Experimental Investigation and Optimization of Cutting Parameters on Surface Roughness and Material Removal Rate in Turning of Nylon 6 Polymer

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Abstract— Plastic materials, having good mechanical properties, are replacing metals in variety of applications. Weight and price of plastic components are lesser than metallic components. For near net shape plastic products, plastic molding processes like injection molding, compression molding, blow molding are generally preferred. However, need of machining of plastics has increased due to requirement of small scale production and good surface quality of machined part. Nylon 6, one of the thermoplastic, is widely used due to its good mechanical properties. This paper discusses optimization of surface roughness and material removal rate during turning on Nylon 6. Empirical investigation of effect of speed, feed and depth of cut is carried out by following Taguchi's design of experiments; and analysis of experimental results is done by signal to noise ratio, analysis of variance and regression analysis for single response optimization, followed by grey relational analysis for multi response optimization. Study identified feed as most significant factor affecting both surface roughness and material removal rate and suggests optimal combination of process parameters.

Keywords— Plastic machining, Machining on polymers, Plastic materials, Processing on polymers, Optimization techniques, Statistical analysis, Grey relational analysis.

INTRODUCTION

Nylon (polyamide-PA 6) is thermoplastic used as replacement material for metals such as bronze, cast iron and aluminum; due to its properties like toughness, rigidity, abrasion resistance, heat resistance, wear resistance, chemical resistance, etc. Nylon 6 and Nylon 6/6 are two common grades of Nylon; widely used in automotive, electronics, textiles, paper and aircraft industries. Specifically it is used for manufacturing of gears, cams, bearings, bushes, valve seats, etc.

Although majority of plastic components are processed by molding, it is not justified for smaller quantities due to costs involved in making mold, process setting time, wastage of material through runners and during trial runs. Such requirements of small quantities are fulfilled by machining process. During machining, surface characteristics gets affected by process parameters like cutting speed, feed rate, depth of cut, etc. Precision machining of plastics is preferred for manufacturing of machine components, electronics and optics; where dimensional accuracy is important along with surface characteristics.

Researchers have studied machining of different plastic materials. During study of ultraprecision machining on Polymethyl Methacrylate (PMMA), Kobayashi and Hirakawa, (2006) advocated machining of plastics for achieving high dimensional accuracy and good surface finish; and observed that surface roughness decreases as the feed rate decreases. Thus, plastic components requiring precision dimensions can be obtained by machining process. Jagtap and Pawade, (2014) observed feed and speed affect surface quality of machined plastic components and concludes spindle speed is most significant parameter affecting surface roughness. If spindle speed is less then surface roughness is better. Study of researchers on PMMA indicating requirement of dimensional accuracy and good surface finish of component can be achieved by machining with considering speed and feed as prime influencing factors. While studying machinability of polymers, Keresztes et al. (2011) noted that injection molding is being widely used for production of plastic components; however machining of plastics is preferred for requirement of plastic products in smaller quantities. This study illustrates importance of machining process in production of small quantities plastic components. For Ultra High Molecular Weight Polyethylene (UHMWPE), Salles and Goncalves, (2003) found that cutting speed doesn't affect much on surface roughness, whereas with increase in feed rate, surface roughness increases. Thus earlier research states that roughness is insignificant for speed in case of UHMWPE; whereas, for PMMA speed affects roughness. There is little agreement in study of plastic machining that effect of speed on surface roughness is material specific.

Jagtap et al. (2012) suggested for Nylon and Polypropylene (PP) that good surface quality can be achieved by primarily considering feed and insert clearance angle. Researchers observed that feed as an effective parameter gives good surface finish at its lower level;

