Multi objective optimization during milling of zirconia ceramic using grey relation analysis and response surface methodology

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Abstract

The present work proposes multi response optimization during milling of zirconia ceramic material with Aluminum Nitride coated tool. The output variables considered for the experiments are surface roughness, material removal rate and flatness, which have been conducted using Taguchi L9 orthogonal array. Multi objective optimizations have been carried out employing grey relation analysis and response surface methodology. The optimum combination of parameters of cutting speed at 9500 rpm, feed at 127 mm/min and depth of cut at 1.2 mm have been found employing response surface methodology. The optimum combination of parameters of cutting speed at 9500 rpm, feed at 75 mm/min and depth of cut at 1.2 mm have been found employing grey relation analysis. Based on the validation of experiments, it can be concluded that response surface methodology provides a better combination of parameters than grey relation analysis.

Keywords: RSM, GRA, MRR, surface roughness, flatness;

1. Introduction

Milling is among among one of the foremost regularly used machining processes, which is carried out extensively. Herein material is removed from the work piece when a rotating tool is forced across the work piece. For the prior five decades, the employment of the ceramics materials has drastically inflated resulting in new applications being frequently added in day to day life. Zirconia based ceramic material finds its application in aerospace, manufacturing, dentistry, medical field, etc. Certain mix of machining parameters, cause process fluctuation causing reverberations which results in decrease in accuracy, inferior surface finish, and reduced tool life. These combinations are not usually provided by the manufacturer and ought to be found out by practical experience. This experience requires a count of experiments to be conducted which utilizes a good amount of time resources and money. Arrays provided by Taguchi results in a good amount of savings of these resources, if utilized properly, reducing the count of experiments required to search the best mix of parameters.

Savas and Ozay [1] have performed improvement of Ra throughout tangential turn milling on SAE 1050 cylindrical piece of work and HSS tool by employing Genetic Algorithm which leads a result that Ra deteriorate with enhancement in depth of cut and feed. Karabulut & Halil [2] have determined the end result of speed, feed, and depth of cut on Ra of Al7075 based SiC open cell foam composite by applying artificial neural networks . It has been calculable that the feed was crucial in favor of the Ra. L27 full factorial OA was employed for this purpose. Sahoo et al. [3] have successfully modeled and optimized five roughness parameters for three distinct materials by selecting various level of input parameters by adopting RSM technique for optimization. Oktem [4] has modeled and optimized Ra and time for milling of AISI 1040 material with TiAlN tool beneath wet circumstances implementing GA and ANN optimization technique. Due to application of GA, Ra improved from 0.67 µm to 0.59 µm and machining time from 1.282 min to 1.0316 min. Aykut and Eyup Bagci [5] have used feed, speed and depth of cut as parameters for cobalt based alloy milling. Effectiveness of the Taguchi methodology was illustrated by a confirmation check with the best level of parameters. Bhuvnesh et al.[6] have developed Box – Cox with RSM for generating Ra model in milling EN 353 material with carbide tool. Speed, feed, depth of cut and radius of nose were the input parameters among which speed was calculable to be affecting Ra. Markopoulos et al. [7] have investigated milling on alloy using ANN and RSM technique of optimization. It was later finalized that ANN technique outperformed RSM technique. Bandapalli et al. [8] have applied three different methods for Ra optimization during high speed titanium milling. It was finalized by the authors that ANN performs higher than the other two techniques and provides accuracy. Wang et al. [9] examined milling operation on metal using energy consumption to develop Ra inconsistency model. The advanced model behaved better in connection to Taguchi methodology of optimization. Mukesh et al. [10] have used style of experiments for modeling and investigating control of input parameters on Ra throughout milling of metal with coated tool. RSM technique was then employed for its improvement. Sakthivel et al. [11] have adopted RSM for modeling, analysis and optimizing Ra of Al7075-T6 material in milling process employing High Speed Steel cutter. The model that has been developed by these authors was capable to accurately compute the Ra of the material. Saurin and George [12] have investigated impact of speed, feed, and depth of cut on Ra and flatness throughout milling of solid steel. The investigation founded that speed and feed has implication on Ra and flatness. The typical error in prediction of actual values for Ra was searched to be 6.86% and for flatness it absolutely was 5.17% victimizing ANOVA. Palanikumar et al. [13] have used RSM and desirability perform approach technique for improvement of Ra throughout turning of metal – carbide composite materials and located feed rate to own bigger influence on surface roughness. Employing desirability approach the optimum level of process parameters was outlined employing Minitab software. Vikas et al. [14] have optimized and compared MRR for two materials and determined that discharge current was the foremost important issue influencing MRR. L27 OA was employed taguchi and ANOVA. Jinka Ranganayakulu et al. [15] have successfully maximized MRR during ECDM for non conducting material. They have searched that voltage during the ECDM process was key factor responsible for change in MRR. Sayak Mukherjee et al. [16] have optimized MRR during CNC turning of SAE 1020 material with carbide tool concluding that out of three parameters d was the manipulating factor for MRR. L25 OA was employed for optimization. Arvind Kumar [17] optimized MRR during turning of 1018 mild steel containing 0.05% to 0.26% carbon employing taguchi methodology and L27 OA. Y. F. Hsiao et al. [18] have optimized the parameters for plasma arc fastening method and concluding that output was enhanced by employing GRA technique. J. Edwin et al. [19] have performed multi-response optimization of weld parameters for underground arc fastening method using GRA concluding that GRA technique had optimized the output parameters. Welding current, speed and arc voltage have been the input parameters selected for the study whereas deposition rate and hardness of weld were the output parameters. L9 OA was employed for the study. Krishnamoorthy et al. [20] and K. Palanikumar et al. [21] have employed grey fuzzy and GRA for the optimizing drilling parameters for CFRP and GFRP composites, thus concluding that multi response gain can be enhanced by employing GRA technique.

