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Designing and Conducting Experiments for Optimization of Adequate Cutting Conditions in Precision Turning

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Abstract: This research work focuses on precision turning of Ti6Al4V material to investigate the machinability of the material. Precision turning is a type of machining where, very low feed rate and depth of cut is being used to machine using a cutting insert with a lower nose radius. The cutting parameters considered for the experiments include the cutting speed, feed rate, depth of cut and nose radius. PVD coated carbide cutting inserts with different nose radius and constant rake and clearance angle are being considered for experimentation. The experimentation was designed based on Taguchi's L 27 orthogonal array. Three different levels of cutting parameters were being considered for the experimentation. The turning experiments were carried out on a conventional variable speed motor lathe under dry working conditions. Based upon the experimental values, Analysis of Variance (ANOVA) was conducted to understand the influence of various cutting parameters on cutting force, surface roughness chip morphology, tool wear and cutting tool temperatures during precision turning of titanium alloy. Optimal levels of parameters were identified using grey relational analysis and significant parameter was determined by analysis of variance. Experimental results indicate that multi-response characteristics.

Key words: Precision Turining · Orthogonal Array · Grey Relational Analysis · Optimization Of Out Parmater · Grey Relational Grade · Grey Relational Coefficient · Ti-6Al-4V

INTRODUCTION

Selecting cutting conditions, tool material and its coating and cutting edge geometry is important not only to increase the productivity of machining operation but also to obtain a desirable surface integrity (i.e.residual stresses, surface roughness, etc.) of the finished machined part. Hence, comprehensive reviews on the machinability of titanium alloys are provided in machining of titanium alloys is a major concern because of its low thermal conductivity that prevents the dissipation of heat easily from the tool chip interface, which in turn heats up the tool due to increasing temperature resulting in lower tool life. Titanium forms alloys easily due to high chemical reactivity that causes weld and smear formation along with rapid cutting tool destruction. Titanium has comparatively low elasticity modulus than steel. Therefore the work piece has a tendency to move away from the cutting tool unless the proper backup is used. Also thin parts may deflect under tool pressures, causing chatter, tool wear and tolerance problems [1]. Selection of cutting conditions, tool material and its coating and cutting edge geometry is important not only to increase the productivity of machining operation but also to obtain a desirable surface integrity (i.e. Residual stresses roughness, etc.) of the finished machined part. Hence, comprehensive reviews on the machinability of titanium alloys are provided [2].

In precision machining operation, the quality of surface finish is an important requirement of many bored work pieces and parameter in precision manufacturing engineering. It is characteristic that could influence the performance of precision mechanical parts and the production cost. Various failures, some time catastrophic, leading to high cost, have been attributed to the surface finish of the component in question [3]. For these reasons there have been research developments with the objective of optimizing the cutting condition to obtain a surface

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Fig. 1: Experimental setup

Table 1: Machining parameters and their level

Cutting parameter	Level 1	Level 2	Level 3
Feed (mm/rev)	0.02	0.04	0.06
Depth of cut (mm)	0.05	0.10	0.15
Cutting speed (m/min)	30	60	90
Nose radius (mm)	0.1	0.2	0.4

finish. During a precision turning operation, the cutting tool and the work piece subjected to a prescribed deformation as a result of the relative motion between the tool and work piece both in the cutting speed direction and feed direction.

The technique of laying out the processing conditions of experiments involving multiple factors was first proposed by Fisher [4-5]. The method is popularly known as the factorial design of experiments. Since most experiments for industrial applications usually involve a significant number of factors, a full factorial design results in a large number of experiments. In order to reduce the number of experiments, only a small set from all possibilities is selected in what is known as a partial factorial experiment. Taguchi constructed a special set of general design guidelines for factorial experiments. Most applications of the Taguchi method only cope with the optimization of a single response process or product. However, in many practical cases, we often have to deal with multi-response problems and these responses may be highly correlated with each other. Hence, in this paper, we systematically present the Taguchi method based on grey relational analysis (GRA) together with the analysis of variance (ANOVA) [6-8] to optimize the powder metallurgy processing parameters.

