APEM journal Advances in Production Engineering & Management 5 (2010) 3, 171-180
ISSN 1854-6250 Scientific paper

APPLICATION OF GREY BASED TAGUCHI METHOD IN MULTI-RESPONSE OPTIMIZATION OF TURNING PROCESS

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Abstract:
Metal cutting is one of the most significant manufacturing process in material removal and turning is the most commonly used method for metal cutting. This paper presents the multi-response optimization of CNC turning parameters using grey based Taguchi method. Experiments are designed and conducted based on Taguchi's L_{27} orthogonal array design. The turning parameters are cutting speed, feedrate, depth of cut and nose radius and the responses are surface roughness and power consumption. Taguchi's signal-to-noise (S/N) ratio are determined based on their performance characteristics. A grey relation grade is obtained by using S/N ratio. Based on grey relational grade value, optimum levels of parameters have been identified by using response table and response graph and the significant contributions of controlling parameters are estimated using analysis of variances (ANOVA). Confirmation test is conducted for the optimal machining parameters to validate the test result. The proposed method is having prediction accuracy and competency. This method may be extended to other machining processes.

Key Words: Power Consumption, Surface Roughness, Multi - Response Optimization, Orthogonal Array, Grey Based Taguchi Method, ANOVA, Turning Process

1. INTRODUCTION

Metal cutting is one of the most significant manufacturing processes in material removal and turning is the most commonly used method for metal cutting. Turning operations are evaluated based on the performance characteristics such as surface roughness, material removal rate (MRR), tool wear, tool life, cutting force and power consumption. These performance characteristics are strongly correlated with cutting parameters such as cutting speed, feed rate, depth of cut, and tool geometry. It is an important task to select cutting parameters for achieving high cutting performance [1, 2]. There is a need to operate these machines as efficiently as possible in order to obtain the required payback [3]. Achieving desired surface quality is of great importance for the functional behaviour of the mechanical parts [4]. With the recent increase in energy demand and constraints in the supply of energy has become a priority for the manufacturing industry. Very few research attempts have been done to estimate the significance of energy required and its cost for the CNC machining process as an integral part of the optimization process. In today's manufacturing industry, special attention is given to surface finish and power consumption. Traditionally the desired cutting parameters are determined based on experience and handbooks [5]. This method is limited in applications.

Optimization problems are solved by conventional and non-conventional optimization techniques [6]. Conventional techniques may be broadly classified into two categories: In the first category, experimental techniques that include statistical design of experiment, such as Taguchi method, and response surface design methodology. In the second category, iterative mathematical search techniques, such as linear programming, non-linear programming and dynamic programming algorithms are included. Non-conventional meta-

heuristic search-based techniques, which are used by researchers in recent times are based on genetic algorithm (GA), Tabu search (TS), simulated annealing (SA).

The approach adopted by Taguchi is very popular for solving optimization problems in the field of manufacturing engineering [5, 7, 8, 9]. The method utilizes experimental design called orthogonal array design, and S/N ratio which serve the objective function to be optimized within experimental domain. Traditional Taguchi method solve only single response optimization problem. But in real time most of the engineering application problems are multi-response in nature. In multiple response optimum setting of control factors, it can be observed that an increase/improvement of one response may cause change in another response, beyond the acceptable limit. To solve multi-response optimization problems, it is convenient to convert all the objectives into an equivalent single objective function. This equivalent objective function, which is the representative of all the quality characteristics of the product, is to be optimized. The more frequently used approach is to assign a weighting for each responses. The weighted S/N ratio of each quality characteristics is used to compute the performance measures [10]. In practice it is not competent because it uses engineering judgment and past experiences to optimize multiple responses. To overcome the limitation the combined approaches are proposed by researchers [11, 12, 13, 14, 15].
The grey relational analysis theory, initialized by Deng [16], makes use of this to handle uncertain systematic problem with only partial known information. This theory is adopted for solving the complicated interrelationships among the multiple responses. The grey relational coefficient can express the relationship between the desired and actual experimental results. A grey relational grade is obtained to evaluate the multi-response. Optimization of the complicated multi-response can be converted into optimization of a single grey relational grade. The integrated grey based Taguchi method combines advantages of both grey relational analysis and Taguchi method. This method was successfully applied to optimize the multi-response of complicated problems in manufacturing processes [14, 17]. Furthermore, ANOVA is performed to see which process parameters are statistically significant [18]. In this study, the effect of CNC turning parameters on power consumption and surface roughness are reported using grey based Taguchi method.

