and cut depth) found in any type of milling machine, as well as other parameters that influence the milling process such as (cutting tool and workpiece material), which can give the designer and worker (operator) flexibility to change, select, and control between them to achieve high quality, maximum productivity, and practical properties of the milling process [2-8].

The end milling process is an important type of milling operation, which is used to machine simple and complex surfaces with faster removal rate and high quality of the surface. The cutting tool used in the end milling process is called an end mill cutter with a diameter less than the width of the work part and has number of flutes (teeth) starting from 2 flutes. The vertical milling machine is used in the end milling process because the cutter rotates vertically against the workpiece. In the end milling process, the tool path required to machining and finish product is performed in one pass or in multi-passes depending on the width of the workpiece, diameter of the cutter and depth of cut [6-8,11].

In recent years, the Computer Numerical Control (CNC) system has been used to convert a manual milling machine into a full automation machine (CNC milling machine), which can control the movement of end mill cutter using coded (G and M) instructions processed by a computer and the capability to perform repeat tasks with high accuracy [2-8].

The used CNC offers additional flexibility, computational capability, provides high enhancement in productivity and quality of the machining surface compared with using a conventional NC machine.

In recent years, AL-alloys have developed as the superior alloys used for different applications such as automobile, aerospace industries and die parts manufacturers because of their desirable characteristics such as high resistance to corrosion and wear, great electrical and thermal conductivity, high strength, less weight. [4,6,8,12,13].

The measurement of surface roughness is a significant performance quality of the machined surface in machining processes, which affects mechanical properties like fatigue, corrosion resistance, creepage, and other useful features like friction, wear, lubrication, electrical conductivity, and so on [3,7-9,13-16].

The rate of metal removal is important performance productivity in machining processes. To increase the productivity which leads to performed machining processes with less time and cost. The rate of metal removal can be estimated depended on cutting parameters with cutter flutes or measurement by difference weight to cutting time [1,6,11].

Micro-hardness is an important element in determining the surface integrity during the machining process. Micro-hardness calculation is used to assess the machined surface's functional activity and to calculate the work hardening effect caused by machining operations. The difference between machining impacted areas and the bulk metal is determined using micro-hardness calculation [3,9,14,15].

However, single objective methods such as Taguchi analysis have a minimal value in deciding the optimum cutting parameters as many distinct and incompatible objectives must be tailored at the same time. As a result, cutting parameter optimization has reported multi-objective methods that consider many distinct and conflicting objectives [1-16].

Grey relational analysis is an important tool for optimizing the complex inter-relationships between multiple output characteristics. In addition, the grey relational grade is obtained by grey relational analysis, which can be determine the various output characteristics. As an outcome, optimization of the complex multiple output characteristics can be translated into the optimization of a single grey relational grade. For combining grey relational method and the Taguchi analysis, the grey-Taguchi method was developed. The grey-Taguchi approach has been used to effectively optimize the various output characteristics of complex manufacturing operations [1-6,10-16].

Many attempted optimization studies have investigated the effect of cutting parameters of the end milling process by using grey relational analysis based on the Taguchi method for multi-response optimization for Al-alloys.

In this study, the effect of cutting parameters (spindle speed, feed and depth) is investigated combining with tool material and geometry on the multi-performance of the end milling process (low surface roughness and micro-hardness, high metal removal rate), through analyzing the measurement of the outputs by used grey relational analysis based on Taguchi method for Al- alloys.

2. Experimental Procedures

2.1 Workpiece Material and Dimension

The raw material used in the experiments was Al-alloy 4032 with chemical compositions and mechanical properties shown in Table 1,2. It was provided in the form of a block with dimensions (60 mm x 90 mm x 70 mm). The workpiece material was cut into nine blocks with dimensions of (60×42×12 mm) from the origin block to perform experiments as shown in figure (1).

This alloy is used in applications such as (Forgings for the automobile industry, engine pistons, valves and hydraulic parts) and has superior wear resistance and low coefficient of thermal expansion. As a result, it is advised that high-temperature materials are needed to be used.