Experimental Procedure: The target material used for the experimentation is Ti-6Al-4V. Gedee Weiler MLZ 250V variable speed adjusting capstan lathe is used for the experiment. And the experimental setup is shows in Fig 1. PVD coated carbide tool with 98 HRC hardness, nose radius of 0.1 0.2 and 0.4 were used for the turning operation. Surface roughness was measured using mitutotyo surftest SJ-301 portable surface roughness tester with a sampling length of 4 mm. The cutting temperature was measured using a thermocouple. The cutting parameters were so selected after comparison with different literature surveyed. The design of experiments and analysis of variance was done using Minitab 15 software.

Design of Experiments and Observation: Design of Experiments is a highly efficient and effective method of optimizing process parameters, where multiple parameters are involved. The design of experiments using the Taguchi approach was adopted to reduce the number of trials. The time and cost for doing an experiment is very high, therefore it is necessary to select an orthogonal array with minimum number of trials. In this research work L27 orthogonal array is chosen which a multilevel experiment is where feed rate, depth of cut, cutting speed and nose radius are the four factors considered in the experiment. Table 1 shows the machining parameters and their levels considered for experimentation.

The proposed work is to perform machining under the selected levels of conditions and parameters and to estimate the, cutting force, cutting temperature and surface roughness generated as the result of the machining process. Table 2 shows the machining parameters and observation for each trail of experiments.

Grey Analysis: In the grey relational analysis, data preprocessing is first performed in order to normalize the raw data for analysis. In this study, a linear normalization of the experimental results for cutting force, chip morphology, surface roughness and the tool wear ratio shown in Table 3 were performed in the range between zero and one, which is also called the grey relational generating [9]. The normalized experimental results Xij can be expressed as:

$$x_{ij} = \frac{y_{ij} - \min_j y_{ij}}{\max_j y_{ij} - \min_j y_{ij}} \tag{1}$$

Yij for the ith experimental results in the jth experiment. Basically, the larger the normalized results correspond to the better performance and the best-normalized results should be equal to one.

Table 2: Experimental layout using an L27 orthogonal array

S. No.	Feed (mm/rev)	Depth Of Cut (mm)	Cutting Speed (mm/min)	Nose Radius (mm)	Saw Tooth width and height (mm)		Chip Width (mm)	Cutting Force(N)	Max. Tool Wear (mm)	Surface roughness	Cutting tool temp
1	0.02	0.05	30	0.1	0.012	0.013	0.149	25	0.038	0.45	47
2	0.02	0.05	60	0.2	0.031	0.023	0.170	34	0.046	0.42	49
3	0.02	0.05	90	0.4	0.021	0.035	0.201	24	0.239	0.47	54
4	0.02	0.10	30	0.2	0.032	0.025	0.203	36	0.101	0.47	59
5	0.02	0.10	60	0.4	0.015	0.021	0.272	38	0.117	0.42	64
6	0.02	0.10	90	0.1	0.023	0.020	0.186	26	0.129	0.65	59
7	0.02	0.15	30	0.4	0.013	0.014	0.145	33	0.222	0.58	63
8	0.02	0.15	60	0.1	0.027	0.017	0.267	32	0.142	0.64	64
9	0.02	0.15	90	0.2	0.024	0.025	0.207	37	0.142	0.43	49
10	0.04	0.05	30	0.1	0.007	0.011	0.087	32	0.134	0.76	51
11	0.04	0.05	60	0.2	0.016	0.023	0.161	38	0.142	0.67	53
12	0.04	0.05	90	0.4	0.021	0.024	0.220	27	0.173	0.6	52
13	0.04	0.10	30	0.2	0.026	0.017	0.223	26	0.15	0.69	62
14	0.04	0.10	60	0.4	0.026	0.037	0.269	22	0.141	0.61	59
15	0.04	0.10	90	0.1	0.024	0.009	0.068	33	0.16	0.79	69
16	0.04	0.15	30	0.4	0.047	0.060	0.276	24	0.202	0.57	76
17	0.04	0.15	60	0.1	0.023	0.025	0.236	38	0.229	0.81	72
18	0.04	0.15	90	0.2	0.033	0.026	0.134	27	0.163	0.71	52
19	0.06	0.05	30	0.1	0.027	0.021	0.089	30	0.288	0.97	57
20	0.06	0.05	60	0.2	0.026	0.025	0.190	25	0.266	0.82	63
21	0.06	0.05	90	0.4	0.015	0.023	0.177	27	0.27	0.68	68
22	0.06	0.10	30	0.2	0.021	0.017	0.240	30	0.221	0.87	69
23	0.06	0.10	60	0.4	0.020	0.024	0.238	21	0.231	0.57	77
24	0.06	0.10	90	0.1	0.013	0.018	0.147	34	0.15	1.12	76
25	0.06	0.15	30	0.4	0.076	0.039	0.282	27	0.19	0.69	83
26	0.06	0.15	60	0.1	0.017	0.012	0.165	35	0.022	1.19	82
27	0.06	0.15	90	0.2	0.025	0.021	0.049	33	0.283	0.89	48

