ENGINEERING RESEARCH JOURNAL (ERJ)

Vol. 1, No. 41 July. 2019, pp. 31-39

Journal Homepage: www.feng.bu.edu.eg

Multi Response Optimization of End Milling Parameters Using Gray Relation Analysis

A.M.Shaabn , T.A. Khalil , B.A. Elmogy

Mechanical Engineering Department, Shoubra Faculty of Engineering, Benha University, Cairo, Egypt.

Abstract. Metal matrix composites reinforce with (macro or micro) size particles have wide application in industry due to excellent mechanical properties. This study has been aimed to evaluate the effect of process variables (machining parameters) in end milling operation of Al-Si/MWCNTs/ Al_2O_3 hybrid nanocomposites. The experiments were designed using Taguchi L27 by selecting number of flutes in end mill, volume fractions of MWCNTs, spindle speed and feed rate as a process inputs parameters. Surface roughness, flatness error and material removal rate in cutting operation as a process output were evaluated using single noise (SN) ratio and analysis of variance (ANOVA) by using gray relation grad. The result showed that number of flutes is the most significant factor on multi objective response with contribution 52.199%, followed by nanofiller (0.0) % volume fraction with 29.40 %.

Keywords:End milling**,**Hybrid nanocomposites, Surface roughness, Flatness error, Taguchimethod, Gray relation grad

1. INTRODUCTION

Surface roughness (Ra), flatness error and material removal rate (MRR) are considered an important target for all machining process used to fabricate flat surfaces components. Therefore, it is important for the researchers to study the relationship between quality of machined parts and the parameters affecting its value.

Zhang et al. [1] applied Taguchi design method to analyze and optimizationSurface roughness in CNC end milling. Spindle speed, feed rate and depth of cut were selected as a control process parameter. The aluminum was selected as a material workpiece. They found that cutting parameters influence on surface roughness. Taguchi technique were also applied for similar studies [2-4]. Mahesh et al. [5] predicted surface roughness for end milling process by using genetic algorithm. They selected spindle speed, feed rate, depth of cut and radial depth of cut as a controlled variable. The surface roughness was only the process response. Their results indicated that depth of cut has the most influence on surface roughness this result was also reported in similar studies [6] . Karabulut [7] used neural network and Taguchi method for prediction surface roughness and cutting force in CNC end milling during AA7039/Al_2O_3 metal matrix composites. They found that feed rate has more effect on surface roughness than other considered parameters. A similar results were reported in reference [8,9] . Tomadia. et al. [10] applied Taguchi orthogonal array (OA) method and ANOVA in their experiments. Cutting speed, feed axial, depth rate were selected as process parameters in CNC end milling of metal matrix composites. They found that cutting response has the most significant effect on surface roughness (Ra) and material removal rate (MRR). The increase of depth of cut increases the surface roughness. Taguchi and ANOVA technique were also applied in similar studies [11,12].

The determination of this relationship remains an open field of research, mainly, because of the advances in machining and material technology and the available modeling techniques.

2. Experimental work

2.1 Workpiece Material

The experiments of this study were carried out on aluminum silicon alloy as a matrix material. The

Al-Si alloy was reinforced by hybrid homogenized (0.25% MWCNTs+ 0.25%Al_2O_3) and (0.50% MWCNTs) by volume. Stir casting method was used to fabricate the metal matrix nanocomposites plates. The chemical composition of Al-Si alloy is indicated in Table 1. The MWCNTs have an average inner and outer diameters of 20 and 40 nm respectively and Al_2O_3 an aluminum oxide (Alumina) has an average diameter of 20 nm and purity of 99.8% .

Table.1 The chemical composition of the Al-Si alloy (wt.%)

Fe	Al	Si	Mn	Ni	Ti
0.221	93.2	5.50	0.014	0.62	0.14

It is noticed that principles of the casting process were taken into consideration such that the preheating of both the nano particales and the mould to avoide the casting defects arises in such cases. The final dimension of workpiece produced has the dimension 300mm (length), 100 mm (width) and 24mm (thicknes).