2. Experiments Procedure

End milling experiments have been conducted employing HAAS CNC machine as shown in Fig. 2 with TiAlN coated end milling cutter as shown in Fig. 1 (b) of diameter size 3mm with two flutes having helix angle of 30° on zirconia ceramic work material as shown in Fig.1 (a). OA 9 array has been employed in which the feed rate (mm/min), spindle speed (rpm) and depth of cut (mm) have been considered as input variables to study their effect on surface roughness (µm), material removal rate (mm^3/min) and flatness (unit less). The spindle speeds which have been considered are 7500, 8500 and 9500 rpm and the feed rate was 75, 105 and 135 mm/min. The depth of cut consideration was 0.4, 0.8 & 1.2 mm. Talysurf 4 was employed for examining surface roughness as shown in Fig. 3 (a), CMM was employed for checking flatness as shown in Fig. 3 (b). The material removal rate was calculated by the volume of material removed to the time taken for its removal. The mix of input parameters of experiments is given in Table 1 and the corresponding measured outputs based on the input are given in Table 2.

Fig. 1. (a) Zirconia Ceramic work piece; (b) TiAln coated tool (Titanium Aluminium Nitride).

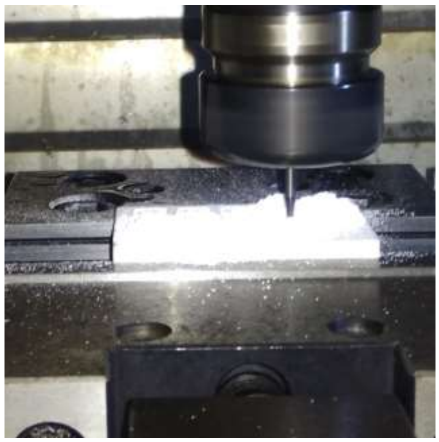

Fig. 2. End milling process.

Fig. 3. (a) Ra measurement; (b) Flatness measurement.

Table 1. Input parameters and their levels.