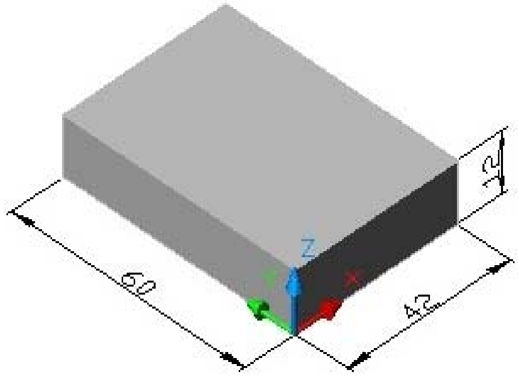

Fig. 1. The workpiece with its dimensions.

Table 1,
Chemical composition for Al-alloy (4032)

Element	Al	Si	Mg	Cu	Ni	Cr	Zn	Fe
Concentration (wt %)	84.2	11.7	1.1	0.7	0.9	0.1	0.1	1.2

Table 2,
Mechanical properties for Al-Alloy (4032)

Tensile strength	Young's Modulus	Vickers Hardness
368 MPa	78 GPa	137 HV

2-2 Cutting Tool

Three cutting tools were used in the experiments as shown in figure (2) and materials, dimensions are presented in the Table 3.

Fig. 2. Tools (end mill cutters) used in experimental work.

Table 3,
Materials and dimensions of cutting tools used in the experiments.

No.	Tool type	Mill diameter (mm)	Shank diameter (mm)	No. of flutes (teeth)	Cut length (mm)	Total length (mm)	Helix angle
1	H.S.S	14	16	4	40	84	30°
2	H.S.S Coated with TiN	14	12	4	26	80	30°
3	Carbide-titanium	14	14	5	26	81	45°

2.3 CNC Vertical Milling Machine

A computerized Numerical Control (CNC) vertical milling machine shown in figure 3, was used to machining workpieces of AL-alloys (4032), using the tools mentioned above at specified cutting parameters (spindle speed, feed rate and cut depth). Description to the specifications of the CNC machine is given in the Tables 4 and 5.

Fig. 3. CNC Vertical Milling Machine used in the experimental work.

Table 4,
Description of the specifications of the CNC machine (Knuth Rapimill 700)

Specifications	Data
Table dimensions	300 x 770 mm
T-slots	16 x 3 x 80 mm
Table load	120 Kg
Movements	
X-axis	400 mm
Y-axis	300 mm
Z-axis	250 mm
Distance from spindle nose to Table surface	100 - 350 mm
Distance from spindle center to bed	350 mm
Feed	
Rapid speed of the axes x, y, z	30000 rpm
Cutting feed x, y, z	4000 rpm
Spindle	
Spindle speed	10000 rpm
Motor	
The required operating air pressure	6 kg / cm2
Dimensions L*W*H	1570 x 2135 x 2175 mm
Machine weight	2200 kg
Motor-spindle CNC	3.7 kW / 4.7 kW
X, Y, Z motor	0,7 Kw
Motor spindle	5.5 kW / 7.5 kW
X, Y, Z servo	1.2 kW

2.4 Experimental Design and Selection of Cutting Parameters

To investigate the influences of cutting parameters, tool material and geometry on the process performance (surface roughness, micro-hardness, metal removal rate), grey relational analysis based on the Taguchi method have been used. For this study, three cutting tools and three cutting parameters (spindle speed, feed rate, and cut depth) were chosen at three levels. Running of the experimental tests depended on a matrix L9 (4 factors * 3 levels) of Taguchi analysis. In order to clarify the reasons for improvements in the results response, changes in the cutting parameters have been made. Nine tests have been performed and the work procedures have been presented in the flow chart as shown in figure 4. As seen in the Table (5), one parameter changed at three different levels in each test, while the other parameters remained unchanged [2,4-8,11,15-18].

