APEM journal **Advances in Production Engineering & Management** 3 (2008) 4, 205-217
ISSN 1854-6250 Scientific paper

TAGUCHI BASED FRACTAL DIMENSION MODELLING AND OPTIMIZATION IN CNC TURNING

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Abstract:
This paper presents an experimental study of fractal characteristics of surface profile produced in CNC turning and optimization of machining parameters based on Taguchi method. Experiments are carried out by utilizing the combination of machining parameters based on L_{27} Taguchi orthogonal design with three machining parameters, viz., depth of cut, spindle speed and feed rate for three different workpiece materials, viz., aluminium, mild steel and brass. It has been observed that feed rate has got the most significant influence in controlling fractal dimension characteristics for all the three materials. In addition, spindle speed has got some influence in case of mild steel and aluminium while depth of cut has some significant influence in case of brass. The interactions between the machining parameters have also got some influence in controlling the fractal dimension. Taguchi analysis is employed to identify optimum machining parameter combination that yields optimum (maximum) fractal dimension.

Key Words: Fractal dimension, CNC turning, Taguchi method, Optimization

1. INTRODUCTION

Surface roughness has large impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life etc. It also affects other functional attributes of machine components like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity etc. As a result, there has been a great many research developments in modeling surface roughness and optimization of the controlling parameters to obtain a surface finish of desired level. Conventionally, the deviation of a surface from its mean plane is assumed to be a random process for which statistical parameters such as the variances of height, the slope and curvature are used for characterization [1]. However, it has been found that the variances of slope and curvature depend strongly on the resolution of the roughness-measuring instrument or any other form of filter and hence are not unique [2-4]. It is also well known that surface topography is a non-stationary random process for which the variance of the height distribution is related to the length of the sample [5]. Consequently, instruments with different resolutions and scan lengths yield different values of these statistical parameters for the same surface. The conventional methods of characterization are therefore fraught with inconsistencies which give rise to the term ‘parameter rash’ [6] commonly used in contemporary literature. The underlying problem with the conventional methods is that although rough surfaces contain roughness at a large number of length scales, the characterization parameters depend only on a few particular length scales, such as the instrument resolution or the sample length. A logical solution to this problem is to characterize rough surfaces with scale-invariant parameter like fractal dimension. Roughness measurements on a variety of surfaces show that the power spectra of the surface profiles follow power laws. This suggests that when a surface is magnified appropriately, the magnified image looks very similar to the original surface. This property can be mathematically described by the concepts of self-similarity and self-affinity. The fractal dimension, which forms the essence of fractal geometry, is both scale-invariant and is closely linked to the concepts of self-similarity and self-affinity [7]. It is therefore essential to use fractal dimension to characterize rough surfaces and provide the geometric structure at all length scales [8, 9]. Accordingly, the fractal approach has recently been used in a number of tribological analyses [10 – 14].

Metal cutting is one of the most significant manufacturing processes in material removal. There are different methods of metal cutting and turning is one of the commonest among these methods. In machining of parts, surface quality is one of the most specified customer requirements where major indication of surface quality on machined parts is surface roughness. Surface roughness is mainly a result of process parameters such as tool geometry and cutting conditions. A considerable number of studies have investigated the general effects of the speed, feed, depth of cut, nose radius and others on the surface roughness and developed empirical models for surface roughness. However, an extensive review of literature on roughness studies of turned surfaces reveals the fact that the centerline average roughness (R_a) has been the focus of most of the investigations. The fractal study of turned surfaces is rarely reported [15] while few recent studies [16, 17] consider the same for milled surfaces. To the best of authors' knowledge, there is no literature available on fractal dimension optimization of surfaces produced by turning. The present study aims at evaluation of fractal dimension for the surface texture generated in CNC turning of three different materials, viz., aluminium, mild steel and brass. The present study considers Taguchi orthogonal design with three machining parameters, viz., depth of cut (A, mm), spindle speed (B, rpm) and feed rate (C, mm/rev) as independent variables to determine the suitable machining parameters for optimum fractal dimension in CNC turning. The surface texture of the machined surfaces is measured in a stylus profilometer to evaluate the fractal dimension. Taguchi analysis is employed to identify optimum machining parameter combination that yields optimum (maximum) fractal dimension. Confirmation experiments are conducted to verify the optimal machining parameter combination as predicted by Taguchi analysis. Analysis of variance was also carried out to observe the level of significance of different factors and their interactions.