No	Parameters	Units	Level 1	Level 2	Level 3
1	Cutting Speed (V)	rpm	7500	8500	9500

2	Feed (f)	mm/min	75	105	135
3	Depth of cut (d)	mm	0.4	0.8	1.2

Table 2. Outcomes of the measured responses.

No	V rpm	f mm/min	d mm	Ra µm	F	MRR mm^3/min
1	7500	75	0.400	0.497	0.0016	31.746
2	7500	105	0.800	0.390	0.0008	73.394
3	7500	135	1.200	0.341	0.0014	240.000
4	8500	75	0.800	0.263	0.0009	64.000
5	8500	105	1.200	0.317	0.0024	115.385
6	8500	135	0.400	0.358	0.0026	78.431
7	9500	75	1.200	0.260	0.0005	95.238
8	9500	105	0.400	0.261	0.0008	39.216
9	9500	135	0.800	0.311	0.0014	156.863

3. Optimization

3.1. Grey Relation Analysis

The grey theory provides capable management upon the uncertainty, multi-input and disconnected data [22]. In GRA, black indicates no information and white indicates all knowledge is available. Grey system holds information which is known and unknown[23] . In other words, in grey system, information is in amidst black and white. The GRA is analysis of sheer value of the data difference amidst outputs, and is also used to check an approximate correlation amidst inputs and outputs[24]. It is an effective means of analyzing the link between the outputs with less data and can analyze many factors .The method for grey relational analysis has been described in the previous research[20].

Following steps were followed for the function of optimization [25]

1 Normalising the experimental results of Ra, MRR and flatness for all experiments.
2 Calculating the deviation sequence from the normalized table.
3 Calculating the grey relational coefficient (GRC) for all responses.
4 Calculating the grey relational grade (GRG) by averaging the GRCs for all experiments.
5 Selecting the optimum levels of process parameters.

Table 3. Responses table.

No	R_a	Flatness	MRR
1	0.497	0.0016	31.746
2	0.390	0.0008	73.394
3	0.341	0.0014	240.000
4	0.263	0.0009	64.000
5	0.317	0.0024	115.385
6	0.358	0.0026	78.431
7	0.260	0.0005	95.238
8	0.261	0.0008	39.216
9	0.311	0.0014	156.863

Table 4. Data pre processing table.

No	R_a	Flatness	MRR
1	0.000	0.476	0.000
2	0.451	0.857	0.200
3	0.658	0.571	1.000
4	0.987	0.810	0.155
5	0.759	0.095	0.402
6	0.586	0.000	0.224
7	1.000	1.000	0.305
8	0.996	0.857	0.036
9	0.785	0.571	0.601

Table 5. Deviation table.

No	R_a	Flatness	MRR
1	1.000	0.524	1.000
2	0.549	0.143	0.800
3	0.342	0.429	0.000
4	0.013	0.190	0.845
5	0.241	0.905	0.598
6	0.414	1.000	0.776
7	0.000	0.000	0.695
8	0.004	0.143	0.964
9	0.215	0.429	0.399

Table 6. GRG rank table.

No	R_a	Flatness	MRR	GRG	Rank
1	0.333	0.488	0.333	0.3850	9
2	0.477	0.778	0.385	0.5464	6
3	0.594	0.538	1.000	0.7108	2
4	0.975	0.724	0.372	0.6904	4
5	0.675	0.356	0.455	0.4955	7
6	0.547	0.333	0.392	0.4242	8
7	**1.000**	**1.000**	**0.418**	**0.8061**	**1**
8	0.992	0.778	0.341	0.7036	3
9	0.699	0.538	0.556	0.5979	5

From Table 6, it is visible that experiment No. 7 is having the foremost grey relational grade i.e. 0.8061, so the optimum parameter for multi objective optimization responsible for having foremost rank is speed at 9500 rpm, feed at 75 mm/min and depth of cut at 1.2 mm.