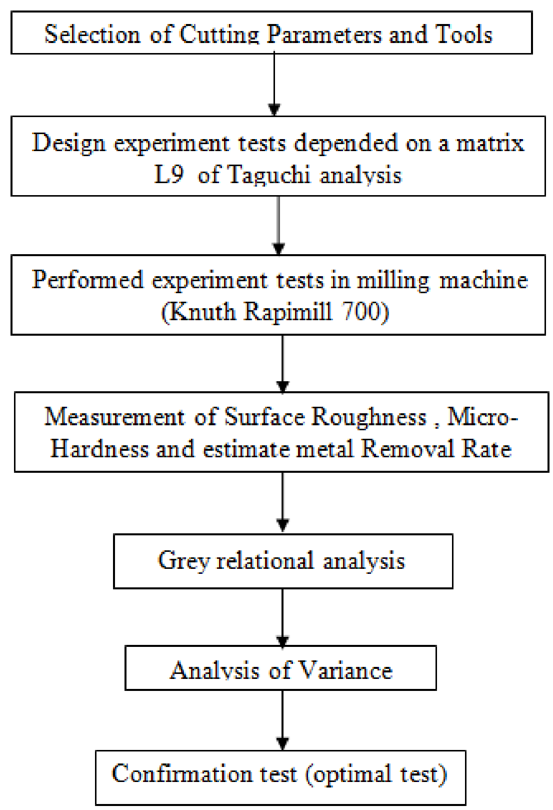

Fig. 4. Flow chart of work procedures.

Table 5,
Cutting tools and machine cutting parameters.

Test No.	Type of tool (A)	Levels of control factors Spindle speed (B) r.p.m	Feed rate(C) mm/tooth	Depth of cut (D) mm
1	H.S.S	2000	0.03	0.5
2		3000	0.06	1
3		4000	0.1	1.5
4	H.S.S Coated with TiN	2000	0.06	1.5
5		3000	0.1	0.5
6		4000	0.03	1
7	Carbide-titanium	2000	0.1	1
8		3000	0.03	1.5
9		4000	0.06	0.5

2.5 Cutting Procedure

Nine samples of Al-alloy (4032) with dimensions of (60 x42 x 12) mm were prepared as a block. Then, the nine samples of Al-alloy (4032) were machined again by an end mill cutter into three lines of each sample, as shown in figure (5).

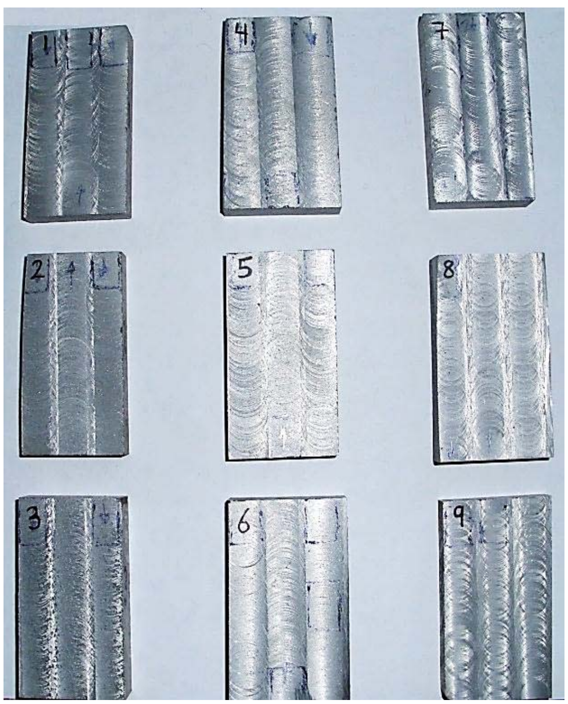

Fig. 5. Cutting procedure using CNC vertical milling machine system for Al-alloy (4032) samples.

3. Measurements

3.1 Surface Roughness (Ra)

Surface roughness was measured on all cutting surfaces of all samples using Pocket surf the portable roughness of the Surface Gauge Mahr federal's patent. Four readings were taken from the (Ra) instrument for each machining line of sample, and the average value of the four readings was recorded. Figure 6 shows the instrument used in the experiments, and the results were presented in the Table (6).

Fig. 6. Measurement of surface roughness.

3.2 Metal Removal Rate (MRR)

The material removal rate was used, which is the important factor of production rate in the milling process used in optimization criterion, to calculate material removal rate applied by equation (1) and the results were presented in the Table (6) [6,10].

$$MRR = n * N * f_t * dc * d_T \quad ...(1)$$

where (n is spindle speed in r/min, N is tool flutes, f_t is feed rate in mm/tooth, dc is depth of cut in mm and d_T is width of cut in mm (diameter of tool)).