2. FRACTAL CHARACTERIZATION

Most rough surfaces including machining ones and corresponding profiles are multiscale in nature. This multiscale property is better expressed as self-similarity or self-affinity in fractal geometry implying that when the surface or the profile is magnified more and more details emerge and the magnified image is statistically similar to the original topography [9]. Statistical self-similarity means that the probability distribution of a small part of a profile will be congruent with the probability distribution of the whole profile if the small part is magnified equally in all directions. However, self-affinity implies unequal scaling in different directions. The qualitative description of statistical self-affinity for a surface profile is shown in Fig. 1. The property of self-affinity can be characterized by the profile fractal dimension D ($1< D <2$). In the present paper,

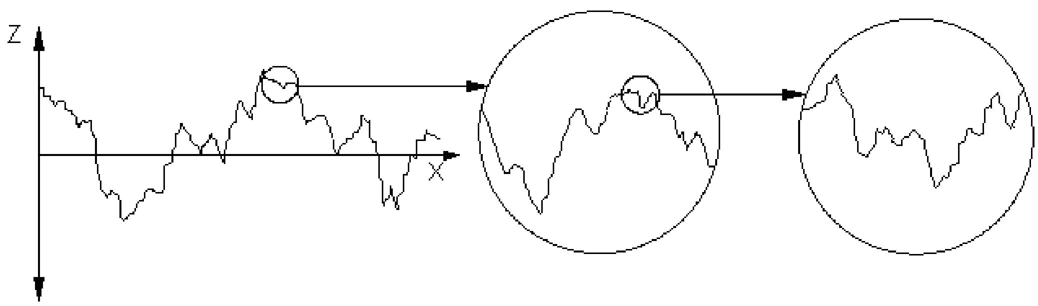


Figure 1: Qualitative description of self-affinity of a surface profile.

isotropic and homogeneous rough engineering surface of dimension D_s ($2 < D_s < 3$) is considered. The property of isotropy means that the probability distribution of heights is invariant when the coordinate axes are rotated and the surface is reflected on any plane. The property of homogeneity of a surface indicates that the probability distribution of the height is independent of the location on the surface [4, 9]. Therefore, the profile, $z(x)$, of such a surface along a straight line and in any arbitrary direction is of dimension $D = D_s - 1$ and is a statistically valid representation of the surface. Thus the profile fractal dimension D is adopted to characterize the fractal nature of the surface in this paper. The profile $z(x)$ in Fig. 1 has the mathematical properties of being continuous everywhere but non-differentiable and is self-affine in roughness structure [4, 9]. These properties are satisfied by the Weierstrass–Mandelbrot (W-M) fractal function, which can be used to characterize the roughness of surface profile and is given as:

$$z(x) = G^{(D-1)} \sum_{n=n_1}^{\infty} \frac{\cos 2\pi\gamma^n x}{\gamma^{(2-D)n}}; \; 1 < D < 2; \; \gamma > 1 \tag{1}$$

where G is a characteristic length scale, $\gamma^{n_1} = 1/L$ where L is the sampling length. $\gamma^n = \omega$, where frequency ω is the reciprocal of wave length and n is called wave number. To provide both the phase randomization and high spectral density [4], γ is selected to be 1.5. The parameters G and D form the set to characterize profile $z(x)$. The methods for calculating profile fractal dimension mainly include the yard-stick, the box counting, the variation, the structure function and the power spectrum methods. Out of these, the power spectrum and structure function methods are most popular. The power spectrum of W–M function is given as:

$$S(\omega) = \frac{G^{2(D-1)}}{2\ln\gamma} \frac{1}{\omega^{(5-2D)}} \tag{2}$$

It can be seen that both G and D are independent of ω, therefore they are scale-invariant. Eqn. (2) shows that the power spectrum follows a power law behavior. If $S(\omega)$ is plotted versus ω on a log–log plot, then the power law behavior would result in a straight line. Using fast fourier transform (FFT), the power spectrum of profile can be calculated. Comparing the power spectrum of W–M function with that of a real surface, D relates to the slope of the spectrum on the log–log plot, G correlates with the intercept of the log–log plot. The structure function $S(\tau)$ of sampling data on the profile curve $z(x)$ can be described as [9, 18]:

$$S(\tau) = \left\langle [z(x+\tau) - z(x)]^2 \right\rangle = K\tau^{(4-2D)} \tag{3}$$

where τ is any displacement along the x direction, $\langle \; \rangle$ is temporal average, K is a constant. Different τ and the corresponding $S(\tau)$ can be plotted verses the τ on a log–log scale. Then the profile fractal dimension D can be related to the slope of the fitting line, m, on log-log plot as $D = (4-m)/2$. In comparison with power spectrum method, the structure function is more exact and easy to operate. For this reason the structure function method is adopted to characterize the fractal character of the surface profiles in this paper and implemented following the procedure explained in [18]. The continuous analogue electric signals of profiles from a measuring basis are put into a computer. After analogue to digital (A/D) translation, the profiles are given with digitalized height values during a traverse over a sampling length. From the dispersed digital signals, the mean line $z(x) = 0$ is fitted by use of least squares method and the deviations of profile z(x) from its mean line are determined. Let the sampling spacing of the computer system is Δt with each sampling length L having N +1 evenly spaced data points with $z(x_i) = z_i (i = 0,1,2,......, N)$ and $\tau = n\Delta t$ (n =1,2,3..). Then the structure function takes the form:

$$S(\tau) = S(n\Delta t) = \left\langle [z(x_i + n\Delta t) - z(x_i)]^2 \right\rangle = \frac{1}{N-n} \sum_{i=0}^{N-n} (z_{i+n} - z_i)^2 \tag{4}$$

By virtue of the above equation *D* can be determined from the structure function plot on log–log coordinates. The magnitude of the fractal dimension *D* determines the contribution of high and low frequency components in the surface profile function *z*(*x*). Thus high values of *D* indicate that high frequency components are more dominant that low frequency components in the surface topography profile. The physical significance of *D* is the extent of space occupied by the rough surface, i.e. larger *D* values correspond to denser profile or smoother topography.

3. TAGUCHI METHOD

Taguchi technique [19, 20] is a powerful tool for design of high quality systems based on orthogonal array experiments that provide much reduced variance for the experiments with an optimum setting of process control parameters. It introduces an integrated approach that is simple and efficient to find the best range of designs for quality, performance and computational cost. This method achieves the integration of design of experiments (DOE) with the parametric optimization of the process yielding the desired results. The orthogonal array (OA) provides a set of well balanced (minimum experimental runs) experiments. Taguchi's method uses a statistical measure of performance called signal–to-noise ratios (S/N), which are logarithmic functions of desired output to serve as objective functions for optimization. The S/N ratio takes both the mean and the variability into account and is defined as 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 three categories of S/N ratios are used: lower-the-better (LB), higher-the-better (HB) and nominal-the-best (NB). The parameter level combination that maximizes the appropriate S/N ratio is the optimal setting. Furthermore, a statistical analysis of variance (ANOVA) [21] is performed to find which process parameters are statistically significant. With the S/N ratio and ANOVA analyses, the optimal combination of the process parameters can be predicted. Finally, a confirmation experiment is conducted to verify the optimal process parameters obtained from the parameter design.