2.2 Tool Specifications

Coated carbide tip of aluminum titanium nitride (AlTiN) material of ISO designation of ZE502160, ZE504160 and ZE506160 shown in Fig.1 and designed to machine tool steel, alloy steel, mold steel and other high hardened materials. The specification of a very good abrasion resistance for wear and hardness at higher milling temperatures than other high speed steels and the deep flutes for chip evacuation and 30^o left hand helix. The tool deamination shows in Table 2 and the tools were chosen according to the manufacturing catalog of WIDIN company considering workpiece material and the recommended other cutting parameter

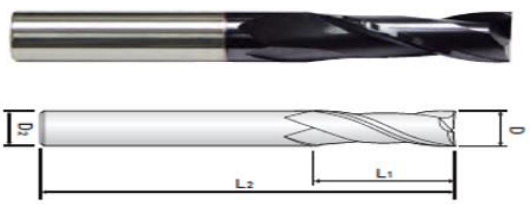

Fig 1 End mills tool for 2 flutes

Table.2 The specification of cutting tool

ISO catalog number	Tip	Series	Dimension (mm)			
			D	L1	L2	D2
ZE502160	coated carbide	ZE502	16	40	90	16

2.3 Milling Process

The experiments were carried out on vertical milling machine "USM30S" givingapproach angle of 45^{o,} and table surface (35x 1150mm). The machine has specifications range of speed (35 – 1600 r.p.m), range of feed speed (4-240 mm/min) and range of feed motor power (0.75kw - 1380rpm).

2.4 Measurement Devices

The surface roughness parameter (R_a) of the workpiece after machining, was measured with Surftest SJ-310 Mitutoyo instrument shown in Fig.2, while the flatness tester (JENA GERMANY) L.R = 0.001 um shown in Fig.3. The uncertainty evaluation is carried out in accordance with the JCGM 100:2008. U is the expanded uncertainty using a coverage factor K = 2, providing a level of confidence of approximately 95 %. (U = $\pm$ 0.002 um.).

All equipment used for measurement are traceable to gauge blocks which were calibrated by optical interferometer at KRISS traceable to SI units, certificate No: 05-03031-001

Fig.2 Surftest instrument

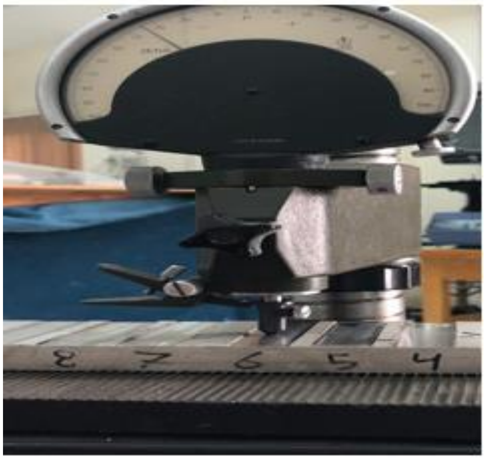

Fig.3 The flatness tester

2.5 Design of experiment

In this work selected the parameters for milling experiments are number of flutes, type of nano filler (0.25% MWCNTs+ Al_2O_3) and (0.50% MWCNTs), spindle speed and feed rate of workpiece material (input variables). While the experimental responses are surface roughness, flatness error and material removal rate (MRR) (outputs).

Taguchi designs experiments were performed using especially constructed tables known as "orthogonal arrays" (OA). The use of these tables makes the design of experiments very easy and consistent. Taguchi method using MINITAB-17 software was applied to plan and analyse the experiments and the results of this investigation.

In this work, four variables were selected with three levels for each and an OA L27 is selected. Each experiment was repeated three times to reduce the signal noise effect. The process parameters, levels and units are shown in the Table (3).

Table.3 Process Parameters and Levels.

Parameter	Unit	Level 1	Level 2	Level 3
Number of flutes(A)	-	2	4	6
nanofiller (B)	Volume %	0 %	0.25% A+C	0.50C %
Spindle speed (C)	(r.p.m)	260	640	1000
Feed rate (D)	(mm /min)	12	17	24

3. Results and discussion

The L_{27} experiments have been carried out according to the experiments according to design of experiment. After completing the experiments, a statistical analysis was done for the experimental data obtained which are shown in Table 4.

Table.4 Experimental Results According to Taguchi DOE

Run	No Flutes	Nano filler (Vol%)	Spindle Speed (r.p.m)	Feed Rate (mm/min)	RA µm	MRR (mm^3/min)	Flatness error µm
1	2	0.0	260	12	1.281	138.7283	0.086
2	2	0.0	260	12	0.825	138.4083	0.08
3	2	0.0	260	12	0.716	138.2488	0.087
4	2	0.25 A+C	640	17	2.993	168.7764	0.109
5	2	0.25 A+C	640	17	2.852	290.5569	0.1
6	2	0.25 A+C	640	17	3.039	168.5393	0.108
7	2	0.50C	1000	24	2.704	273.3485	0.1
8	2	0.50C	1000	24	2.686	272.7273	0.108
9	2	0.50C	1000	24	2.232	270.8804	0.109
10	4	0.0	640	24	2.989	348.8372	0.098
11	4	0.0	640	24	2.601	346.8208	0.09
12	4	0.0	640	24	3.143	345.8213	0.097
13	4	0.25 A+C	1000	12	2.058	158.5205	0.08
14	4	0.25 A+C	1000	12	1.538	159.1512	0.086
15	4	0.25 A+C	1000	12	2.189	158.9404	0.087