3.3 Micro-Hardness

The Vickers micro-hardness instrument was used in this study, and hardness micro-measurement was performed at three locations along each line of milled surface samples, with the average value considered for further analysis using the automatic micro hardness tester as shown in figure (7). This device operates on the concept of impressing a diamond in the shape of a square-based pyramid onto the examined surface of a load-bearing material. The hardness testing was done by taking a 200 g indentation load with a dwell time of 15 s. The results are presented in the Table (6).

Fig. 7. Digital micro-hardness tester.

Table 6,
Experimental results of measured outcomes quality characteristics.

Test NO.	Levels of control factors: Type of tool (A)	Spindle speed (B) r.p.m	Feed rate (C) mm/tooth	Depth of cut (D) mm	Ra(µm) mean	MRR (mm^3/min)	Surface hardness HV0.2
1	H.S.S	2000	0.03	0.5	2.344	1680	159.45
2		3000	0.06	1	3.141	10080	154.32
3		4000	0.1	1.5	3.442	33600	167.19
4	H.S.S Coated with TiN	2000	0.06	1.5	3.925	10080	178.27
5		3000	0.1	0.5	2.204	8400	148.63
6		4000	0.03	1	1.964	6720	151.54
7	Carbide-titanium	2000	0.1	1	2.678	14000	163.72
8		3000	0.03	1.5	2.017	9450	140.81
9		4000	0.06	0.5	1.883	8400	143.39

4. Analysis Methods to Estimate Optimal Cutting Parameters (Results and Discussion)

4.1 Grey Relational Analysis

The GRA is a method for determining and clarifying relationships among multiple responses. The grey relational analysis consists of four steps, as detailed below [1-6,10-16]:

1- Grey relational generation, which normalizes outputs in the range (0 to 1), this step is known as data pre-processing by Input the experimental results to calculate GRA performance characteristic. For the Grey relational generation, there are two forms of data pre-processing.

Surface roughness and micro-hardness data pre-processing, which has the lower-the-better performance characteristic, it is possible to express as follows in this equation.

$$X_i^*(k) = \frac{\max X_i^0(k) - X_i^0(k)}{\max X_i^0(k) - minX_i^0(k)} \quad ...(2)$$

The metal removal rate data pre-processing, which has a higher-the-better performance characteristic, can be described as follows:

$$X_i^*(k) = \frac{X_i^0(k) - minX_i^0(k)}{\max X_i^0(k) - minX_i^0(k)} \quad \text{... (3)}$$

where i is the test number, from 1 to 9; k represents the k^{th} performance characteristic ; $X_i^*(k)$ is the normalized value; $X_i^0(k)$ is the original value; $minX_i^0(k)$ is the smallest value of $X_i^0(k)$ and $\max X_i^0(k)$ is the largest value of $X_i^0(k)$.

2- Grey relational coefficients, which is an equation for expressing the relationship between ideal and true normalized experimental outcomes. This is how the Grey relational coefficient is expressed:

$$\xi_i(k) = \frac{\Delta\min + \varepsilon\, \Delta\max}{\Delta_{oi}\,(k) + \varepsilon\, \Delta\max} \quad \text{... (4)}$$

Where Δmin is the minimum value of Δ_{oi} in this study which is equal to (0); Δmax is the maximum value of Δ_{oi} in this study which is equal to (1); $\Delta_{oi}\,(k)$ the deviation sequence determine using the equation $\Delta_{oi}\,(k) = \|X_0^*(k) - X_i^*(k)\,\|$, ε is a positive number (0, 1). The value of ε may be changed to fit the needs of the service users, and a smaller value of ε means better distinguishing ability. In this study, ε was set to 0.5.

3- Determine the grey relational grade, which adds a grade to each of the coefficients for each performance attribute in order to rank the experiments.

$$GRG = \frac{1}{n}\sum_{k=1}^{n} \xi_i(k) \quad \text{... (5)}$$

where n denotes the number of output characteristics (n = 3 in this study) and the results of grey relational analysis for three steps showed in Tables (7and 8).

Table 7,
Normalized and deviation values from grey relational generation of output.