4. EXPERIMENTAL DETAILS

4.1 Design of experiment

The design of experiments technique is a very powerful tool, which permits us to carry out the modeling and analysis of the influence of process variables on the response variables. The response variable is an unknown function of the process variables, which are known as design factors. There are a large number of factors that can be considered for machining of a particular material in CNC turning. However, the review of literature shows that the following three machining parameters are the most widespread among the researchers and machinists to control the turning process with respect to surface roughness: depth of cut (A, mm), spindle speed (B, rpm) and feed rate (C, mm/rev). In the present study these are selected as design factors while other parameters have been assumed to be constant over the experimental domain. The machining variables / design factors with their values on different levels are listed in Table I. The selection of the values of the variables is limited by the capacity of the machine used in the experimentation as well as the recommended specifications for different workpiece - tool material combinations. Based on Taguchi method, an orthogonal array is employed to reduce the number of experiments for determining the optimal machining parameters. An orthogonal array provides the shortest possible matrix of combinations in which all the parameters are varied to consider their direct effect as well as interactions simultaneously. In the present investigation, an L27 orthogonal array [20] which has 27 rows corresponding to the number of tests (26 degrees of freedom) with 13 columns at three levels is chosen. The 1st column is assigned to depth of cut (A), 2nd column is assigned to spindle speed (B), 5th column is assigned to feed rate (C) and the remaining columns are assigned to the two-way interactions of factors.

Table I: Variable levels used in the experimentation.

Levels	Depth of cut (A, mm)	Spindle speed (B, rpm)	Feed rate (C, mm/rev)
1	0.1	800	0.07
2	0.2	1200	0.14
3	0.3	1600	0.21

4.2 Response variable selected

The response variable used to accomplish the present study on surface topography characterization is the profile fractal dimension D. The machining parameters are optimized with an objective to maximize the fractal dimension D, i.e., to yield a smoother surface topography.

4.3 Machine used

The machine used for the turning tests is a Jobber XL CNC Lathe having the control system FANUC Series Oi Mate-Tc. For generating the turned surfaces, CNC part programs for tool paths were created with specific commands.

4.4 Cutting tool used

Coated carbide tools are known to perform better than uncoated carbide tools. Thus commercially available CVD coated carbide tools were used in this investigation. The tool holder is used as the PTGNR-25-25 M16 050, WIDIA and insert used as the TNMG 160404 –FL, WIDIA. The tool is coated with titanium nitride coating having hardness, density and transverse rupture strength as 1570 HV, 14.5 g/cc and 3800 N/mm^2. The compressed coolant WS 50-50 with a ratio of 1:20 with water was used as cutting environment.

4.5 Work piece materials

The present study was carried out with three different workpiece materials, viz., 6061-T4 aluminium, mild steel (AISI 1040) and medium leaded brass UNS C34000. All the specimens were in the form of bar with diameter 20 mm and length 60 mm.

4.6 Profile measurement and fractal calculation

Roughness profile measurement was done using a stylus-type profilometer, *Talysurf* (Taylor Hobson, Surtronic 3+). The profilometer was set to a cut-off length of 0.8 mm, Gaussian filter, traverse speed 1 mm/sec and 4 mm evaluation length. Roughness measurements on the work pieces were repeated four times and average of four measurements was recorded. The measured profile is digitized and processed through the dedicated advanced surface finish analysis software *Talyprofile*.

5. RESULTS

5.1 Results and Discussion for Aluminium

The traditional method of calculating the desirable factor levels is to look at the simple averages of the results. But it does not capture the variability of the results within a trial condition. That's why the signal to noise ratio analysis is done here with the fractal dimension as the performance index. The S/N ratio for fractal dimension is calculated using HB (higher-the-better) criterion and the same is given by:

$$S/N = -10\log\left(\frac{1}{n}\sum\frac{1}{y^2}\right) \tag{5}$$

where y is the observed data and n is the number of observations. Table II shows the experimental results for fractal dimension of turned surfaces and the corresponding S/N ratios for all three materials. Since the experimental design is orthogonal, it is then possible to separate out the effect of each machining parameter at different levels. For example, the mean S/N ratio for factor A at levels 1, 2 and 3 can be calculated by averaging the S/N ratios for the experiments 1-9, 10-18, and 19-27, respectively. The mean S/N ratio for each level of the other factors can be computed in the similar manner. The mean S/N ratio for each level of the factors *A*, *B* and *C* for three materials is presented in Table III. The corresponding main effects plots are shown in Fig. 2. It is seen from Fig. 2(a) that parameter *C* is the most significant parameter among all the three parameters considered in the present study in case of aluminium. Also there is moderate interaction between the parameters *A*, *B* and *C*. Using Minitab [22], ANOVA is performed to determine which parameter and interaction significantly affect the performance characteristics. Table IV shows the ANOVA result for fractal dimension of aluminium surfaces. If the calculated value of *F*-ratio is higher than the tabulated value of *F*-ratio, then the factor is significant at desired α level. In general, when *F* value increases the significance of the parameter also increases. ANOVA table shows the percentage contribution of each parameter. It is seen that parameter *C*, i.e., feed rate has got the most significant influence on fractal dimension of aluminium surfaces at the confidence level of 95% within the specific test range while parameter *B* (spindle speed) has got some influence on fractal dimension of aluminium surfaces. The two-way interactions of the parameters also have got some influence. The optimal machining parameter combination for maximum fractal dimension is found to be *A*1*B*1*C*1.

After the optimal level of machining parameters has been found out, a verification test needs to be carried out in order to check the accuracy of analysis. The estimated S/N ratio, $\hat{\gamma}$, using the optimal level of the machining parameters can be calculated as:

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{o} \left(\bar{\gamma}_i - \gamma_m \right) \tag{6}$$

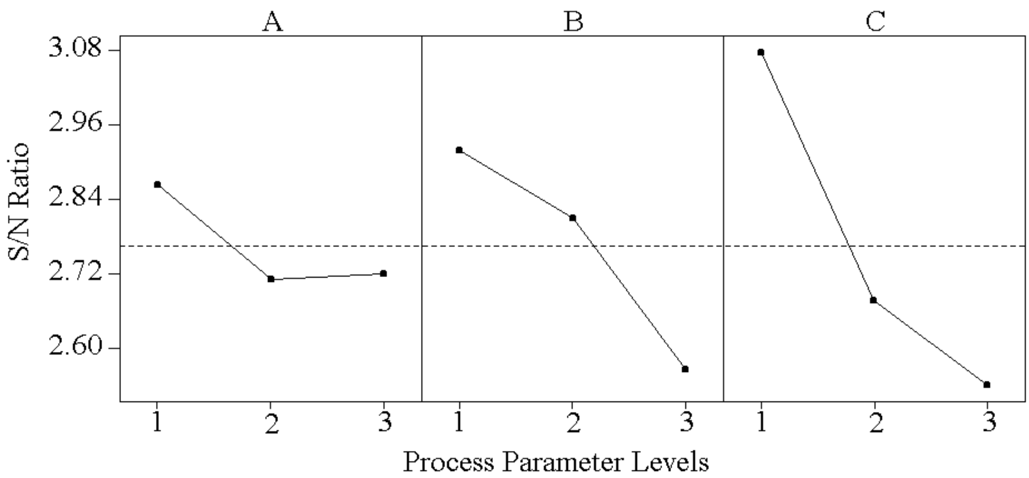
where γ_m is the total mean S/N ratio, $\bar{\gamma}_i$ is the mean S/N ratio at the optimal level, and o is the number of the main design parameters that significantly affect the fractal dimension of aluminium surfaces. Table V shows the comparison of the estimated S/N ratio with the actual S/N ratio using the optimal parameters. It may be noted that there is good agreement between the estimated and actual S/N ratios observed. The increase of the S/N ratio from the initial machining parameters to the optimal machining parameters is 0.1523dB, which means the fractal dimension is improved by about 5%.