and larger degree insert clearance angle gives better surface quality than the smaller degree insert clearance angle. This study indicates that along with cutting parameters, insert clearance angle needs to be considered for achieving better surface characteristics. Lazarevic et al. (2011) suggested that for polyamide 6, cutting speed can be set at the highest level to obtain higher material removal rate. Authors observed that feed rate, depth of cut and tool nose radius are proportionally affecting on surface roughness for polyamide 6 (PA 6). However, the influence of cutting speed is negligible. Apparently, behavior of cutting parameters on roughness for machining of plastic materials is changing. Davim et al. (2009) carried out turning on polyamide and reinforced polyamide; and analyzed that surface roughness for the polyamide increases with feed rate; whereas it is insensitive to reinforced polyamide. This study indicates that machining behavior of plastic and reinforced plastic is not same. While carrying out experimental investigation Gaitonde et al. (2008) observed that more machining force, cutting power are required for PA6 than for PA66 GF30 polyamides. Authors detected machining force and cutting power both increase with feed rate and experimentation has performed by using carbide tool during turning. This study illustrates that machining nature of PA66 GF30 is better than PA6. While machining on composites of polyamide Haghi et al. (2013) noticed that content of nano calcium carbonate in polyamide 6 decreases the cutting forces, but it doesn't have any effect on surface roughness. Cutting force is maximum for lower cutting speed. From this study, it can be seen that composites of polyamides give better machinability.

Researchers have carried out machining on Glass fiber reinforced plastic (GFRP) and studied effect of cutting parameters on surface quality. Kini and Chincholkar (2015) found that surface roughness is inversely proportional to feed rate and cutting speed. For lower tool nose radius, the depth of cut and feed rate, the material removal rate is small. Gupta and Kumar (2013) observed that depth of cut followed by feed rate have great influence on surface roughness and material removal rate. Hussain et al. (2011) found that surface roughness increases with increase in feed rate and it decreases with increase in cutting speed. Depth of cut has very little effect on surface roughness. Cutting forces are highly influenced by feed followed by cutting speed. Study on GFRP indicates that composition of GFRP is affecting its machining nature and cutting speed and feed rate are primarily considered as important parameters for better surface quality. Kumar et al. (2012) observed machining on unidirectional GFRP is different from the metals. Bending rupture, shearing and plastic deformation are perceived during machining of composites. Surface roughness is inversely proportional to cutting speed and directly proportional to feed rate and depth of cut. It is realized from study that surface quality of machined plastic component is depending on directions of glass fiber reinforcement.

This paper discusses investigation of effect of processing parameters like cutting speed, feed rate and depth of cut, during turning on Nylon 6 polymer. Considering the responses surface roughness and material removal rate individually and simultaneously, analysis of experimental results have carried out to optimize control factors. By using analysis tools like Signal to noise (S/N) ratio, analysis of variance (ANOVA) and regression analysis for single response optimization and grey relational analysis for multi-response optimization results are discussed. Considering scope for study, experimentation details have been discussed in next section.

EXPERIMENTATION DETAILS

For present study, objective was to simultaneously optimize surface roughness and material removal rate during machining of Nylon 6. Considering responses as surface roughness and material removal rate and process parameters as speed (v), feed (f) and depth of cut (d), machining on CNC was carried out on workpiece material Nylon 6. Rod of Nylon 6 having 48 mm diameter and 70 mm length were turned on CNC lathe (JYOTI, India), maximum speed 4000 rpm, 20 KW power using carbide insert TNMG 160404 under dry cutting condition. Levels of process parameters have been selected based on levels recommended by researchers Lazarevic et al. (2012) for study and few pilot experiments. Pilot experiments, for selection of levels of one process parameter, have been conducted by varying only one process parameter and keeping other process parameters constant. Then after responses were measured and as per requirement of responses, levels of process parameter were selected. The process parameters and their levels are presented in Table 1.

Table 1
Process parameters and their levels

Levels	Cutting speed v (m/min)	Feed rate f (mm/rev)	Depth of cut d (mm)
1	214.3	0.049	2
2	254.6	0.098	3
3	295.2	0.196	6

Literature suggested use of experimental design recommended by Taguchi in the form of standard L_9 orthogonal array. Experiments were designed and conducted accordingly. Three replications of each experiments have been conducted to minimize the effect of noise factor. Experiments are conducted in random order to avoid systematic error.

After experimentation, surface roughness is measured by MITUTOYO SURFTEST SJ-210 (Surface roughness measuring tester) and material removal rate is obtained by measuring weight of the component before and after machining in terms of g/min.

RESULTS AND DISCUSSION

For single response optimization of surface roughness or material removal rate has been done by using S/N ratio, ANOVA and regression analysis. S/N ratio gives parametric combination of process parameters for single response; ANOVA has been performed to see significance of control factors on response. Regression analysis gives correlation of control factors and response parameters by regression equation. In case of multi response optimization, two or more responses are considered simultaneously. For present study, grey relational analysis has been used as multi response optimization tool to obtain optimal combination of control factors considering both responses simultaneously. These analysis tools have discussed in upcoming subsections.