2. GREY BASED TAGUCHI METHOD

The integrated Grey based Taguchi method combines the algorithm of Taguchi method and grey relational analysis to determine the optimum process parameters for multiple responses.

2.1 Taguchi Method

The concept of the Taguchi method is that the parameter design is performed to reduce the sources of variation on the quality characteristics of product, and reach a target of process robustness [19]. It utilizes the orthogonal arrays from experimental design theory to study a large number of variables with a small number of experiments [3, 20]. Furthermore, the conclusions drawn from small scale experiments are valid over the entire experimental region spanned by the control factors and their level settings. A loss function is defined to calculate the deviation between the experimental value and the desired value. The value of the loss function is further transformed into an S/N ratio. Usually, there are three categories of performance characteristic in the analysis of the S/N ratio, i.e. lower-the-better, higher-the-better, and nominal-the-best. The S/N ratio η_{ij} for the ith performance characteristic in the jth experiment can be expressed as:

$$\eta_{ij} = -10\log(L_{ij}) \tag{1}$$

The loss function L_{ij} for higher-the-better performance characteristic can be expressed as:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n}\frac{1}{y_{ijk}^2} \tag{2}$$

L_{ij} - loss function of the ith process response in the jth experiment, k- number of tests, y_{ijk} - experimental value of the ith performance characteristic in the jth experiment at the kth tests

For lower-the-better performance characteristic, the loss function L_{ij} can be expressed as:

$$L_{ij} = \frac{1}{n}\sum_{k=1}^{n} y_{ijk}^2 \tag{3}$$

For nominal-is-best performance characteristics, the S/N ratio can be expressed as:

$$\eta_{ij} = 10\log\left(\bar{y}^2/\sigma\right) \tag{4}$$

The S/N ratio for each level of process parameters is computed based on the S/N analysis. Regardless of the category of the performance characteristic, a larger S/N ratio corresponds to a better performance characteristic. This S/N ratio value can be considered for the optimization of single response problems. However, optimization of multi-response cannot be straightforward as in the optimization of a single response [21]. The higher S/N ratio for one response may correspond to the lower S/N ratio for another response. To overcome the limitation combined approaches are proposed by researchers. In this, grey based Taguchi method is adopted to optimize the multi-response.

2.2 Grey Relational Analysis

The grey relational analysis based on the grey system theory can be used to solve the complicated interrelationships among the multiple responses effectively. In a grey system, some information is known and some information is unknown. It is applied in optimization of WEDM process, EDM process, chemical-mechanical polishing process and drilling operation with multi-responses [12, 13, 14, 22, 23].

Data pre-processing is the first stage in grey analysis since the range and unit in one data sequence may differ from the others. Data pre-processing is a means of transferring the original sequence to a comparable sequence. Depending on the characteristics of a data sequence, there are various methodologies of data pre-processing available for this analysis.

Experimental data y_{ij} is normalized as Z_{ij} ($0 \le Z_{ij} \le 1$) for the ith performance characteristics in the jth experiment can be expressed as:

For S/N ratio with Larger-the-better condition

$$Z_{ij} = \frac{y_{ij} - \min\left(y_{ij}, i = 1, 2, ...n\right)}{\max\left(y_{ij}, i = 1, 2, ...n\right) - \min\left(y_{ij}, i = 1, 2, ...n\right)} \tag{5}$$

For S/N ratio with smaller-the-better

$$Zij = \frac{\max\left(y_{ij}, i = 1, 2, ...n\right) - y_{ij}}{\max\left(y_{ij}, i = 1, 2, ...n\right) - \min\left(y_{ij}, i = 1, 2, ...n\right)} \tag{6}$$

For S/N ratio with nominal-the-best

$$Zij = \frac{(y_{ij} - \text{Target}) - \min(|y_{ij} - \text{Target}|, i = 1, 2, ...n)}{\max(|y_{ij} - \text{Target}|, i = 1, 2, ...n) - \min(|y_{ij} - \text{Target}|, i = 1, 2, ...n)} \quad (7)$$

According to Deng [15], larger normalized results correspond to better performance and the best normalized result should be equal to one. Then, the grey relational coefficients are calculated to express the relationship between the ideal (best) and the actual experimental results.