Test No.	Normalized values of output Ra	MRR	hardness HV0.2	Deviation values of output Ra	MRR	hardness HV0.2
1	0.774	0.000	0.502	0.226	1.000	0.498
2	0.384	0.263	0.639	0.616	0.737	0.361
3	0.237	1.000	0.296	0.763	0.000	0.704
4	0.000	0.263	0.000	1.000	0.737	1.000
5	0.843	0.211	0.791	0.157	0.789	0.209
6	0.960	0.158	0.714	0.040	0.842	0.286
7	0.611	0.386	0.388	0.389	0.614	0.612
8	0.934	0.243	1.000	0.066	0.757	0.000
9	1.000	0.211	0.931	0.000	0.789	0.069

Table 8,
Grey relational coefficients and grades with ranking.

Test No.	Grey Relational Coefficients Ra	MRR	hardness HV0.2	Grey Relational grade	Rank
1	0.689	0.333	0.501	0.509	6
2	0.448	0.404	0.581	0.478	8
3	0.396	1.000	0.415	0.604	5
4	0.333	0.404	0.333	0.357	9
5	0.761	0.388	0.705	0.618	4
6	0.926	0.373	0.636	0.645	3
7	0.562	0.449	0.450	0.487	7
8	0.884	0.398	1.000	0.761	1
9	1.000	0.388	0.879	0.756	2
Setting (0.5, 0.5,0.5)					

4- Rank deduction of each grey relational grade according to the higher value: The grey relational grade for each test using the L9 orthogonal array depending on MINITAB software is shown in Table 8. The product quality improves as the grey relational grade increases. As a result, the factor influence can be calculated and the optimum level for each controllable factor can be determined using grey relational grade. Table 9 describes and shows the mean of the grey relational grade for each level of the parameter. In addition, for each of the nine tests, the total mean of the grey relational grade is estimated and described in Table 9. The grey relational grade chart for the levels of the processing parameters is as seen in figure 8. The higher the grey relational grade, which leads to the greater the multiple output characteristics. However, the relative value of the parameters for the multiple output characteristics would need to be known in order to effectively calculate the optimum combinations of the method parameter levels [1-6,10-16].

Table 9,
Mean Grey Relational Grade.

Level	Tool	Spindle Speed	Feed rate	Depth of cut
1	0.5303	0.4511	0.6383 #	0.6277 #
2	0.5400	0.6188	0.5301	0.5365
3	0.6677 #	0.6681 #	0.5695	0.5738
Delta (max – min)	0.1375	0.2169	0.1082	0.0911
Rank	2	1	3	4

Mean Grey Relational Grade of all levels = 0.5793
Optimal level of each parameter

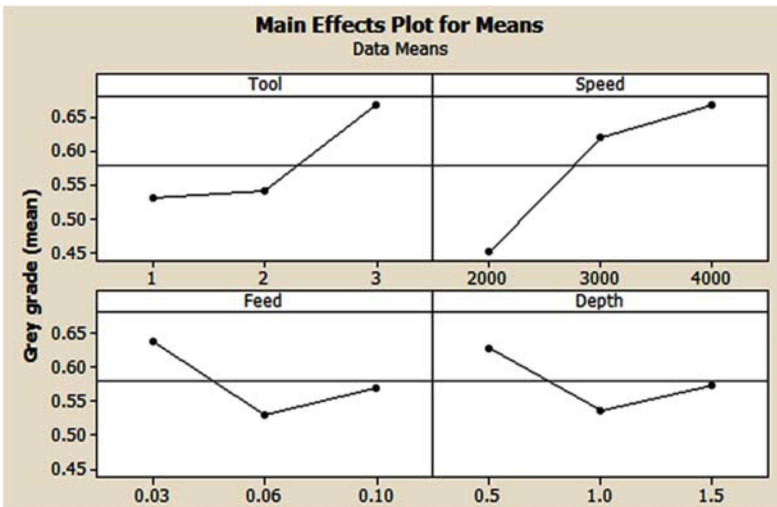

Fig. 8. Main effects chart of the grey relational grade to the levels of the processing parameters.

4.2 Analysis of Variance (ANOVA)

ANOVA is a statistical tool for determining the percentage contribution of each important variable to the operation response. The main objective of ANOVA is to show which operation parameter has a major effect on performance characteristics. A higher percentage of contribution means that the factor has a larger effect on output characteristics [1-7,10,11,15-18]. Table 10 shows the ANOVA outcomes for the Grey relational grade and the contribution percentages of each operation variable in order of importance. Table 11 shows the definition symbols and description found in ANOVA.