Lower surface roughness in general, and, higher material removal rate in particular, are the indicators of better performance in turning process. Hence, for surface roughness (Ra) 'lower-the-better' and for material removal rate (MRR) 'higher-the-better' criterion have been used for analysis of experimental results.

1. Parametric combination for surface roughness and material removal rate (S/N ratio)

The term S/N indicates that ratio of signal to noise. The word 'signal' (S) represents desirable characteristics and word 'noise' (N) represents undesirable characteristics of the process.

S/N ratio, (Sahoo et al., 2012; Ganta and Chakradhar, 2014) has been calculated for surface roughness of smaller-the-better criterion as:

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} y_i^2\right) \tag{1}$$

Where, y_i is the value of surface roughness for the i^{th} test, n is number of measured data samples for one particular run.

Similarly for material removal rate, having criterion 'higher-the-better' is given by

$$S/N = -10\log_{10}\left(\frac{1}{n}\sum_{i=1}^{n} \frac{1}{y_i^2}\right) \tag{2}$$

Where, y_i is the value of material removal rate for the i^{th} test, n is number of measured data samples for one particular run.

S/N ratio for experimental results are presented in Table 2.

Table 2
Experimental results and S/N ratios

Run No.	Speed (m/min)	Feed (mm/rev)	Depth of cut (mm)	Experimental results of Ra			S/N Ratio for Ra	Experimental results of MRR			S/N ratio for MRR
				Ra_1 (μm)	Ra_2 (μm)	Ra_3 (μm)		MRR_1 (g/min)	MRR_2 (g/min)	MRR_3 (g/min)	
1	214.3	0.049	2	1.559	1.015	0.817	-1.3864	26.144	26.406	25.254	28.2728
2	214.3	0.098	3	1.658	1.647	1.881	-4.7711	72.075	71.588	71.483	37.1121
3	214.3	0.196	6	2.053	2.253	2.467	-7.0975	254.596	253.900	254.526	48.1083
4	254.6	0.049	3	1.451	1.289	1.584	-3.2056	43.431	42.748	42.934	32.6764
5	254.6	0.098	6	1.814	1.904	2.254	-6.0193	151.179	150.517	151.221	43.5779
6	254.6	0.196	2	2.224	2.188	2.359	-7.0752	118.543	119.288	119.702	41.5237
7	295.2	0.049	6	0.897	1.229	1.391	-1.5126	88.654	87.839	88.247	38.9138
8	295.2	0.098	2	1.612	1.754	1.771	-4.6793	70.935	69.784	69.209	36.8976
9	295.2	0.196	3	1.638	1.904	2.324	-5.9141	197.409	198.177	198.848	45.9395

Higher value of S/N ratio gives near to optimal combination of control parameters. Ranks are allotted to each process parameter from higher to lower values of difference between minimum and maximum of mean of S/N ratios (delta). Mean of S/N ratios at each level and for each factor has been calculated and presented in Table 3.

Table 3
Mean S/N ratio response

Process parameters	Mean of S/N ratio for Ra				Rank		Mean of S/N ratio for MRR				Rank
	Level 1	Level 2	Level 3	Delta			Level 1	Level 2	Level 3	Delta	
v	-4.4183	-5.4334	-4.0353	1.3981	2		37.83	39.26	40.58	2.75	3
f	-2.0349	-5.1566	-6.6956	4.6607	1		33.29	39.20	45.19	11.90	1
d	-4.3803	-4.6303	-4.8765	0.4962	3		35.56	38.58	4353	7.97	2

Table 3 clearly indicates that feed rate is much affecting parameter on both responses. Thenafter, for surface roughness, speed followed by depth of cut are affecting; whereas depth of cut followed by speed are affecting on material removal rate. Main effect plot i.e. graph of level vs mean of S/N ratio gives optimal parametric combination of control factors. Main effect plot for Ra and MRR are shown in Fig. 1 and Fig. 2 respectively.