Table 3: Data preprocessing of the experimental result for each performance characteristic Grey Coefficient

Exp. Run	Feed rate	Depth of cut	Cutting speed	Nose radius	GC CW	GC CF	GC TW	GC SR	GC CT
1	0.02	0.05	30	0.1	0.538	0.685	0.892	0.927	1
2	0.02	0.05	60	0.2	0.490	0.395	0.847	1	0.9
3	0.02	0.05	90	0.4	0.433	0.739	0.38	0.885	0.72
4	0.02	0.1	30	0.2	0.430	0.361	0.627	0.885	0.6
5	0.02	0.1	60	0.4	0.343	0.333	0.583	1	0.514
6	0.02	0.1	90	0.1	0.459	0.629	0.554	0.626	0.6
7	0.02	0.15	30	0.4	0.548	0.414	0.399	0.706	0.529
8	0.02	0.15	60	0.1	0.348	0.435	0.525	0.636	0.514
9	0.02	0.15	90	0.2	0.424	0.346	0.525	0.974	0.9
10	0.04	0.05	30	0.1	0.754	0.435	0.542	0.531	0.818
11	0.04	0.05	60	0.2	0.509	0.333	0.525	0.606	0.75
12	0.04	0.05	90	0.4	0.405	0.586	0.468	0.681	0.782
13	0.04	0.1	30	0.2	0.401	0.629	0.509	0.587	0.545
14	0.04	0.1	60	0.4	0.346	0.894	0.527	0.669	0.6
15	0.04	0.1	90	0.1	0.859	0.414	0.490	0.509	0.45
16	0.04	0.15	30	0.4	0.339	0.739	0.424	0.719	0.382
17	0.04	0.15	60	0.1	0.383	0.333	0.391	0.496	0.418
18	0.04	0.15	90	0.2	0.578	0.586	0.485	0.570	0.782
19	0.06	0.05	30	0.1	0.744	0.485	0.333	0.411	0.642
20	0.06	0.05	60	0.2	0.452	0.684	0.352	0.490	0.529
21	0.06	0.05	90	0.4	0.476	0.586	0.349	0.596	0.461
22	0.06	0.1	30	0.2	0.378	0.485	0.400	0.461	0.45
23	0.06	0.1	60	0.4	0.381	1	0.388	0.719	0.375
24	0.06	0.1	90	0.1	0.543	0.395	0.509	0.354	0.382
25	0.06	0.15	30	0.4	0.333	0.586	0.434	0.587	0.333
26	0.06	0.15	60	0.1	0.501	0.377	1	0.333	0.339
27	0.06	0.15	90	0.2	1	0.414	0.337	0.450	0.947

Where :Grey Relational Coefficient GC;SR Surface Roughness; CT Cutting Temperature; CF Cutting Forces; TW Tool Wear; CW Chip With;

Table 4: Grey relational analysis for the experimental results chip morphology, cutting forces cutting temperature, surface roughness and tool wear

