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Optimization of Machining Parameters for Nylon 6 Composite in CNC Lathe Using PCA-Based TOPSIS

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ABSTRACT

This work investigates the parametric optimization of CNC turning operation for Nylon 6 with principal component analysis (PCA) and technique for order preference by similarity to ideal solution (TOPSIS) based on Taguchi approach. Taguchi's L_{16} orthogonal array takes 16 experimental runs to execute the design matrix of turning parameters through PCA coupled with TOPSIS, utilizing relevant experimental data as obtained through experimentation. Turning speed (TS), feed rate (FD) and depth of cut (DOC) are optimized with the consideration of multiple performance characteristics, namely surface roughness R_a (µm), R_z (µm), material removal rate (MRR) (cm^3/sec), and machining time (MT) (sec). The capabilities of the above proposed models have been tested through the analysis of variance. Lastly, confirmation tests were executed to sort a comparison between the experimental results and predicted values. It is found that FD is the most significant parameter followed by TS and DOC. The surface roughness parameters (R_a, R_z) and machining time as smaller the better and MRR as larger the better.

Keywords: CNC turning, Machining parameters, Nylon 6, PCA, Taguchi approach, TOPSIS.

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INTRODUCTION

CNC machine tools are the best available methods to provide greater improvements in productivity and increase the quality of the turned parts and require less operator input in recent time. Turning is one of the most usable machining operations in industries. It is the commonly used machining process because of its capability to remove material with easiness and quicker with a realistically good surface quality. It is used for machine materials that have flat, curved or irregular surface by feeding the tool against a rotating work piece. CNC turning machine is a machine tool that cuts metal with single-point cutting tool. It is widely used in a variety of manufacturing industries, where quality is an important factor in the production with precision.

In this study, surface roughness, material removal rate (MRR) and machining time (MT) can be considered as the most important factors for better product quality. Manufacturing of goods has two most significant problems: process modelling and optimization. In recent years, various significant advantages have been found in turning, and many researchers have studied the different parameters of the machine surface in CNC turning process in the previous few years by using different optimization methods. Some of the literature studies are given as follows.

V. Jaiganesh, S. Manivannan and S. Manivannan[1]: optimization of process parameters on friction stir welding (FSW) of nylon 6 polymer plate. Nowadays, the uses of thermoplastics have been increased in many fields due to its various properties. Joined thermoplastics find a wide application in most of the fields due to its mechanical properties, and therefore, a suitable method for joining should be adapted. Nylon 6 is the material that was chosen to be welded and analysed accordingly. Nylon 6 is a thermoplastic material that has good mechanical properties and has many applications in automobile and aerospace industries. One of the suitable methods of joining the polymer is FSW.

Arun Kumar Parida, Ratnakar Das, A. K. Sahoo, B. C. Routara[2]: optimization of cutting parameters for surface roughness in machining of GFRP composites with graphite/fly ash filler. In the present work, an attempt has been made to assess the influencing parameters on the machining of GFRP composites. Using Taguchi method, an L9 orthogonal array has been used for experimentation. The experiments were conducted on all geared lathe using carbide tool with three levels of input parameters such as cutting speed, depth of cut (DOC) and feed rate (FD).

Bandit Suksawat[3]: development of in-process surface roughness evaluation system for cast nylon 6 turning operation. This paper aims to develop in-process surface roughness evaluation system for cast nylon 6 turning operation. The construction of the developed system comprises data acquisition system and fuzzy logic system. The data acquisition system includes a miniature load cell inserted in a tool holder, signal conditions and a signal interface card in order to detect the cutting force signal and transmit signal to the data analysis module constructed by Lab VIEW program. The Mamdani-type fuzzy inference system was utilized and 20 fuzzy rules were determined based on the relationship of cutting speed, FD and cutting force for prediction, both of surface roughness value (R_z) and symbolic representation.