The Grey relational Co-efficient γ_{ij} can be expressed as:

$$\gamma_{ij} = \frac{\Delta \min + \xi \Delta \max}{\Delta_{oj}(k) + \xi \Delta \max} \quad (8)$$

Where,

a. j=1,2…n; k=1,2…m, n is the number of experimental data items and m is the number of responses.
b. $y_o(k)$ is the reference sequence ($y_o(k)$=1, k=1,2…m); $y_j(k)$ is the specific comparison sequence.
c. $\Delta_{oj} = \|y_o(k) - y_j(k)\|$ = The absolute value of the difference between $y_o(k)$ and $y_j(k)$
d. $\Delta_{\min} = \min_{\forall j \in i} \min_{\forall k} \|y_o(k) - y_j(k)\|$ is the smallest value of $y_j(k)$
e. $\Delta_{\max} = \max_{\forall j \in i} \max_{\forall k} \|y_o(k) - y_j(k)\|$ is the largest value of $y_j(k)$
f. ξ is the distinguishing coefficient which is defined in the range $0 \le \xi \le 1$ (the value may adjusted based on the practical needs of the system)

The Grey relational grade $\overline{\gamma_j}$ is expressed as:

$$\overline{\gamma_j} = \frac{1}{k} \sum_{i=1}^{m} \gamma_{ij} \quad (9)$$

Where $\overline{\gamma_j}$ is the grey relational grade for the jth experiment and k is the number of performance characteristics. The grey relational grade shows the correlation between the reference sequence and the comparability sequence. The evaluated grey relational grade varies from 0 to 1 and equals 1 if these two sequences are identically coincident. The higher grey relational grade implies the better product quality; on the basis of grey relational grade, the factor effect can be estimated and the optimal level for each controllable factor can also be determined. The structure of the integrated grey based Taguchi algorithm is illustrated in Figure 1.

3. DETERMINATION OF OPTIMAL MACHINING PARAMETERS

3.1 Experimental details

A CNC lathe (FANUC control) with 7.5KW spindle power and maximum spindle speed of 4500 rpm is used to perform the machining operation. A schematic diagram of the experimental set-up used in this study is shown in Figure 2. FLUKE 43B Power Quality Analyzer is connected to the power supply of CNC turning center for measuring the power consumption (Watts) of cutting process. Power consumption is measured for each setting of machining operation and idle running operation. The surface roughness (Ra in μm) is measured using Taylor-Hobson Talysurf which is a stylus and skid type instrument is working on carrier modulating principle. The work material is AISI304 Stainless Steel in the form of

round bars with 50mm diameter and 200 mm cutting length. Carbide tool inserts of standards CNMG1200404, CNMG1200408 and CNMG1200412 are used for machining.

To perform the experimental design, three levels of machining parameters cutting speed, feed rate, depth of cut and nose radius are selected and are shown in Table I. To select an appropriate orthogonal array for the experiments, the total degrees of freedom need to be computed. The degrees of freedom for the orthogonal array should be greater than or equal to those for the process parameters. In this study, an L_{27} orthogonal array is used because it has 26 degrees of freedom more than the 8 degrees of freedom in the machining parameters. The experimental combinations of the machining parameters using the L_{27} orthogonal array are presented in Table II. Based on the designed orthogonal array combination turning operations are performed in CNC lathe. The experimental results are summarized in Table II.

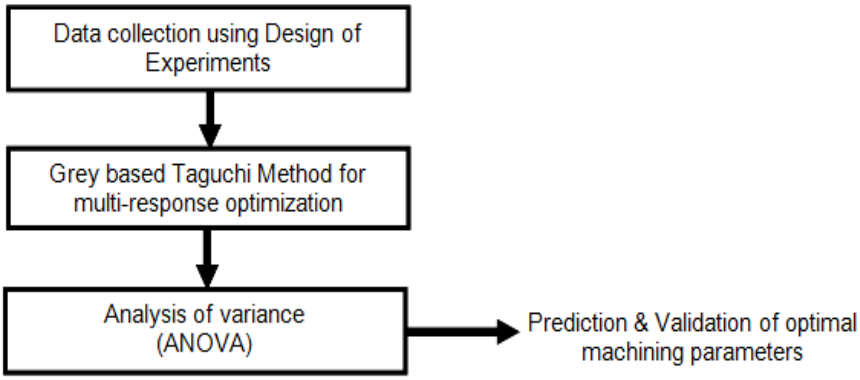

Figure 1: Structure of Grey based Taguchi method.