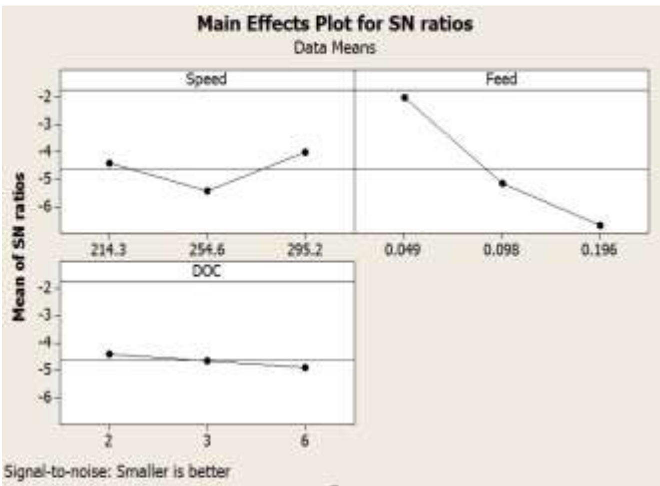

Fig. 1. Main effect plot of S/N ratios for Ra.

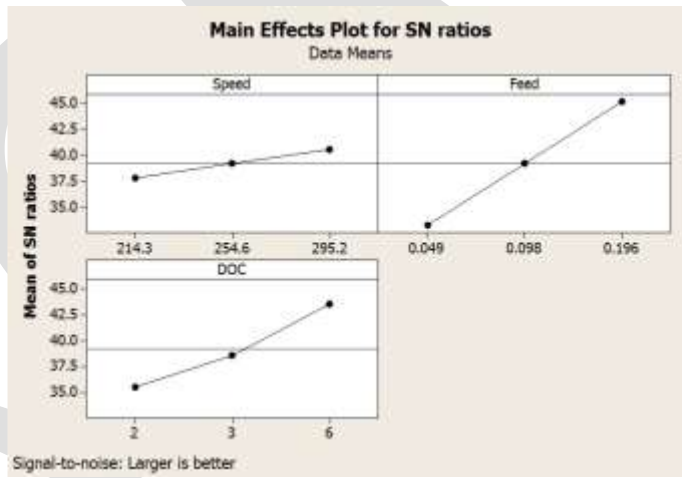

Fig. 2. Main effect plot of S/N ratios for MRR.

Main effect plot for S/N ratios shows that optimal parametric combinations for surface roughness is v3–f1–d1; i.e. cutting speed at level 3 (295.2 m/min), feed at level 1 (0.049 mm/rev) and depth of cut at level 1 (2 mm); and for material removal rate, optimal parametric combinations are v3–f3–d3 i.e. Cutting speed at level 3 (295.2 m/min), feed at level 3 (0.196 mm/rev) and depth of cut at level 3 (6 mm).

Next subsection discusses ANOVA to check significance of control factors on individual response.

2. Analysis of Variance (ANOVA)

Significant factors and its percentage contribution of effect on responses has been studied by Analysis of Variance (ANOVA). Most of the researchers have analyzed the results at 95% confidence level; therefore analysis of present study is carried out at 95% confidence level. ANOVA for surface roughness is presented in Table 4.

Table 4
ANOVA for surface roughness (Ra)

Source	DOF	SS	MS	F-ratio	P	Contribution (%)	Remarks
v	2	3.1316	1.5658	5.22	0.161	8.25	
f	2	33.8360	16.9180	56.38	0.017	89.19	Significant
d	2	0.3692	0.1846	0.62	0.619	0.98	
Error	2	0.6002	0.3001			1.58	
Total	8	37.9370				100	

$\mathbf{F}_{0.05,2,2}$= 19 for F-test.

ANOVA table indicates that feed is the most influencing factor having 89.19 % contribution of effect on surface roughness. F-ratio calculated value (56.38) is greater than F-ratio at Critical values of F-distribution (at 5 %). Hence, based on F-test and P-value feed is most significant factor. Cutting speed and depth of cut do not have significant effect on surface roughness.
Similarly, ANOVA for MRR is performed and is presented in Table 5.

Table 5
ANOVA for MRR

Source	DOF	SS	MS	F-ratio	P	Contribution (%)	Remarks
v	2	11.370	5.685	1173.21	0.001	3.54	Significant
f	2	212.520	106.260	21928.10	0.000	66.20	Significant
d	2	97.142	48.571	10023.20	0.000	30.26	Significant
Error	2	0.010	0.005				
Total	8	321.042				100	

For material removal rate feed is the most affecting factor contributing 66.20 %. F-test and probability significance show that speed, feed and depth of cut all are significant factors.
Regression analysis quantifying simultaneous effect of each control factor on response variable is presented in next subsection.