Table 10,
The ANOVA outcomes.

Source	DF	SS	Adj MS	F	P	PC %
Tool	2	0.0353	0.0177	1.737	0.429	24
Spindle Speed	2	0.0776	0.0388	4.223	0.214	52.75
Feed rate	2	0.018	0.009	0.723	0.629	12.23
Depth of cut	2	0.0126	0.0062	0.407	0.728	8.57
Error	2	0.0036	0.0018			2.45
Total	10	0.1471				100.00

Table 11,
The symbols and description found in Analysis of Variance.

symbol	meaning	description
DF	Degrees of freedom from each factor	If a factor has three levels, the degrees of freedom is 2 (n-1)
SS	Sum of squares	The sum of squares between groups (factor) and the sum of squares within groups (error)
Adj MS	Mean squares	Can be found by dividing the sum of squares by the degrees of freedom
P	Probability	use to determine whether a factor is significant
F	Fisher ratio (variance ratio)	calculated by dividing the factor MS by the MS error
PC %	Contribution percentages of each factor	calculated by dividing the SS of each factor to total of SS and use to determine whether a factor is significant

4.3 Confirmation test (optimal test)

The confirming test is the last step in the process of predicting the output characteristic using the optimum combination of operation factors and ensuring the efficiency and repeatability of the optimization approach used in this analysis.
The following equations can be used to estimate the predicted grey relational grade in the desired condition [1-5,11,15]:

$$g_{predicted} = g_{mean} + \sum_{i=0}^{q} g_i - g_{mean} \qquad \dots (6)$$

where g_{mean} is the total mean of the grey relational grade (0.5793), g_i is the mean grey relational grade at the optimum level, and q is the number of the operation parameters that significantly affect the multiple performance characteristics (the major influencing parameters on multi-objective response are spindle speed and cutting tool with grey relational grade at high level are 0.6677and 0.6681, respectively). Therefore $\boldsymbol{g_{predicted}}$ = 0.5793 + (0.6677- 0.5793) + (0.6681- 0.5793) = 0.7565.

Table 12 shows a comparison of the predicted Grey relational grade using favored operation parameters, experimental grey relational grade using favored operation parameters (A_3 B_3 C_1 D_1), and experimental grey relational grade using original operation parameters (A_3 B_2 C_1 D_3). In addition, the outcomes of the confirmation experiment using the optimum machining parameters are shown in Table 12. The material removal rate (MRR) is reduced from 8400 to 4200 mm^3/min , the surface roughness (Ra) and micro-hardness (HV0.2) are reduced from (2.017 to 1.742 µm) (140.81 to138.34 HV 0.2) respectively, with the Grey relational grade increased from 0.761 to 0.784 (2.3% improvement).

This indicates that the optimum combination of milling process parameters is sufficient to cover the requirement of surface quality (reduced surface roughness and micro-hardness), but the productivity (max metal removal rate) is reduced because in this study the metal removal rate is quantity value depended on end milling process parameters and number of flute for tool according equation (1).

Table 12,
The outcomes of the confirmation experiment using the optimum machining parameters.

	Original process parameters	Favored process parameters	
		Prediction	Experiment
Level setting	A_3 B_2 C_1 D_3	A_3 B_3 C_1 D_1	A_3 B_3 C_1 D_1
Surface roughness	2.017 µm		1.742 µm
Material removal rate	8400 mm^3/min		4200 mm^3/min
Micro-hardness	140.81 HV0.2		138.34 HV0.2
Grey relational grade	0.761	0.7565	0.784

5. Conclusions

The combined Taguchi method and Grey relational analysis were used to provide an efficient methodology for optimizing the end milling operation of Al-alloy (4032) with multi-performance outputs. The following conclusions can be taken from the results of this study:

1- The results of ANOVA showed that the major influencing parameters on multi-objective response were spindle speed and cutting tool (type of material and No. of flutes) with contribution percentage (52.75%, 24%), respectively, while the minor influencing parameters on multi-objective response were feed rate and depth of cut with contribution percentage (12.23%, 8.57%), respectively.