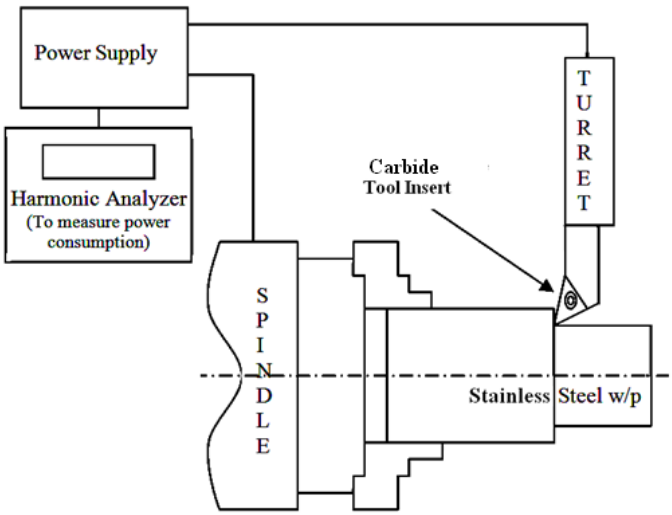

Figure 2: Schematic diagram of experimental set-up.

Table I: Cutting parameters and their levels.

Factor	Cutting Parameter	Unit	Level 1	Level 2	Level 3
A	Cutting speed ‘V’	m/min	100	125	150
B	Feed rate ‘f’	mm/rev	0.05	0.1	0.15
C	Depth of cut ‘d’	mm	0.20	0.35	0.50
D	Nose radius ‘NR’	mm	0.4	0.8	1.2

3.2 Optimization of machining parameters

Initially, the S/N ratios for a given responses are computed using one of the (1), (2), (3) and (4) depending upon the type of quality characteristics. Power consumption and surface roughness have lower-the-better criterion.

The normalized values for each response S/N ratios are estimated using (5), (6) and (7). The computed S/N ratios for each quality characteristic and the normalized values of S/N ratios are shown in Table III.

Table II: Experimental design using L_{27} orthogonal array and their responses.

Exp. No.	A	B	C	D	Power consumption (Watts)	Surface roughness (Ra in μm)
1	1	1	1	1	213	2.04
2	1	1	2	2	320	1.74
3	1	1	3	3	332	2.02
4	1	2	1	2	283	1.25
5	1	2	2	3	340	1.1
6	1	2	3	1	393	1.02
7	1	3	1	3	275	1.5
8	1	3	2	1	350	1.12
9	1	3	3	2	620	1.35
10	2	1	1	2	392	1.82
11	2	1	2	3	438	1.52
12	2	1	3	1	441	1.78
13	2	2	1	3	391	1.04
14	2	2	2	1	570	0.84
15	2	2	3	2	668	1.02
16	2	3	1	1	394	1.16
17	2	3	2	2	617	1.26
18	2	3	3	3	760	1.48
19	3	1	1	3	448	2.02
20	3	1	2	1	516	1.54
21	3	1	3	2	585	1.94
22	3	2	1	1	476	1.08
23	3	2	2	2	625	1.16
24	3	2	3	3	765	1.42
25	3	3	1	2	528	1.46
26	3	3	2	3	706	1.38
27	3	3	3	1	873	1.64

Grey relational coefficient for each response has been calculated using (8). The value for ξ is taken as 0.5 since both the process parameters are of equal weight. The results are shown in Table III. The grey relational grade can be calculated by using (9), which is the overall representative of both the responses shown in Table III. Now, the multi-response optimization problem has been transformed into a single equivalent objective function optimization problem using this approach. The higher grey relational grade is said to be close to the optimal. The mean response table for overall grey relational grade is shown in Table IV and is represented graphically in Figure 3. The mean grey relational grade for the cutting speed at levels 1, 2 and 3 can be calculated by averaging the grey relational grades for the experiments 1-9, 10-18 and 19-27 respectively. The mean grey relational grade for each level of the other parameters can be computed in the similar way. With the help of the Table

IV and Fig 3, the optimal parameter combination has been determined. The optimal factor setting condition is $A_1B_2C_1D_1$.