EXPERIMENTAL DETAILS

Material and Processes

The material used in this turning process is Nylon 6 which is made up of repeating units linked together by amide bonds, and they are frequently known as polyamides (PA). Nylon was the first synthetic thermoplastic polymer which was successful. The properties of a nylon 6 thermoplastic polymer could be determined by R and R' groups in the monomers of the polymer composites. Nylon 6 is a product of condensation polymerization. In this reaction, monomers combine each other, and a by-product called molecules is produced. This by-product is something like HCl or water. Nylon 6,6 has a tighter molecular structure than nylon 6 polymer due to the higher level of hydrogen bonding and maximum alignment between hydrogen chains. The chemical bonding of nylon 6 polymer can be stated as $(C_{12}H_{22}N_2O_2)_n$. It clearly shows that nylon 6 has 12 carbon atoms, 22 hydrogen atoms and 2 nitrogen atoms along with 2 atoms of oxygen, which are bonded together and repeating one over other and form a polymer. The physical properties of the nylon 6 polymer like impact strength, tensile strength, density, thermal expansion coefficient, melting and boiling points also play an important role in CNC turning capabilities. [4-7]

Plan of Experiments

Taguchi analysis uses a greater design of orthogonal arrays, which offers a set of balanced design matrix of experimentations with less number of experimental runs. Taguchi method uses a statistical measure of performance called signal-to-noise (S/N) ratio. The S/N ratio takes both the mean and the variability into account. The S/N ratio is the ratio of the mean (signal) to the standard deviation (noise). The ratio depends on the quality characteristics of the product/process to be optimized. The standard S/N ratios generally used are as follows: nominal-is-best (NB), lower-the-better (LB) and higher-the-better (HB). The optimal setting is the parameter combination, which has the highest S/N ratio, because, irrespective of the quality criteria (NB, LB, HB), S/N ratio should always be maximized. Once the experimental data (quality attribute value) are normalized using NB/LB/HB criteria, the normalized value lies in between zero and one. Zero represents the worst quality to be rejected and one represents the most satisfactory quality. Since the S/N ratio is expressed as mean (signal) to the noise (deviation from the target), maximizing S/N ratio ensures minimum deviation and hence it is (S/N ratio) to be maximized. Figure 1-2.

Fig. 1. *Polymer 6 specimens.*

The methodology of Taguchi for three factors at four levels is used for the execution of the plan of experiments in this work. The degrees of freedom required for the study are three and Taguchi's L_{16} orthogonal array is used to define the 16 trial conditions. In the present experimental study, turning speed (TS), FD and DOC have been considered as process variables. Surface roughness (R_a, R_z) (µm), MRR (cm^3/sec) and MT (sec) have been taken as response variables. Only main effects of parameters are taken into account and factor interactions are not studied. The process parameters and their levels are listed in Table 1. Each of the 16 trials is replicated twice, and the average response values are used for the optimum results. Table 2 shows the experimental design matrix and the corresponding average values of each parameter. [8-9]

Table 1. *Process parameters and their levels.*

Symbol	Parameters	Units	Level 1	Level 2	Level 3	Level 4
TS	Turning speed	RPM	1200	1400	1600	1800
FD	Feed rate	mm/rev	0.030	0.050	0.070	0.090
DOC	Depth of cut	mm	0.20	0.40	0.60	0.80

Table 2. *Experimental design matrix with their results.*

Run no.	Turning speed (TS)	Feed rate (FD)	Depth of cut (DOC)	R_a (μm)	R_z (μm)	Material removal rate (cm^3/sec)	Machining time (sec)
1.	1200	0.030	0.20	4.43	31.04	0.832	23.00
2.	1200	0.050	0.40	2.05	18.42	0.392	51.00
3.	1200	0.070	0.60	2.60	28.30	0.342	56.00
4.	1200	0.090	0.80	3.00	16.75	0.503	38.00
5.	1400	0.030	0.40	3.30	28.76	1.275	15.00
6.	1400	0.050	0.20	0.26	5.60	1.196	16.00
7.	1400	0.070	0.80	1.59	16.71	0.380	48.00
8.	1400	0.090	0.60	2.37	18.01	0.468	39.00
9.	1600	0.030	0.60	3.40	23.60	1.429	14.00
10.	1600	0.050	0.80	3.59	23.67	0.315	58.00
11.	1600	0.070	0.20	5.23	38.14	0.425	43.00
12.	1600	0.090	0.40	1.36	16.85	0.547	35.00
13.	1800	0.030	0.80	1.99	12.40	1.366	14.00
14.	1800	0.050	0.60	2.18	20.12	0.351	52.00
15.	1800	0.070	0.40	1.40	4.57	0.491	39.00
16.	1800	0.090	0.20	1.67	13.91	0.617	31.00