Exp. Run	Feed rate	Depth of cut	Cutting speed	Nose radius	Normalized CW	Normalized CF	Normalized TW	Normalized SR	Normalized CT
1	0.02	0.05	30	0.1	0.571	0.764	0.939	0.96	1
2	0.02	0.05	60	0.2	0.480	0.235	0.909	1	0.944
3	0.02	0.05	90	0.4	0.347	0.823	0.184	0.935	0.805
4	0.02	0.1	30	0.2	0.339	0.117	0.703	0.935	0.666
5	0.02	0.1	60	0.4	0.0429	0	0.642	1	0.527
6	0.02	0.1	90	0.1	0.412	0.705	0.597	0.701	0.666
7	0.02	0.15	30	0.4	0.587	0.294	0.248	0.792	0.555
8	0.02	0.15	60	0.1	0.0643	0.352	0.548	0.714	0.527
9	0.02	0.15	90	0.2	0.322	0.058	0.548	0.987	0.944
10	0.04	0.05	30	0.1	0.836	0.352	0.578	0.558	0.888
11	0.04	0.05	60	0.2	0.519	0	0.548	0.675	0.833
12	0.04	0.05	90	0.4	0.266	0.647	0.432	0.766	0.861
13	0.04	0.1	30	0.2	0.253	0.705	0.518	0.649	0.583
14	0.04	0.1	60	0.4	0.0557	0.941	0.552	0.753	0.666
15	0.04	0.1	90	0.1	0.918	0.294	0.481	0.519	0.388
16	0.04	0.15	30	0.4	0.025	0.823	0.323	0.805	0.194
17	0.04	0.15	60	0.1	0.197	0	0.221	0.493	0.305
18	0.04	0.15	90	0.2	0.635	0.647	0.469	0.623	0.861
19	0.06	0.05	30	0.1	0.828	0.470	0	0.285	0.722
20	0.06	0.05	60	0.2	0.394	0.764	0.082	0.480	0.555
21	0.06	0.05	90	0.4	0.450	0.647	0.067	0.662	0.416
22	0.06	0.1	30	0.2	0.180	0.470	0.251	0.415	0.388
23	0.06	0.1	60	0.4	0.188	1	0.214	0.805	0.166
24	0.06	0.1	90	0.1	0.579	0.235	0.518	0.090	0.194
25	0.06	0.15	30	0.4	0	0.647	0.349	0.649	0
26	0.06	0.15	60	0.1	0.502	0.176	1	0	0.027
27	0.06	0.15	90	0.2	1	0.294	0.018	0.389	0.972

Table 4 shows the normalized results for chip morphology, surface roughness,cutting force and tool wear ratio. Basically, the larger normalized result corresponds to the better performance and the best-normalized results should be equal to one. Fig. 2. Next, the grey relational coefficient is calculated to express the relationship between the ideal and the actual normalized experimental results [10]. The grey relational coefficient ξij can be expressed as:

$$\xi_{ij} = \frac{\min_i \min_j \left| x_i^o - x_{ij} \right| + \xi \max_i \max_j \left| x_i^o - x_{ij} \right|}{\left| x_i^o - x_{ij} \right| + \xi \max_i \max_j \left| x_i^o - x_{ij} \right|} \quad (2)$$

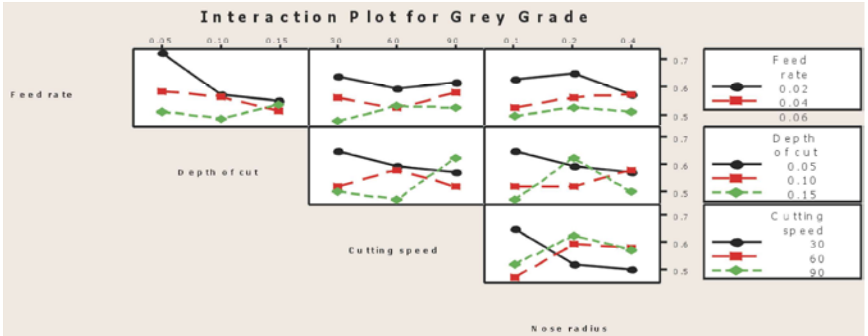
where xi0 is the ideal normalized results for the ith performance characteristics and ξ is the distinguishing coefficient which is defined in the range $0 \le \xi \le 1$. Next, the grey relational coefficient is calculated to express the relationship between the ideal (best) and actual normalized experimental results.

Then, the grey relational grade is computed by averaging the grey relational coefficient corresponding to each performance characteristics [11]. The overall evaluation of the multiple performance characteristics is based on the grey relational grade, that is:

$$\gamma_j = \frac{1}{m} \sum_{i=1}^{m} \xi_{ij} \quad (3)$$

where γj is the grey relational grade for the jth experiment and m is the number of performance characteristics.