3. Regression Model

Regression is the determination of a statistical relationship between two or more variables. For present study, regression model is developed at 95% confidence level in statistical software package – Minitab 15. Regression model for speed, feed and depth of cut as independent parameters affecting Ra is presented in equation 3.

$$Ra = 1.26 - 0.00115\,v + 5.80\,f + 0.0282\,d \qquad (3)$$

Terms R^2 and R^2 (adjusted) help to judge the adequacy of regression model developed. For this regression model values of R^2 and R^2 (adjusted) are presented.

$R^2 = 81.6$ %, R^2 (adj) = 70.5 %

Value of R^2 indicates that 81.6 % of the total variations are explained by the model. The range of R^2 may be written as $0 \leq R^2 \leq 1$. When R^2 value approaches to unity; it gives possibility of reduction of variability in responses. However, this prediction is not always favorable, because addition of factors in model may increase value of R^2. Hence adjusted value of R^2 also need to be considered while checking of fitting of the model. Because addition of factors in model does not always increase value of adjusted R^2, rather it decreases when insignificant factor is added in the model. Considerable difference between values of R^2 and R^2 (adjusted) indicates maximum possibility of insignificant factor being present in the model.

For regression model, there is considerable difference (11.1 %) between values of R^2 and R^2 (adjusted); therefore there is maximum possibility of insignificant factor may present in the model. However, to study this possibility ANOVA for regression model can be done.

Although R^2 value explains variability of model, still it doesn't explain significance of regression model developed. Therefore, to study significance of regression model, ANOVA has been performed and presented in Table 6.

Table 6
ANOVA for surface roughness (Ra) regression model

Source	DOF	SS	MS	F-ratio	P	Remarks
Regression	3	1.1664	0.3888	7.38	0.028	Significant
Residual Error	5	0.2635	0.0527			
Total	8	1.4298				

$\mathbf{F}_{0.05,3,5}$= 5.41 for F-test.

ANOVA of regression model shows that regression model is significant based on F-test and probability significance. Significance of factors in model is supported by ANOVA for Ra; in which speed and depth of cut are found insignificant factors. Therefore, regression model consisting control factors speed and depth of cut are obviously insignificant.

Montgomery, (2013) suggested use of normal probability plot to study the significance of regression model developed.

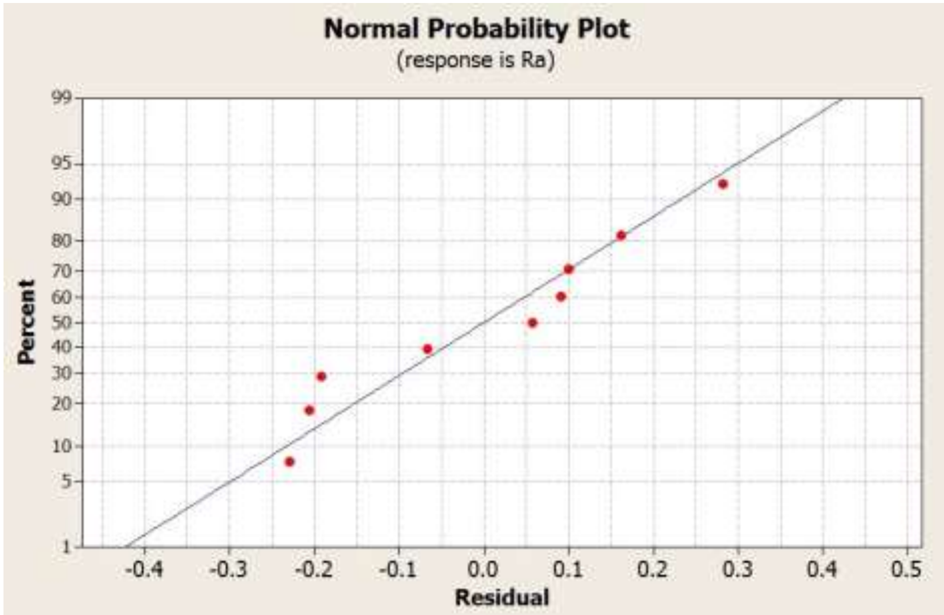

Fig. 3. Normal probability plot for Ra.