DETERMINATION OF OPTIMAL MACHINING PARAMETERS

Principal Component Analysis

Joint methodology is used for the effective optimization of turning parameters over different performance characteristics. This methodology is the combination of principle component analysis (PCA), technique for order preference by similarity to ideal solutions (TOPSIS) and Taguchi philosophy. [10-12]

PCA is a tool to find designs in correlated data and declaring the data in such a manner so as to point out their matches and differences. The main advantage of PCA is that once the patterns in data have been identified, the data can be compressed, i.e. by reducing the number of dimensions, without much loss of information. The steps involved in PCA are discussed below:

Step 1: Data is normalized using the following equation:

For HB entity,

$$x_j^*(j) = \frac{x_i^{(0)}(j) - \min x_i^{(0)}(j)}{\max.\ x_i^{(0)}(j) - \min x_i^{(0)}(j)} \quad (1)$$

For LB entity,

$$x_i^*(j) = \frac{\max x_i^{(0)}(j) - x_i^{(0)}(j)}{\max x_i^{(0)}(j) - \min x_i^{(0)}(j)} \quad (2)$$

where $x_i(j)$ and $x_i^{(0)}(j)$ are the normalized and experimental values, respectively, for the *i*th experiment using the *j*th response. $\min x_i^{(0)}(j)$ and $\max x_i^{(0)}(j)$ are the smallest and largest values of $x_i^{(0)}(j)$ in the *j*th response, respectively.

Table 3 shows the normalized values of responses with respect to their S/N ratio values. This table clearly shows that a higher S/N ratio is desirable. In case of MRR, experiment no. 9 is having higher S/N ratio value, so it is having value 1. Likewise, R_a, R_z and MT are having values of higher S/N ratio at experiment nos. 11 and 10, respectively, so these are having value 1.

Table 3. S/N ratio with their normalized values of each performance parameters.

Sl. No.	S/N ratios				Normalized values			
	R_a	R_z	MRR	MT	R_a	R_z	MRR	MT
1	-12.9281	-29.8384	-1.5975	-27.2346	0.9447	0.9029	0.6423	0.3493
2	-6.2351	-25.3058	-8.1343	-34.1514	0.6880	0.6570	0.1446	0.9095
3	-8.2995	-29.0357	-9.3195	-34.9638	0.7672	0.8594	0.0543	0.9753
4	-9.5424	-24.4803	-5.9686	-31.5957	0.8148	0.6122	0.3095	0.7025
5	-10.3703	-29.1758	2.1102	-23.5218	0.8466	0.8670	0.9246	0.0486
6	11.7005	-14.9638	1.5546	-24.0824	0.0000	0.0958	0.8823	0.0940
7	-4.0279	-24.4595	-8.4043	-33.6248	0.6033	0.6110	0.1214	0.8669
8	-7.4950	-25.1103	-6.5951	-31.8213	0.7363	0.6464	0.2618	0.7208
9	-10.6296	-27.4582	3.1006	-22.9226	0.8565	0.7738	1.0000	0.0000
10	-11.1019	-27.4840	-10.0338	-35.2686	0.8746	0.7752	0.0000	1.0000
11	-14.3700	-31.6276	-7.4322	-32.6694	1.0000	1.0000	0.1981	0.7895
12	-2.6708	-24.5320	-5.2403	-30.8814	0.5512	0.6150	0.3650	0.6447
13	-5.9771	-21.8684	2.7090	-22.9226	0.6781	0.4706	0.9702	0.0008
14	-6.7691	-26.0726	-9.0939	-34.3201	0.7084	0.6986	0.0716	0.9232
15	-2.9226	-13.1983	-6.1784	-31.8213	0.5609	0.0000	0.2935	0.7208
16	-4.4543	-22.8665	-4.1943	-29.8272	0.6197	0.5246	0.4446	0.5593