16	4	0.50C	260	17	1.926	176.2115	0.076
17	4	0.50C	260	17	1.921	176.7305	0.07
18	4	0.50C	260	17	1.873	175.9531	0.077
19	6	0.0	1000	17	0.856	193.2367	0.07
20	6	0.0	1000	17	0.847	193.8611	0.076
21	6	0.0	1000	17	0.954	193.5484	0.078
22	6	0.25 A+C	260	24	4.475	277.1363	0.07
23	6	0.25 A+C	260	24	5.36	275.2294	0.064
24	6	0.25 A+C	260	24	4.372	275.8621	0.069
25	6	0.50C	640	12	0.792	144.7527	0.078
26	6	0.50C	640	12	0.541	145.1028	0.075
27	6	0.50C	640	12	0.643	144.9275	0.071

3.1 Gray Relation Analysis

This method is most useful for optimization of multi- objective process responses. In the grey relational analysis, experimental data of the output responses are first normalized between the ranges of 0 to 1. This process is known as grey relational generation after normalization grey relational coefficient are calculated to express relationship between actual and desired experimental data. Then overall grey relational grade is calculated by averaging the grey relation coefficient of the output responses. The overall quality characteristic of the multi-objective process depends on the determined grey relation grade

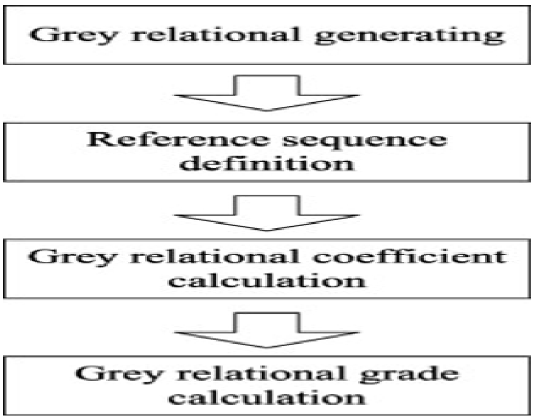

Fig 4 Steps of gray relation analysis

In the grey relational analysis, first, experimental data of the output responses are normalized between the ranges of 0 to 1 shown in Table.5. There are three different cases of normalization, the first is higher -the-better by using equation (1)

$$X_i(k) = Y_i(k) - \min Y_i(k) / \max Y_i(k) - \min Y_i(k) \qquad (1)$$

and the second is, lower-the-better and the finally nominal the best one by using equation (2)

$$X_i(k) = \max Y_i(k) - Y_i(k) / \max Y_i(k) - \min Y_i(k). \qquad (2)$$

Where X_i is the value obtained after grey relational generation. Min $Y_i(k)$ is smallest value of $Y_i(k)$ and max $Y_i(k)$ is the maximum value of $Y_i(k)$.

Table.5 Normalized values of multi response

Ex.no	MRR (mm^3/min)	Ra [µm]	Flatness error [um]
1	0.002	0.846	0.511
2	0.001	0.941	0.644
3	0.000	0.964	0.489
4	0.145	0.491	0.000
5	0.723	0.520	0.200
6	0.144	0.482	0.022
7	0.642	0.551	0.200
8	0.639	0.555	0.022
9	0.630	0.649	0.000
10	1.000	0.492	0.244
11	0.990	0.573	0.422
12	0.986	0.460	0.267
13	0.096	0.685	0.644
14	0.099	0.793	0.511
15	0.098	0.658	0.489
16	0.180	0.713	0.733
17	0.183	0.714	0.867
18	0.179	0.724	0.711
19	0.261	0.935	0.867
20	0.264	0.937	0.733
21	0.263	0.914	0.689
22	0.660	0.184	0.867
23	0.650	0.000	1.000
24	0.653	0.205	0.889
25	0.031	0.948	0.689
26	0.033	1.000	0.756
27	0.032	0.979	0.844

The second step, grey relational coefficient is calculated to express relationship between actual and desired experimental data shown in Table.6 by using equation (3)

$$\boldsymbol{\varepsilon}(\boldsymbol{x}) = \Delta\text{min} + ½\ \Delta\text{max} / \text{x} + ½\ \Delta\text{max}. \qquad (3)$$