Normal probability plot of residuals shows that the residuals lie approximately close to a straight line; indicating model is significant. Sahoo et al. (2012) considered reasonable limit of maximum residual at 1.875. Present regression model having maximum residual 0.281 is within the reasonable limit; hence, it indicates significance of model developed.

Similarly, Regression model for MRR is presented in equation 4.

$$MRR = - 81.2 + 0.018\, v + 941\, f + 22.5\, d \qquad (4)$$

R^2 = 94.6%; R^2(adj) = 91.4%

R^2 indicates that 94.6 % of the total variations are explained by the model. Difference between values of R^2 and R^2 (adjusted) are less. This indicates that all factors present in the model having maximum possibility of being significant. ANOVA for MRR presented in Table 5 supports the indication of all control factors being significant.

Table 7

ANOVA for material removal rate (MRR) regression model

Source	DOF	SS	MS	F-ratio	P	Remarks
Regression	3	42917	14306	29.42	0.001	Significant
Residual Error	5	2431	486			
Total	8	45348				

$\mathbf{F}_{0.05,3,5}$= 5.41 for F-test.

Significance of regression model developed is confirmed by probability significance and F-test in ANOVA for regression model of MRR presented in Table 7.

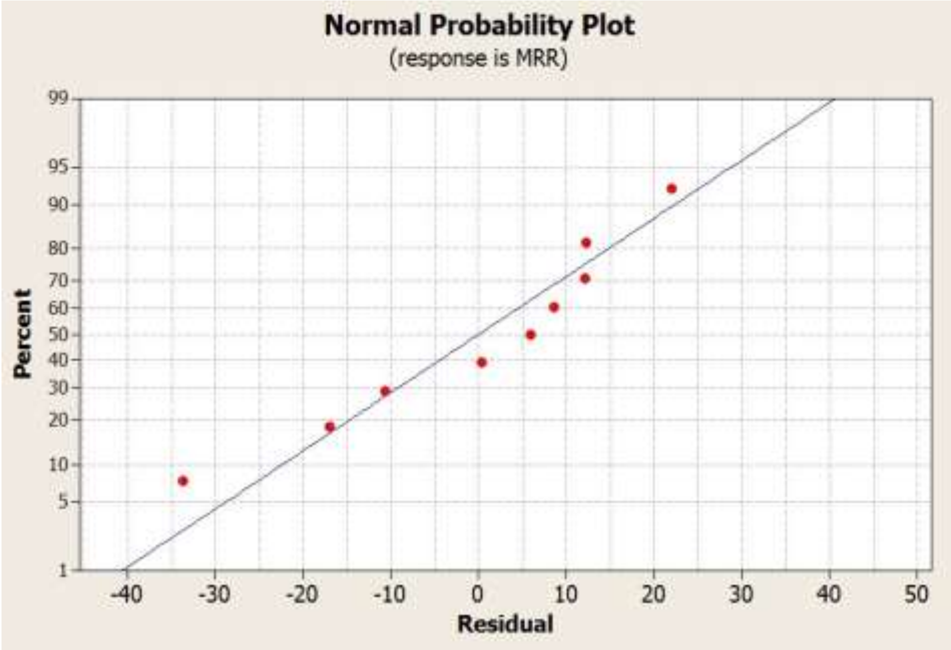

Fig. 4. Normal probability plot for MRR.

Normal probability plot of residuals shows that the residuals lie reasonably close to a straight line indicating that model is significant. Analysis of experimental results of surface roughness and material removal rate have been studied separately. To study combine effect of both responses simultaneously, multi response optimization by using grey relational analysis is discussed in next subsection.

4. Multi response optimization using grey relational analysis

Grey relational analysis (GRA) enables optimization of multiple responses simultaneously. For present study, multiple responses are surface roughness (Ra) and material removal rate (MRR). GRA starts with 'grey relational generation i.e. normalization of experimental results of "lower-the-better" criterion in the case of surface roughness and "larger-the-better" criterion for material removal rate in range of zero to one.

Normalization of Ra data, having criterion of lower-the-better, is obtained by equation 5,

$$x_i^*(k) = \frac{\max x_i^o(k) - x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{5}$$

Similarly. Normalization of MRR data, having criterion of larger-the-better, can be obtained by equation 6,

$$x_i^*(k) = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \tag{6}$$

Where, $x_i^*(k)$ is Normalized value for i^{th} run, $x_i^0(k)$ is value of response for i^{th} run, 'max $x_i^0(k)$' is maximum value of response from all runs, 'min $x_i^0(k)$' is minimum value of response from all runs.