Step 2: Normalized data are used to find out a covariance matrix as

$$A = \begin{bmatrix} x_{11} & \cdots & x_{1n} \\ \vdots & \ddots & \vdots \\ x_{m1} & \cdots & x_{mn} \end{bmatrix}$$

where *m* is the number of experiments, *n* is the number of quality characteristics and *x* is the coefficient of quality characteristics. In this problem, *m* = 16, *n* = 4.

Step 3: Compute correlation coefficient array:

$$R_{j1} = \frac{cov\left(\left(x_i(j),\ x_i(1)\right)\right)}{\sigma_{xi}(j) * \sigma_{xi}(1)} \quad (3)$$

Step 4: The eigen values and eigen vectors are calculated from correlation coefficient array:

$$(R - \lambda_K I_M)\ V_{IK} = 0 \quad (4)$$

where λ_K is the eigen value and V_{IK} is the eigen vector corresponding to respective eigen values.

Table 4 shows the eigen values and eigen vectors which are calculated by Equations (3) and (4).

Step 5: Compute principal component:

$$\beta_i = \sum_{i=1}^{n} Xm(i)\ Vik \quad (5)$$

where β_1 is the first principal component, β_2 is the second principal component and so on.

Step 6: Estimate the quality loss for each variable:

Loss estimate is defined as the absolute values of the difference between the *i*th experimental value for the *k*th response and the desired (ideal) value. [13-18]

Table 4. *PCA results: Eigen values, eigen vectors, AP, CAP.*

	PC1	PC2	PC3	PC4
Eigen value	2.2896	1.5195	0.1896	0.0013
Eigen vectors	0.442	-0.548	0.710	-0.005
	0.426	-0.568	-0.704	0.007
	-0.559	0.433	0.019	0.707
	0.558	0.435	-0.007	0.707
AP	0.572	0.380	0.047	0.000
CAP	0.572	0.952	1.000	1.000

Table 5. *Major principal components with quality loss estimates.*

Sl. No.	Major principal components				Computed quality loss elements			
	VPC1	VPC2	VPC3	VPC4	VPC1	VPC2	VPC3	VPC4
Ideal solution	0.867	-0.248	0.018	1.416				
1	0.63806	-0.600481	0.044854	0.702658	0.2289	0.3525	-0.0269	0.7133
2	1.01065	-0.291956	0.022333	0.746408	-0.1437	0.0440	-0.0004	0.6696
3	1.21907	-0.460797	-0.066101	0.730107	-0.3521	0.2128	0.0841	0.6859
4	0.83992	-0.354639	0.148482	0.715695	0.0271	0.1066	-0.1305	0.7003
5	0.25381	-0.534900	0.007945	0.689888	0.6132	0.2869	0.0101	0.7261
6	-0.39994	0.368511	-0.051337	0.690915	1.2670	-0.6165	0.0693	0.7251
7	0.94281	-0.247989	-0.005563	0.699989	-0.0759	-0.0001	-0.0236	0.7160
8	0.85667	-0.343740	0.067636	0.695541	0.0103	0.0957	-0.0496	0.7205
9	0.14921	-0.475880	0.082360	0.708134	0.7178	0.2279	-0.0644	0.7079
10	1.27481	-0.484594	0.068225	0.708053	-0.4078	0.2367	-0.0502	0.7079
11	1.19780	-0.686790	0.004237	0.700233	-0.3308	0.4389	0.0138	0.7158
12	0.66133	-0.212888	-0.039186	0.715407	0.2057	-0.0351	0.0572	0.7006
13	-0.04170	-0.218455	0.168577	0.686401	0.9087	-0.0295	-0.1506	0.7296
14	1.08584	-0.352413	0.006048	0.704672	-0.2188	0.1044	0.0120	0.7113
15	0.48606	0.133260	0.398770	0.714306	0.3809	-0.3813	-0.3808	0.7017
16	0.56095	-0.201761	0.075201	0.710331	0.3061	-0.0462	-0.0572	0.7057

Table 5 shows the major principal components with quality loss estimates calculated by Equation (5).