2- The optimal combination of end milling operation parameters and their levels for the end milling process's optimal multi-performance characteristics are A_3 B_3 C_1 D_1 (i.e Tool NO.3, spindle speed = 4000 m/min, feed rate = 0.03 mm/tooth and cutting depth = 0.5 mm).

3- The results of the confirmation experiment using the optimum machining parameters are the material removal rate (MRR) is reduced from 8400 to 4200 mm^3/min, the surface roughness (Ra) and micro-hardness (HV0.2) are reduced (from 2.017 to 1.742 µm) and (from 140.81 to138.34 HV 0.2), respectively with the Grey relational grade increased from 0.761 to 0.784 (2.3 improvement percentage).

6. References

[1] S. Ajith Arul Daniel, R. Pugazhenthi, R. Kumar, S. Vijayananth, "Multi objective prediction and optimization of control parameters in the milling of aluminum hybrid metal matrix composites using ANN and Taguchi-grey relational analysis," Defence Technology, vol. 15, no.4, pp. 545-556, 2019.

[2] J Santhakumar, U Mohammad Iqbal, M Prakash. "Optimization of one direction tool path orientation for pocket milling of Ti-6Al-4V using taguchi based grey relational analysis," IOP Conference Series: Materials Science and Engineering, vol. 402, no.1, pp.1-15, 2018.

[3] Luis Wilfredo Hernández-González, Roberto Pérez-Rodríguez, Ana María Quesada-Estrada & Luminita Dumitrescu. "Effects of cutting parameters on surface roughness and hardness in milling of AISI 304 steel," dyna rev.fac.nac.minas, Medellín , vol. 85, no. 205, pp. 57-63, June. 2018.

[4] A.Ranga Subbaiah, N.M.Sivaram and P.Senthil, "Effect of Milling Parameters on Surface Quality of AA6063-T6 Aluminium Alloy During High Speed CNC Face Milling," International Journal of Chem Tech Research, vol.10, no.3, pp.410-421, 2017.

[5] Shunyao Du, Minghe Chen, Lansheng Xie, Zhishou Zhu, Xinnan Wang. "Optimization of process parameters in the high-speed milling of titanium alloy TB17 for surface integrity by the Taguchi-Grey relational analysis method," Advances in Mechanical Engineering, vol. 8, no.10, pp. 1-12,2016.

[6] Sk. Mahaboob johny, Ch. Ramya sri sai, v. Ramakrishna rao, B. Govind singh," Multi-Response Optimization of Aluminum alloy using GRA & PCA by employing Taguchi Method," International Research Journal Engineering Technology, vol. 03, no. 01, Jan.2016.

[7] A.Venkata Vishnu, K. B. G. Tilak, G.Guruvaiah Naidu, Dr. G.Janardhana Raju, "Optimization of Different Process Parameters of Aluminium Alloy 6351 in CNC Milling Using Taguchi Method," International Journal of Engineering Research and General Science, vol. 3, no. 2, Part 2, March-April. 2015.

[8] Lakshmipathi Tammineni, Hari Prasada Reddy Yedula, "Investigation of Influence of Milling Parameters on Surface Roughness and Flatness," International Journal of Advances in Engineering & Technology, vol. 6, no. 6, pp. 2416-2426, Jan. 2014.

[9] Krolczyk, G., Nieslony, P. and Legutko, S. "Microhardness and surface integrity in turning process of duplex stainless steel (DSS) for different cutting conditions," Journal of Materials Engineering and Performance, vol. 23, no. 3, pp.859–866, 2014.

[10] Jihong Yan, Lin Li, "Multi-objective optimization of milling parameters - the trade-offs between energy, production rate and cutting quality," Journal of Cleaner Production, vol. 52, pp.462-471, 2013.

[11] Lohithaksha M. Maiyar, R. Ramanujam, K. Venkatesan, J. Jerald, "Optimization of Machining Parameters for end Milling of Inconel 718 Super Alloy Using Taguchi based Grey Relational Analysis," Procedia Engineering, vol. 64, pp.1276-1282, 2013.