By using normalized data of response, deviation sequence (Δ_0) for each run is evaluated. Deviation sequence is difference between reference sequence (maximum value of grey relational generation from all runs) and comparability sequence (value of grey relational generation of respective run). Deviation sequence is required for calculation of grey relational coefficient.

Normalized data of responses and values of deviation sequence are presented in Table 8.

Table 8
Grey relational generation

Run No.	Grey relational generation			Deviation sequence (Δ_{0i})	
	Ra	MRR		Ra	MRR
1	1	0		0	1
2	0.4690	0.2004		0.5310	0.7996
3	0	1		1	0
4	0.7243	0.0749		0.2757	0.9251
5	0.2367	0.5474		0.7633	0.4526
6	0.0009	0.4082		0.9991	0.5918
7	0.9628	0.2728		0.0372	0.7272
8	0.4840	0.1928		0.5160	0.8072
9	0.2686	0.7540		0.7314	0.2460

Next step is calculation of Grey relational coefficients by equation 7,

$$\xi_i(k) = \frac{\Delta_{min} + \zeta \Delta_{max}}{\Delta_{oi}(k) + \zeta \Delta_{max}} \qquad (7)$$

Where, ξ_i (k) is grey relational coefficient for respective run, Δ_{min} is minimum value of deviation sequence from all runs, Δ_{max} is maximum value of deviation sequence from all runs, Δ_{oi} (k) is value of deviation sequence for respective run.

Distinctive coefficient (ζ) is used to regulate the difference of the relational coefficient. It is in the range of 0 to 1 ($\zeta \in [0,1]$). Following the practices followed by Nayak et al. (2014) and Sahoo et al. (2012) for present study, ζ is taken as 0.5. Grey relational grade is the average of grey relational coefficients of all responses for each run. Grey relational coefficients and grey relational grade are presented in Table 9.

Table 9
Grey relational coefficient and grey relational grade

Run No.	Grey relational coefficient		Grey relational grade	Rank
	Ra	MRR		
1	1	0.3333	0.6667	2
2	0.4850	0.3847	0.4348	8
3	0.3333	1	0.6667	3
4	0.6446	0.3508	0.4977	5
5	0.3958	0.5249	0.4604	6
6	0.3335	0.4580	0.3958	9
7	0.9308	0.4074	0.6691	1
8	0.4921	0.3825	0.4373	7
9	0.4060	0.6702	0.5381	4

Larger grey relational grade gives better multiple performance characteristics. In other words, parameter combination having higher grey relational grade is closer to the optimal. Response table for mean grey relational grade is presented in Table 10.

Table 10
Mean response table for grey relational grade

Process parameters	Mean of grey relational grade				Rank
	Level 1	Level 2	Level 3	Max-Min	
v	0.5894	0.4513	0.5482	0.1381	2
f	0.6112	0.4442	0.5335	0.1670	1
d	0.4999	0.4902	0.5987	0.1085	3

From mean response table for grey relational grade, it is observed that feed is most influencing parameter, followed by cutting speed and depth of cut. Main effect plot for grey relational grade is presented in Fig. 5.