3.2. Response Surface Methodology

Response Surface Methodology (RSM) seeks the association between many inputs with one or more responses[13]. The strategy was popularized by George E. P. Box and K. B. Wilson in 1951. The most plan of RSM is to use an array of designed experiments to get an optimum response [26]. They acknowledge that this model is barely an approximation; however, they use it as a model that is simple to estimate and apply [27]. In the present work, cutting speed, feed, depth of cut have been considered as the process parameters, and surface roughness, material removal rate, and flatness are taken as response variables. The selected design plan has chosen 9 experiments.

The objective of RSM optimization using the model is set for minimization of surface roughness, flatness whereas maximization of material removal rate. For optimization with respect to the objectives, a response optimizer in MINITAB is used. In this process, this response optimizer searches for a mix of input variables that mutually optimizes a set of responses by satisfying the need for each response in the set.

Table 7. Set values for optimization using RSM in Minitab.

Response	Goal	Lower	Target	Upper	Weight	Importance
MRR	Maximum	31.7460	240.000		1	1
Flatness	Minimum		0.001	0.0026	1	1
R_a	Minimum		0.260	0.4970	1	1

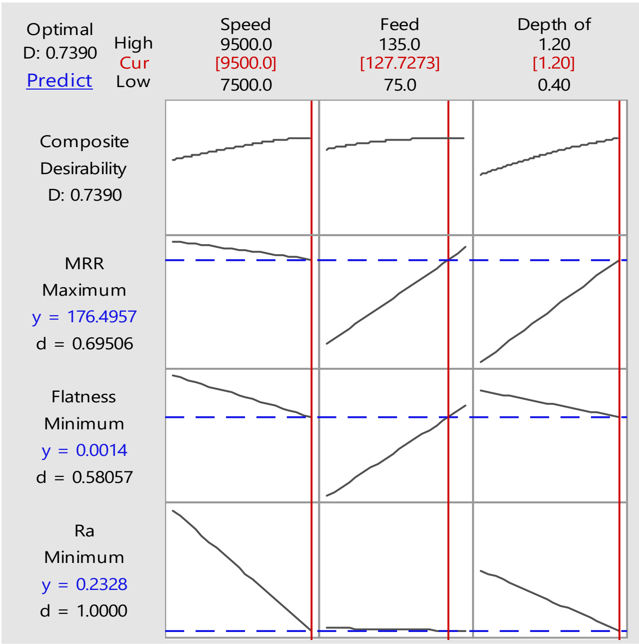

Fig. 4. Optimized parameters values by Minitab using RSM.

Table 7. shows the values set for multi objective optimization using RSM in Minitab package. It is visible that the minimum values are set as target for Ra and flatness as they are to be minimized whereas maximum value is set as target for MRR as it is to be maximized. From Fig. 4, it is visible that the optimum level of parameters for multi objective optimization is 9500 rpm of speed, 127.72 mm/min of feed and 1.20 mm of depth of cut.

4. Results and Discussion

Table 8. Comparison of outputs by the techniques.

Technique	V	f	d	R_a	F	MRR
RSM	9500	127	1.2	0.318	0.0001	279.07
GRA	9500	75	1.2	0.348	0.0002	101.69
Improvement %				8.62	50	63.56

Table 8.depicts the parameters at which the confirmatory runs were conducted based on the two optimization

techniques and their corresponding values of output recorded. It can be seen that the Ra has improved by 8.62 %, flatness by 50 % and MRR has improved by 63.56 %. From the results it is visible that the result of RSM technique is better than that of GRA technique. GRA technique provides best optimum input parameters only from the available input whereas RSM technique searches for a better option outside the input provided to the technique. The feed rate of 127 mm/min was not provided but RSM technique has searched for a better solution. Thus it can be concluded that RSM technique outperformed GRA technique for milling of zirconia ceramic material using TiAlN coated tool.

5. Conclusion

Based on the experiments performed and the results obtained the following points may be concluded:

1. GRA technique can be effectively used to optimize the responses based on input parameters only.
2. RSM technique optimizes the responses based on a broader area of input parameters which may be other than the input parameters.
3. Using RSM and GRA techniques the resources required for optimization can be reduced to a limited number of experiments.

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