Technique for Order Preference by Similarity to Ideal Solution

The Concept of this method is that selected alternatives would have the shortest distance from the positive best solution and the extreme distance from negative ideal solution [19-20]. The solution that maximizes the benefit conditions and minimizes adverse criteria is known as positive ideal solution, whereas the solution that maximizes the adverse conditions and minimizes the benefit conditions is known as negative ideal solution. The steps included in TOPSIS methodology is described as follows:

Step 1: The matrix format is developed in this step.

The alternatives are represented by the row of this matrix and attributes are allocated to each column of the matrix. The decision-making matrix can described as

$$D = \begin{bmatrix} A_1[x_{11}\ x_{12}\ \ldots.\ x_{ij}\ \ldots.\ x_{1j}] \\ A_2[x_{21}\ x_{22}\ \ldots.\ x_{2j}\ \ldots.\ x_{2n}] \\ A_i[x_{i1}\ x_{12}\ \ldots.\ x_{ij}\ \ldots.\ x_{in}] \\ A_m[x_{m1}\ x_{m2}\ \ldots.\ x_{mj}\ \ldots.\ x_{mn}] \end{bmatrix}$$

Here $A(i$ 1, 2, …, $m)$ represents the possible alternatives $X(j$ 1, 2, …, $n)$ represents the attributes relating to alternative performance, j 1, 2, …, n and x_{ij} is the performance of A_i with respect to attribute X_j.

Step 2: Normalization of decision matrix is performed in this step. Formula used is as follows:

$$r_{ij} = \frac{x_{ij}}{\sqrt{\sum_{i=1}^{m} x_{ij}^2}} \quad (6)$$

Here r_{ij} represents the normalized performance of A_i with respect to attribute X_j.

Step 3: Development of weighted normalized decision matrix:

$$V = [V_{ij}]$$

It can be found as

$$V = w_j r_{ij} \quad (7)$$

$$\sum w_j = 1$$

Table 6. *Normalized and weighted normalized values of quality loss estimates.*

Sl. No.	Normalized values of quality loss estimates				Weighted normalized values of quality loss estimates			
	VPC1	VPC2	VPC3	VPC4	VPC1	VPC2	VPC3	VPC4
1	0.1126	0.3338	-0.0582	0.2516	0.0563	0.1669	-0.0291	0.1258
2	-0.0707	0.0417	-0.0008	0.2362	-0.0354	0.0209	-0.0004	0.1181
3	-0.1732	0.2015	-0.1818	0.2419	-0.0867	0.1008	-0.0909	0.1210
4	0.0133	0.1009	-0.2821	0.2470	0.0006	0.0506	-0.1411	0.1235
5	0.3017	0.2716	0.0218	0.2561	0.1509	0.1358	0.0109	0.1281
6	0.6234	-0.5837	0.1498	0.2558	0.3117	-0.2919	0.0749	0.1279
7	-0.0373	-0.0009	-0.0510	0.2526	-0.0187	-0.0004	-0.0255	0.1263
8	0.0005	0.0906	-0.1072	0.2541	0.0002	0.0453	-0.0536	0.1271
9	0.3532	0.2158	-0.1392	0.2497	0.1766	0.1079	-0.0696	0.1249
10	-0.2007	0.2241	-0.1085	0.2497	-0.1004	0.1121	-0.0543	0.1249
11	-0.1628	0.4156	0.0298	0.2525	-0.0814	0.2078	0.0149	0.1263
12	0.1012	-0.0332	0.1237	0.2471	0.0506	-0.0166	0.0619	0.1236
13	0.4471	-0.0279	-0.3256	0.2574	0.2236	-0.0140	-0.1628	0.1287
14	-0.1077	0.0988	0.0259	0.2509	-0.0539	0.0494	0.0130	0.1255
15	0.1874	-0.3610	-0.8232	0.2475	0.0937	-0.1805	-0.4116	0.1238
16	0.1506	-0.0437	-0.1237	0.2489	0.0753	-0.0219	-0.0619	0.1245

Table 6 shows the normalized and weighted normalized values of quality loss estimates calculated by Equations (6) and (7).