[12] Liu, Y., Zhang, L.T. and Xu, Z.H., "Experimental investigation on high-speed milling of aluminum alloys," In Advanced Materials Research, Trans Tech Publications, vol. 418, pp.1141-1147, 2012.

[13] Surasit Rawangwong, Jaknarin Chatthong, R. Burapa and W. Boonchouytan, "An investigation of optimum cutting conditions in face milling aluminum 7075-T6 using design of experiment," In 4th International Conference on Applied Operational Research, Proceedings, vol. 4, pp. 125-135. 2012.

[14] Thakur, D.G., Ramamoorthy, B. and Vijayaraghavan, L., "Effect of cutting parameters on the degree of work hardening and tool life during high-speed machining of Inconel 718," The International Journal of Advanced Manufacturing Technology, vol. 59, no. 5, pp.483-489, 2012.

[15] Pankul Goel, Zahid A. Khan, Arshad Noor Siddiquee, Shahrul Kamaruddin, Rajeev Kumar Gupta., "Influence of slab milling process parameters on surface integrity of HSLA: a multi-performance characteristics optimization," The International Journal of Advanced Manufacturing Technology, vol. 61, pp.859–871, 2012.

[16] C. C. Tsao. "Grey–Taguchi method to optimize the milling parameters of aluminum alloy," The International Journal of Advanced Manufacturing Technology, vol. 40, pp.41-48, 2009.

[17] Aqeel Sabree Bedan, Halah Ali Habeeb, "An investigation study of tool geometry in single point incremental forming (SPIF) and their effect on residual stresses Using ANOVA Model," Al-Khwarizmi Engineering Journal, vol. 14, no.2, pp. 1- 13, June. 2018.

[18] Aseel Jameel Haleel,"Optimization Drilling Parameters of Aluminum Alloy Based on Taguchi Method," Al-Khwarizmi Engineering Journal, vol. 14, no.2, pp. 14 - 21, June. 2018.

امثلية متغيرات عملية القطع بالتفريز لسبيكة المنيوم (4032) باستخدام طريقة تاكوشي مع التحليل العلائقي الرمادي

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الخلاصة

الهدف من هذا العمل هو دراسة تأثير متغيرات عملية القطع بالتفريز، بالإضافة إلى مادة والشكل الهندسي لعدة القطع على استجابة المخرجات المتعددة لسبيكة المنيوم (4032). يمكن القيام بذلك عن طريق اقتراح نهج يجمع بين طريقة تاكوشي مع التحليل العلائقي الرمادي(Grey Relation Analysis) . تم اختيار ثلاث متغيرات للقطع (سرعة القطع ، معدل التغذية وعمق القطع) مع ثلاثة مستويات لكل متغير. كما تم استخدام ثلاث عدد قطع بمواد وشكل هندسي مختلف (عدد الحدود القاطعة) لتصميم الاختبارات التجريبية والتشغيل بناءً على المصفوفة L9. يتم حل استجابة العديد من خصائص الإخراج لعملية القطع بالتفريز بالاعتماد على درجة التحليل العلائقي الرمادي (Grey Relation Grade) الناتجة عن التحليل العلائقي الرمادي (Grey Relation Analysis) . أظهرت نتائج تحليل التباين (ANOVA) بالاعتماد على درجة التحليل العلائقي الرمادي (Grey Relation Grade) أن العوامل الرئيسية المؤثرة على استجابة المخرجات متعددة الأهداف هي سرعة القطع وعدة القطع (نوع المادة وعدد الحدود القاطعة) مع نسبة مساهمة من العملية الكلية (٥٢,٧٥٪ ، ٢٤٪) على التوالى .بالإضافة إلى ذلك ، تم التحقق من صحة التركيب الامثل لمتغيرات عملية القطع بالتفريز التي تم الحصول عليها من خلال التحليل العلائقي الرمادي (Grey Relation Analysis) عن طريق إجراء اختبار نهائي لتأكيد تحديد التحسن في استجابة المخرجات المتعددة . اظهرت اختبارات التأكيد للحصول على الحد الأدنى من (خشونة السطح والصلادة) والحد الأقصى لمعدل إزالة المعدن (MRR) مع درجة التحليل العلائقي الرمادي (Grey Relation Grade) (٠,٧٨٤) و نسبة التحسن (٢,٣٪).