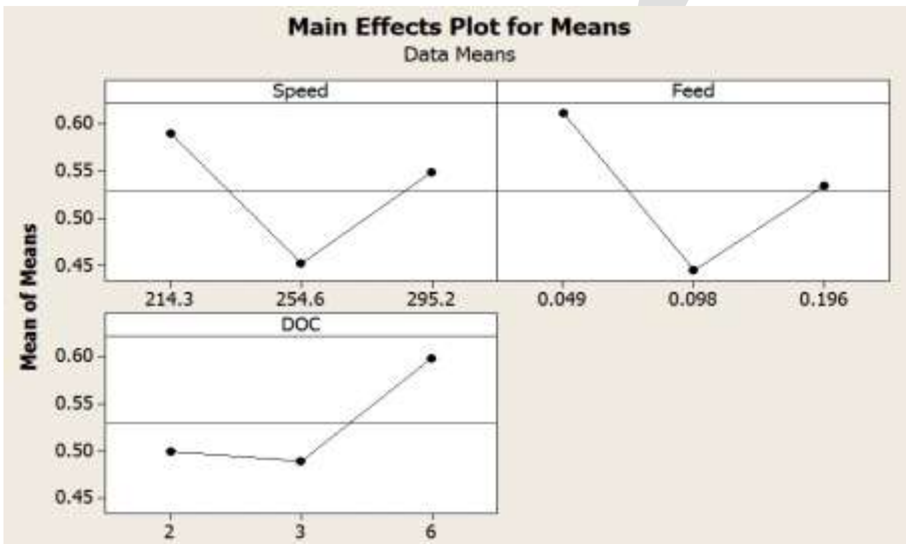

Fig. 5. Main effect plot for grey relational grade.

From main effect plot for grey relational grade, it is observed that cutting speed (v) at level 1, feed (f) at level 1 and depth of cut (d) at level 3 is the optimal combination of parameters. (V1-f1-d3).

v=214.3 m/min; f= 0.049 mm/rev; d=6 mm

These optimal results obtained by GRA need to be validated by performing experiment. Next section discusses about validation of results.

CONFIRMATORY TEST

Experimentation is carried out on optimal levels of process parameters to check validation of results. Following experimental observations have been obtained:

Ra= 1.1316 µm, MRR= 66.6493 g/min

For the obtained experimental observations, grey relation grade for experiment is calculated by procedure discussed in section 3. Obtained GRG for experiment is 0.6876. Ganta and Chakradhar, (2012) studied prediction of GRG by equation 8.

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{o} (\bar{\gamma}_i - \gamma_m) \tag{8}$$

Where, γ_m is the total mean of the grey relation generation, $\bar{\gamma}_i$ is the mean grey relation generation at the optimal level, o is the number of the design parameters.

For combination of confirmatory experiment, grey relation generation is calculated,

$$\hat{\gamma} = 0.5296 + [(0.5894 - 0.5296) + (0.6112 - 0.5296) + (0.5987 - 0.5296)]$$

$$\hat{\gamma} = 0.7401$$

Predicted value and experimental value of GRG are very close and higher than grey relational grade of rank one run. Therefore, it validates the results and gives an optimal combination of control factors.

Conclusions drawn on present study are discussed in next section.

CONCLUSION

Nylon 6 is replacing metals in few applications. Its applications are gears, cams, bushes, etc. Requirement of small quantities of plastic product can be fulfilled by machining process, rather than molding process. The empirical work of CNC turning on Nylon 6 polymer by carbide insert has been carried out to study effect of machining parameters on surface roughness and material removal rate. Further experimental results are analyzed by using statistical tools like S/N ratio, ANOVA, regression analysis and grey relational analysis. Following conclusions are drawn based on the study.

1. While obtaining surface roughness on Nylon 6 by turning, feed rate is the significant factor, whereas cutting speed and depth of cut are insignificant. As feed increases, surface roughness also increases. Optimal combination of process parameters for surface roughness: v3 = 295.2 m/min, f1 = 0.049 mm/rev, d1 = 2 mm.
2. Material removal rate gets affected significantly and is directly proportional to all three machining parameters i.e. v, f and d. Optimal combination for M.R.R: v3 = 295.2 m/min, f3 = 0.196 mm/rev, d3 = 6 mm. Effect of all parameters are not equally contributed. Contribution of effect of parameters are: speed = 3.54%, feed = 66.20%, depth of cut= 30.26%.
3. For material removal rate, feed rate is most affecting parameter followed by depth of cut and cutting speed.
4. Regression equations for surface roughness and material removal rate provide guidelines for prediction of response values within given range.
5. While considering surface roughness and material removal rate simultaneously, feed rate is found most significant factor. And optimal combination is v1 = 214.3 m/min, f1 = 0.049 mm/rev, d3 = 6 mm.
6. While considering both responses, feed is most influencing parameter followed by cutting speed and depth of cut. Further observation of analyzed results suggests that interaction effect of speed and depth of cut help to predict responses.
7. Earlier researchers claimed that cutting speed can be increased for achieving higher material removal rate. However, considering surface roughness and material removal rate, optimum cutting speed is observed at level one i.e. 214.3 m/min.
8. This study will provide guidelines to select levels of control factors to industries for machining of Nylon 6.
9. Study on machining on Nylon 6 can be extended to consideration dimensional accuracy.

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