Step 4: Identified positive ideal (best) and negative ideal (worst) solution:

Positive ideal solution can be expressed as

$$A^+ = \{(\max V_{ij}, jcJ)\ (\min V_{ij}, jcJ)\} = \{V_1^+, V_2^+, \ldots, V_j^+, \ldots, V_n^+\} \quad (8)$$

Negative ideal solution can be expressed as

$$A^- = \{(\min V_{ij}, jcJ)\ (\max V_{ij}, jcJ)\} = \{V_1^-, V_2^-, \ldots, V_j^-, \ldots., V_n^-\} \quad (9)$$

Here $J = \{J = 1, 2, \ldots, n\}$

Table 7. *Positive ideal and negative ideal solutions.*

Sl. No.	Positive ideal	Negative ideal
1	-0.1004	0.3117
2	-0.2919	0.2078
3	-0.4116	0.0749
4	0.1181	0.1287

Step 5: Determination of distance measures:

$$S_i^+ = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_f^+)^2 . i = 1,2, \ldots \ldots, m} \quad (10)$$

$$S_i^- = \sqrt{\sum_{j=1}^{n} (V_{ij} - V_f^-)^2 . i = 1,2, \ldots \ldots, m} \quad (11)$$

Step 6: Identify relative closeness to the Ideal solution:

$$C_i^+ = \frac{S_i^-}{S_i^+ + S_i^-} \quad (12)$$

Step 7: Ranking of performance order. The best choice can be obtained with alternative of the largest relative coefficient.

RESULTS AND DISCUSSION

This segment of the paper presents the results and discussion of experiments and turning operation which have done on the nylon 6 material specimen. Numerical techniques are commonly used to improve the quality of a product or process. Such techniques enable the operator to explain and study the effect of every single condition possible in an experiment, where several aspects are involved. In the present work, a statistical technique called Taguchi method and analysis of variance (ANOVA) are used to optimize the process parameters of the present investigation. Table 7- 8.

Table 8. *Computed values of equation measures.*

Sl. No.	S^+	S^-
1	0.4381	0.2788
2	0.5207	0.4015
3	0.5072	0.4447
4	0.4480	0.3795
5	0.6517	0.1874
6	0.6377	0.4997
7	0.4907	0.4032
8	0.5892	0.3741
9	0.5946	0.2216
10	0.5394	0.4424
11	0.6573	0.3977
12	0.5682	0.3446
13	0.4942	0.3368
14	0.5468	0.4032
15	0.2239	0.6588
16	0.4755	0.3569

Table 9. *Closeness coefficient with their ranking.*

Sl. No.	C_i^+	S/N ratio	RANK
1	0.3889	-8.2032	11
2	0.4354	-7.2222	7
3	0.4672	-6.6099	2
4	0.4586	-6.7713	3
5	0.2233	-13.0222	16
6	0.4393	-7.1448	6
7	0.4511	-6.9145	4
8	0.3884	-8.2144	12
9	0.2715	-11.3246	15
10	0.4506	-6.9242	5
11	0.3770	-8.4732	14
12	0.3775	-8.4617	13
13	0.4053	-7.8445	10
14	0.4244	-7.4445	9
15	0.7463	-2.5417	1
16	0.4288	-7.3549	8

Fig. 2. *Specimens of each experiments.*

In this work, various tables are calculated with the help of the proposed methodology, and finally, the result comes in the form of closeness coefficient. The optimum conditions represent the combination of control factor levels that are expected to produce the best results. Observed values are recorded for experimental run, and finally, the closeness coefficient is calculated as shown in Table 9. From the table, it is clear that the higher closeness coefficient (0.7463) is assigned with rank 1. The graph plotted on the basis of S/N ratio values of closeness coefficient, the optimum parametric combination setting for Ra, Rz, MRR and MT is obtained. All the experimental runs are associated to larger-the-better characteristic. Plot for process parameter values versus closeness coefficient values is shown in Figure 3.