Using the grey relational grade value, ANOVA is formulated for identifying the significant factors. The results of ANOVA are presented in Table V. From ANOVA, it is clear that cutting speed (35.47%) influences more on turning of Stainless steel AISI 304 followed by feed rate (26.12%), depth of cut (18.16%) and nose radius (10.63%).

Table III: S/N ratios and Grey relational coefficients of responses and Grey relational grade.

Exp. No.	S/N ratios		Normalized values of S/N ratios		Grey Relational Coefficient of		Grey relational grade
	Power Consumption	Surface Roughness	Power Consumption	Surface Roughness	Power Consumption	Surface Roughness	
1	-46.5676	-6.1926	1.0000	0.0000	1.0000	0.3333	0.6667
2	-50.1030	-4.8110	0.7115	0.1793	0.6341	0.3786	0.5063
3	-50.4228	-6.1070	0.6854	0.0111	0.6138	0.3358	0.4748
4	-49.0357	-1.9382	0.7986	0.5520	0.7128	0.5274	0.6201
5	-50.6296	-0.8279	0.6685	0.6961	0.6013	0.6220	0.6116
6	-51.8879	-0.1720	0.5658	0.7812	0.5352	0.6956	0.6154
7	-48.7867	-3.5218	0.8189	0.3465	0.7341	0.4335	0.5838
8	-50.8814	-0.9844	0.6479	0.6758	0.5868	0.6066	0.5967
9	-55.8478	-2.6067	0.2426	0.4653	0.3976	0.4832	0.4404
10	-51.8657	-5.2014	0.5676	0.1286	0.5362	0.3646	0.4504
11	-52.8295	-3.6369	0.4889	0.3316	0.4945	0.4279	0.4612
12	-52.8888	-5.0084	0.4841	0.1537	0.4922	0.3714	0.4318
13	-51.8435	-0.3407	0.5694	0.7593	0.5373	0.6750	0.6062
14	-55.1175	1.5144	0.3022	1.0000	0.4174	1.0000	0.7087
15	-56.4955	-0.1720	0.1897	0.7812	0.3816	0.6956	0.5386
16	-51.9099	-1.2892	0.5640	0.6362	0.5342	0.5789	0.5565
17	-55.8057	-2.0074	0.2460	0.5430	0.3987	0.5225	0.4606
18	-57.6163	-3.4052	0.0983	0.3617	0.3567	0.4392	0.3980
19	-53.0256	-6.1070	0.4729	0.0111	0.4868	0.3358	0.4113
20	-54.2530	-3.7504	0.3728	0.3169	0.4436	0.4226	0.4331
21	-55.3431	-5.7560	0.2838	0.0566	0.4111	0.3464	0.3788
22	-53.5521	-0.6685	0.4300	0.7168	0.4673	0.6384	0.5528
23	-55.9176	-1.2892	0.2369	0.6362	0.3959	0.5789	0.4874
24	-57.6732	-3.0458	0.0936	0.4083	0.3555	0.4580	0.4068
25	-54.4527	-3.2871	0.3565	0.3770	0.4372	0.4452	0.4412
26	-56.9761	-2.7976	0.1505	0.4405	0.3705	0.4719	0.4212
27	-58.8203	-4.2969	0.0000	0.2460	0.3333	0.3987	0.3660

Table IV Response table (mean) for overall grey relational grade.

Factors	Level-1	Level-2	Level-3
A	0.5684	0.5124	0.4332
B	0.4683	0.5720	0.4738
C	0.5432	0.5208	0.4501
D	0.5475	0.4804	0.4861

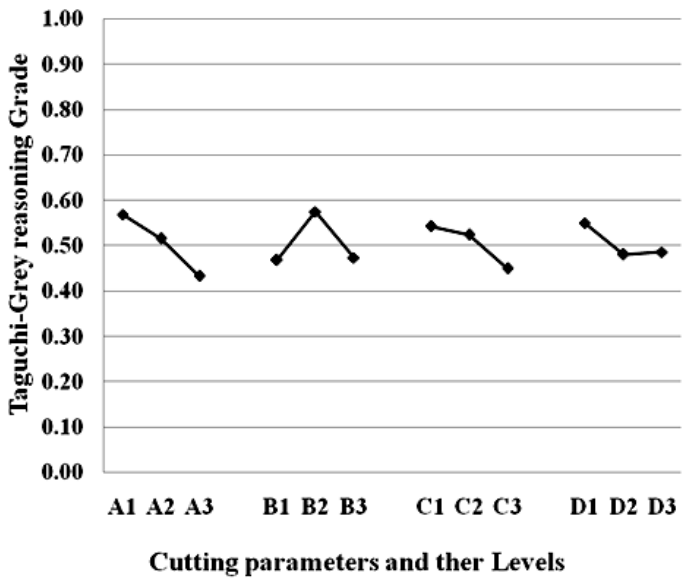

Figure 3: The response graph for each level of machining parameters.