Table 5 shows the grey relational grade for each experiment using the L27orthogonal array. The higher grey relational grade represents that the corresponding experimental result is closer to the ideals normalized value. Experiment 1 has the best multiple performance characteristics among 27 experiments because it has the highest grey relational grade. In other words, optimization of the complicated multiple performance characteristics can be converted into optimization of a single grey relational grade. Fig. 3. Since the experimental design is orthogonal, it is then possible to separate out the effect of each machining parameter on the grey relational grade at different levels [12-14]. For example, the mean of the grey relational grade for the workpiece polarity at levels 1 and 2 can be calculated by averaging the grey relational grade for the experiments 1 to 9 and 10 to 27, respectively. Grey relational analysis for the experimental results chip morphology, cutting forces cutting temperature, surface roughness and tool waer [15].



Response Table for Means:

Level	Feed rate	D OC	Cutting Speed	Nose radius
1	0.6135	0.6034	0.5549	0.5457
2	0.5511	0.5380	0.5461	0.5765
3	0.5066	0.5298	0.5701	0.5491
Delta	0.1069	0.0736	0.0240	0.0308
Rank 1 2 4		3		

Main Effects Plot (data means) for Means

Analysis of Variance for grey grade, using Adjusted SS for Tests

Source DF	Seq SS	Adj SS	Adj MS	F	P
Feed rate 2	0.051912	0.051912	0.025956	4.24	0.031
Depth of cut 2	0.029298	0.029298	0.014649	2.39	0.120
Cutting speed 2	0.002655	0.002655	0.001327	0.22	0.807
Nose radius 2	0.005140	0.005140	0.002570	0.42	0.663
Error 18	0.110177	0.110177	0.006121		
Total	26 0.199182				

Fig. 2: Interaction plot for gray grade

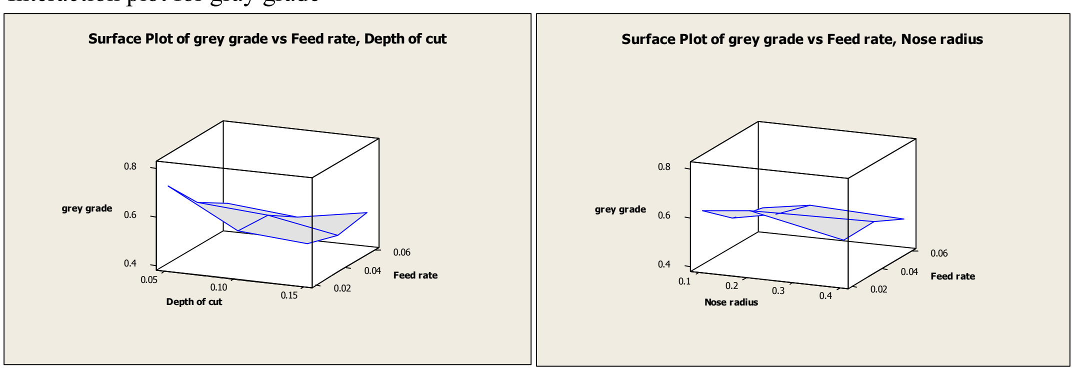
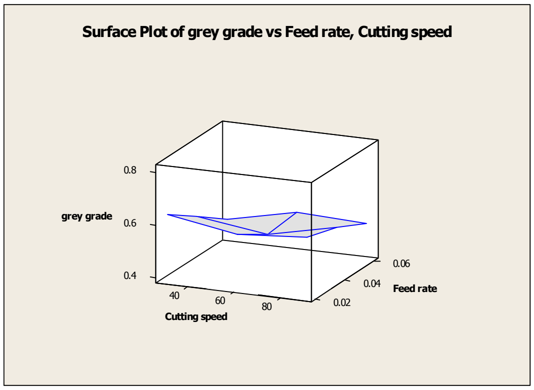


Fig. 3: Surface Plot of grade vs Feed rate, cutting speed, Depth of cut and Nose radius

Table 5: Grey relational grade for each experimental

Ex.No	GRADE	Rank	11	0.5450	14	21	0.4940	22
1	0.8076	1	12	0.5847	9	22	0.4352	26
2	0.7266	2	13	0.5346	16	23	0.5729	12
3	0.6316	4	14	0.6076	7	24	0.4371	25
4	0.5809	10	15	0.5450	15	25	0.4550	24
5	0.5548	13	16	0.5211	18	26	0.5103	20
6	0.5738	11	17	0.4047	27	27	0.6299	5
7	0.5196	19	18	0.6005	8			
8	0.4921	23	19	0.5236	17			
9	0.6343	3	20	0.5010	21			
10	0.6164	6						