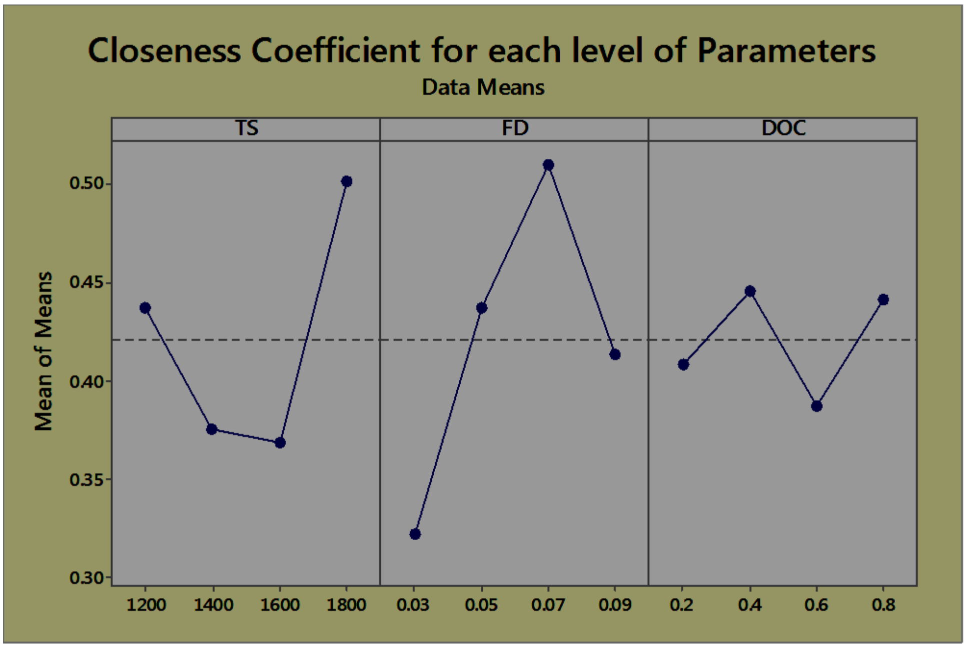

Fig. 3. *Process parameters versus closeness coefficient (C_i^+).*

Figure 3 shows the effect of each control factor with response graph. This figure helps to investigate the ideal turning parameters (the level with the highest point on the graphs) as well as to find out the influence of each parameter on C_i^+ mean value (the general slope of the line). The line in the figure, which connects between the levels, can clearly show the powerful impact of each control factor. The main effect plots are used to conclude the optimal conditions to obtain the optimum value of output. The graph clearly exposes optimal machining setting for optimal results as (TS = 1800 rpm, FR = 0.07 mm/rev and DOC = 0.40 mm).

Table 10. *Mean response closeness coefficient (C_i^+).*

Level	TS	FD	DOC
1	0.4375	0.4374	**0.4456**
2	0.3755	**0.5104**	0.3879
3	0.3691	0.4133	0.4414
4	**0.5012**	0.3223	0.4085
Delta	0.1321	0.1881	0.0578
Rank	2	1	3

In addition, the mean values of closeness coefficients for each level of machining parameters, and the total mean of C_i^+ are illustrated in Table 10. The larger value of C_i^+ means comparability sequence has a strong correlation to the reference sequence. Bold values indicate the larger-the-better characteristics at each level of all the factors.