Table. 6 Grey relation coefficient

Ex.no	**MRR(mm^3/min)**	**Ra [µm]**	**Flatness error [µm]**
Ideal.seq	**1**	**1**	**1**
1	0.998	0.154	0.489
2	0.999	0.059	0.356
3	1.000	0.036	0.511
4	0.855	0.509	1.000
5	0.277	0.480	0.800
6	0.856	0.518	0.978
7	0.358	0.449	0.800
8	0.361	0.445	0.978
9	0.370	0.351	1.000
10	0.000	0.508	0.756
11	0.010	0.427	0.578
12	0.014	0.540	0.733
13	0.904	0.315	0.356
14	0.901	0.207	0.489
15	0.902	0.342	0.511
16	0.820	0.287	0.267
17	0.817	0.286	0.133
18	0.821	0.276	0.289
19	0.739	0.065	0.133
20	0.736	0.063	0.267
21	0.737	0.086	0.311
22	0.340	0.816	0.133
23	0.350	1.000	0.000
24	0.347	0.795	0.111
25	0.969	0.052	0.311
26	0.967	0.000	0.244
27	0.968	0.021	0.156

The last step, overall grey relational grade is calculated by averaging the grey relation coefficient of the output responses shown in Table.7 using equation (4)

$$\hat{\alpha}_i = 1/n \sum_{k=1}^{n} \gamma i_{(k)} \qquad (4)$$

Where n is total number of responses (n=3).

Table. 7 Grey relation grade

Ex.no	G.R	Rank
1	0.535	18
2	0.604	11
3	0.587	15
4	0.399	26
5	0.513	21
6	0.399	27
7	0.498	23
8	0.483	24
9	0.499	22
10	0.631	7
11	0.661	4
12	0.619	10
13	0.518	20
14	0.523	19
15	0.482	25
16	0.555	16
17	0.602	12
18	0.552	17
19	0.692	1
20	0.648	5
21	0.625	8
22	0.588	14
23	0.641	6
24	0.598	13
25	0.621	9
26	0.671	3
27	0.688	2

3.2. Optimization of Machining Parameters on Gray Relation Grade

The average performance and S/N ratio were calculated for different responses using Taguchi analysis. The main effects plot of S/N ratios is shown in Fig.4. from Fig 4 the most significant on the multi response are the number of flutes followed by nanofiller (0.0) % followed by spindle speed and feed rate. The main effect plots are used to determine the optimal combination of machining parameters to obtain the multi-objective. It is evident from Fig.4 and that multi-objective is maximum at level A3B1C1D3.

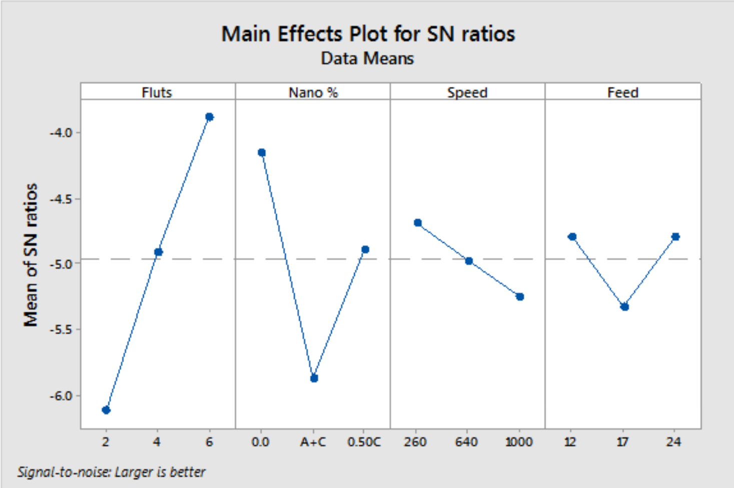

Fig.4 main effects plot of SN ratios for gray relation grad

3.3 Analysis of Variance (ANOVA)

Analysis of variance (ANOVA) was performed to determine the most significant input parameter and to quantify their effects on each output. The results are presented in Tables 8. From Table (7), it is clear that number of flutes has the highest contribution % of 52.199% on multi-objective, followed by nanofiller type of (0.0) % with 29.408%.

Table.8 ANOVA for gray relation grad

Source	DF	Adj SS	Adj MS	F-Value	P-Value	Contribution
No Flutes	2	0.087502	0.043751	37.06	0.000	52.19918
Nano filler	2	0.049298	0.024649	20.88	0.000	29.40864
Spindle Speed	2	0.005363	0.002681	2.27	0.132	3.199289
Feed Rate	2	0.004220	0.002110	1.79	0.196	2.517434
Error	18	0.021249	0.001180			12.67606
Total	26	0.167631				100%

Conclusions

In this investigation, gray relation grad by using Taguchi and ANOVA techniques have been applied to analyze the effect of the workpiece material and different cutting parameters on surface quality and MRR and flatness. The following conclusions are drawn :

(1) The number of flutes has the most significant effect on multi-objective response with 52.199% contribution followed by nanofiller (0.0) % with 29.40 %.

(2) For maximum multi-response, the optimal parametric combination is A3B1C1D3.

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