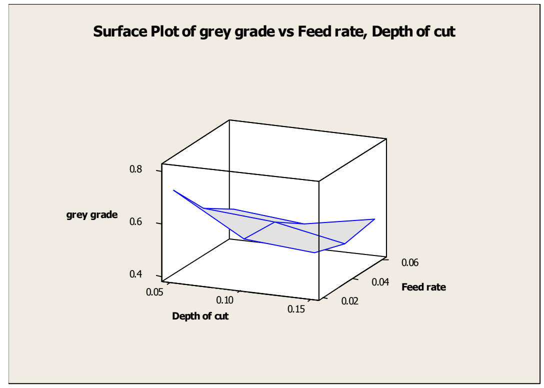


Fig. 4: Main effects plot for Grey grade

The mean of the grey relational grade for each level of the other machining parameters can be computed in the similar manner. Fig. 4 shows the grey relational grade graph and the dash line indicated in is the value of the total mean of grey relational grade. Basically, the larger the grey relational grade, the better is the multiple performance characteristics. However, the relative importance among the machining parameters for the multiple performance characteristics still needs to be known so that the optimal combinations of the machining parameter levels can be determined more accurately [16]. Table 4 Grey relational analysis of the experimental results chip morphology, cutting forces cutting temperature, surface roughness and tool wear.

Analysis of Variance: Analysis of Variance (ANOVA) is a method of apportioning variability of an output to various inputs. Table - 5 shows the results of ANOVA analysis. The purpose of the analysis of variance is to investigate which machining parameters significantly affect the performance characteristic. This is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey relational grade, in contributions by each machining parameter and the error [17]. First, the total sum of the squared deviations SST from the total mean of the grey relational grade γm can be calculated as:

$$SS_T = \sum_{j=1}^{p} (\gamma_j - \gamma_m)^2 \tag{4}$$

where p is the number of experiments in the orthogonal array and γj is the mean grey relational grade for the j th experiment.

The total sum of the squared deviations SST is decomposed into two sources: the sum of the squared deviations ceased due to each machining parameter and its interaction effects and the sum of the squared error SSe. The percentage contribution of each of the machining parameters in the total sum of the squared deviations SST can be used to evaluate the importance of the machining parameter change on the performance characteristic. In addition, the Fisher's F- test can also be used to determine which machining parameters have a significant effect on the performance characteristic. Usually, the change of the machining parameters has a significant effect on performance characteristic when F is large. This is accomplished by separating the total variability of the grey relational grades, which is measured by the sum of the squared deviations from the total mean of the grey relational grade, into contributions by each machining parameter and the error. First, the total sum of the squared deviations SST from the total mean of the grey relational grade gm can be calculated as: [18].

The total sum of the squared deviations SST is decomposed into two sources: the sum of the squared deviations SSd due to each machining parameter and the sum of the squared error SSe. The percentage contribution by each of the machining parameters in the total sum of the squared deviations SST can be used to evaluate the importance of the machining parameter change on the performance characteristic [19].

In addition, the Fisher's F tester can also be used to determine which machining parameters have a significant effect on the performance characteristic. Usually, the change of the machining parameter has a significant effect on the performance characteristic when *F* is large. Results of analysis of variance indicate that workpiece polarity is the most significant machining parameter for affecting the multiple performance characteristics.

CONCLUSION

The use of the orthogonal array with grey relational analysis to optimize the precision turining process with the multiple performance characteristics has been reported in this paper. A gray relational analysis of the experimental results of chip morphological, cutting forces cutting temperature, surface roughness and tool wear can convert optimization of the multiple performance characteristics into optimization of a single performance characteristic called the grey relational grade. Effect of tool wear and chip morphology on the cutting conditions was examined in the machining of Titanium alloy. The work is of interest because of its relevance to increasing hard machining. Implemented as a quicker, cleaner and practical alternative to finish grinding. Cutting condition was quantified to measure the effect of Chip Morphology and Tool wear. The following conclusions can be drawn based on this study.As a result, optimization of the complicated multiple performance characteristics can be greatly simplified through this approach.

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