Analysis of Variance

Most suitable method of identifying the significant parameters that affects the performance characteristics is the ANOVA. This is accomplished by separating the total variability of the closeness coefficients. The statistical insinuation of parameters is estimated by its percentage contribution in ANOVA table. The term sum of square in ANOVA table is used to determine the square of deviation from the grand mean. *F*-ratio is used to check the acceptability of the model in which the calculated value of *F* should be greater than the *F*-table value. The model is adequate at 95% confidence level, since the *F* calculated value is greater than the *F*-table value. When the value of *P* from the ANOVA table is less than or equal to 0.05 (or 95% confidence), the obtained models are considered to be statistically significant.

Table 11. *Analysis of variance (ANOVA) for C_i^+.*

Source	DF	Adj. SS	Adj. MS	*F*-value	Contribution	Rank
TS	3	0.045846	0.015282	1.76	**25.56%**	**2**
FD	3	0.072290	0.024097	2.77	**40.30%**	**1**
DOC	3	0.009104	0.003035	0.35	5.08%	**3**
Error	6	0.052129	0.008688		29.06%	
Total	15				100.00%	

Table 11 clearly shows the ANOVA) for closeness coefficient (C_i^+) values. From the table, it is observed that FD is the most influential parameter as shown in the ANOVA table, with the percentage contribution of 40.30%, while the changes in the range of TS are moderate with the percentage contribution 25.56%, and DOC has very little effect on performance characteristics with the percentage contribution of 5.08%.

Confirmation Test

Once the optimal level of machining parameters is identified, the last step is to predict and verify the improvement of the performance characteristics using the optimal setting of machine parameters. The estimated or predicted value using the optimal parameter setting can be calculated as follows:

To identify that the applied optimization method is effective for quality improvement, the initial machining conditions are assumed as TS = 1800 rpm, FR = 0.07 mm/rev and DOC = 0.40 mm. At this initial machine setting, the experimental values of surface roughness (R_a) and (R_z), MRR and MT are 1.40 µm, 4.57 µm, 0.491 cm^3/sec and 39.00 sec, respectively. The result of confirmation test using the optimal machining setting is shown in Table 12.

Table 12. *Confirmation test result.*

Response	Initial machining condition	Optimal machining condition	
		Predicted	Experimented
Setting level	$TS_4FD_3DOC_2$	$TS_4FD_3DOC_2$	$TS_4FD_3DOC_2$
Surface roughness (R_a)	1.40	0.907	0.948
Surface Roughness (R_z)	4.57	7.1925	9.9923
Material removal rate (MRR)	0.491	1.0337	1.2474
Machining Time (MT)	39.00	14.25	18.75
Closeness coefficient (C_i^+)	0.7463	0.6160	0.6487

*Improvement in closeness coefficient (C_i^+) = **0.1303***

CONCLUSION

In this study, optimal combination of machining parameters is achieved with the optimization of multiple responses such as surface roughness (R_a, R_z), MRR and MT. This is capable of improving the production by producing desired surface quality in a lesser time with minimum cost. The following points may be concluded from the analysis of experimental data and the result in connection with multi-response optimization of CNC turning:

- This work summarizes the application of PCA that makes the optimization problem little easier by reducing the number of variables selected for this research work based on their accountability proportion.
- This research work defines the application of Taguchi's orthogonal array combined with PCA and TOPSIS

to optimize the multi-objective performance characteristics of surface roughness (R_a, R_z), MRR and MT of nylon 6 material.
- The results obtained by ANOVA for closeness coefficient (C_i^+) shows that the parameter FD is the dominant parameter that affects the responses most with the percentage contribution of 40.30%, while the changes in the range of TS are moderate with the percentage contribution 25.56%, and DOC has very little effect on performance characteristics with the percentage contribution of 5.08%.
- The affectability of the applied methodologies was further tested by confirmation test. Based on this, it was found that the closeness coefficient (C_i^+) for performance characteristics is improved by 0.1303 by using this method.
- The optimal setting of process parameters was found to be TS = 1800 rpm, FR = 0.07 mm/rev and DOC = 0.40 mm. The predicted value of C_i^+ was found to be 0.6160.
- The integrated approach of PCA with TOPSIS has been found very effective and useful for solving the multi-response optimization.

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