Table V: Results of the ANOVA.

Factor	DOF	SS	MS	F value	% Contribution
A	2	0.0831	0.0416	33.20	35.47
B	2	0.0612	0.0306	24.45	26.12
C	2	0.0426	0.0213	16.99	18.16
D	2	0.0249	0.0125	9.95	10.63
Error	18	0.0225	0.0013	-	9.62
Total	26	0.2344	-	-	100.00

3.3 Predicted optimum condition

In order to predict the optimum condition, the expected mean at the optimal settings (μ) is calculated by using the following model.

$$\mu = \bar{A}_1 + \bar{B}_2 + \bar{C}_1 + \bar{D}_1 - 3\times\bar{T}_{gg} \tag{10}$$

Where, $\bar{A}_1$, $\bar{B}_2$, $\bar{C}_1$ and $\bar{D}_1$ are the mean values of the grey relational grade with the parameters at optimum levels and $\bar{T}_{gg}$ is the overall mean of average grey grade. The expected mean (μ) at optimal setting is found to be 0.7171.

Confidence interval (CI) is calculated as

$$CI = \sqrt{F_\alpha(1, f_e)V_e\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \tag{11}$$

= $\pm$0.0857

Where, $F_\alpha(1, f_e)$ is the F ratio at a significance level of α%, α is the risk, f_e is the error degrees of freedom, V_e is the error mean square, n_{eff} is the effective total number of tests and R is the number of confirmation tests

$$n_{eff} = \frac{\text{Total number of observations}}{1+\text{Total degrees of freedom associated with items used in estimating } \mu} \quad (12)$$

Therefore 95% confidence interval of the predicted optimum condition is given by following model, where μ = the Grey relational grade value after conducting the confirmation experiments with optimal setting point, i.e., $A_1B_2C_1D_1$

$(0.7171-0.0857) < \mu < (0.7171+0.0857)$

$(0.6314) < \mu < (0.8028)$

4. CONFIRMATION TEST

Once the optimal level of the process parameters has been determined, the final step is to predict and verify the improvement of the responses using the optimal level of process parameters. Table VI shows the comparison of the multi-response for initial and optimal machining parameters. The initial designated levels of machining parameters are A_1, B_1, C_2 and D_2 which is the second experiment shown in the Table II. As noted from Table VI, the surface roughness Ra is decreased from 1.74 µm to 1.14 µm and the power consumption is decreased from 320 watts to 245 watts respectively. The estimated grey relational grade is increased from 0.5063 to 0.7134, which is the largest value obtained in all the experimental results in Table III. It is clearly shown that the multi-responses in the turning process are together improved by using this method.

Table VI: The comparison results of initial and optimal turning responses.

Initial turning parameters		Optimal turning parameters	
		Prediction	Experiment
Levels	$A_1B_1C_2D_2$	$A_1B_2C_1D_1$	$A_1B_2C_1D_1$
Power consumption (Watts),	320	-	245
Surface roughness (Ra)	1.74	-	1.14
Taguchi based grey relational grade	0.5063	0.7171	0.7134
Improvement of Taguchi based grey relational grade		0.2108	0.2071

5. CONCLUSION

Experiments are designed and conducted on CNC machine with carbide tool inserts and Stainless Steel AISI304 as work material to optimize the turning parameters. The power consumption and surface roughness are the responses. The proposed Grey based Taguchi method is constructive in optimizing the multi-responses. It is identified that cutting speed influences (35.47%) more, followed by feed rate (26.12%), depth of cut (18.16%) and nose radius (10.63%). Confirmation test results proved that the determined optimum condition of turning parameters satisfy the real requirements.

ACKNOWLEDGEMENT

The authors express their sincere thanks to the National Institute of Technology Tiruchirappalli, India for giving the sponsorship under its research grant scheme.

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