Table II: Experimental results for fractal dimension (*D*) and S/N ratios (dB).

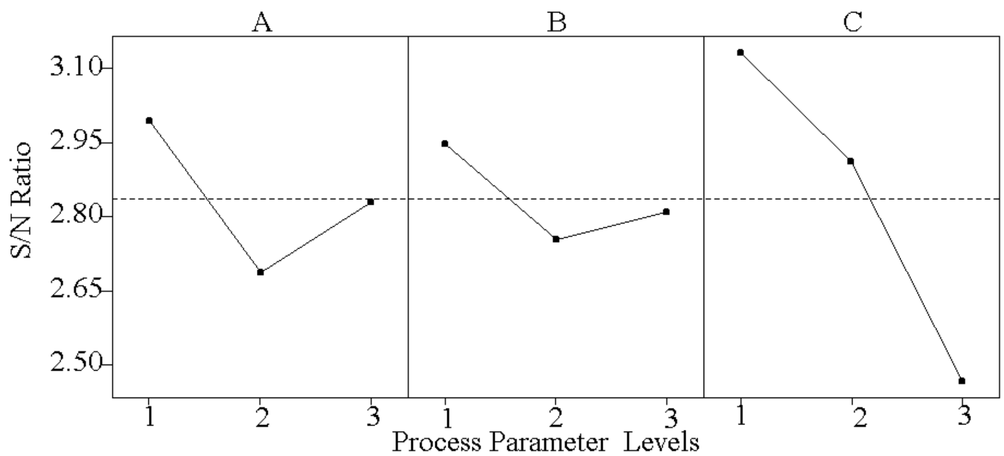
Exp. No.	Aluminium		Brass		Mild steel	
	D	S/N ratio	*D*	S/N ratio	*D*	S/N ratio
1	1.4375	3.15216	1.4700	3.34635	1.3475	2.59058
2	1.4250	3.07630	1.4650	3.31675	1.3375	2.52588
3	1.4150	3.01513	1.4550	3.25726	1.3350	2.50963
4	1.4725	3.36111	1.4150	3.01513	1.3525	2.62275
5	1.2975	2.26215	1.3650	2.70265	1.3100	2.34543
6	1.4025	2.93806	1.3550	2.63879	1.3325	2.49334
7	1.3825	2.81330	1.4625	3.30192	1.3575	2.65480
8	1.3625	2.68673	1.4325	3.12189	1.3425	2.55829
9	1.3275	2.46069	1.2950	2.24540	1.3650	2.70265
10	1.4550	3.25726	1.3700	2.73441	1.3525	2.62275
11	1.3800	2.79758	1.3825	2.81330	1.2950	2.24540
12	1.3625	2.68673	1.3200	2.41148	1.2875	2.19494
13	1.4825	3.41989	1.3975	2.90704	1.3475	2.59058
14	1.4125	2.99977	1.3850	2.82900	1.3550	2.63879
15	1.2950	2.2454	1.3000	2.27887	1.3325	2.49334
16	1.3050	2.31221	1.3975	2.90704	1.3525	2.62275
17	1.3225	2.42791	1.4025	2.93806	1.3725	2.75025
18	1.2950	2.24540	1.3125	2.36199	1.2950	2.24540
19	1.4650	3.31675	1.4650	3.31675	1.3725	2.75025
20	1.3825	2.81330	1.4225	3.06105	1.3025	2.29555
21	1.2800	2.14420	1.3000	2.27887	1.2925	2.22861
22	1.3825	2.81330	1.4600	3.28706	1.3425	2.55829
23	1.3125	2.36199	1.3625	2.68673	1.3475	2.59058
24	1.3925	2.87590	1.3225	2.42791	1.3225	2.42791
25	1.4525	3.24232	1.4750	3.37584	1.3525	2.62275
26	1.3575	2.65480	1.3700	2.73441	1.3975	2.90704
27	1.2950	2.24540	1.3025	2.29555	1.2925	2.22861

Table III: S/N ratio response table for fractal dimension.

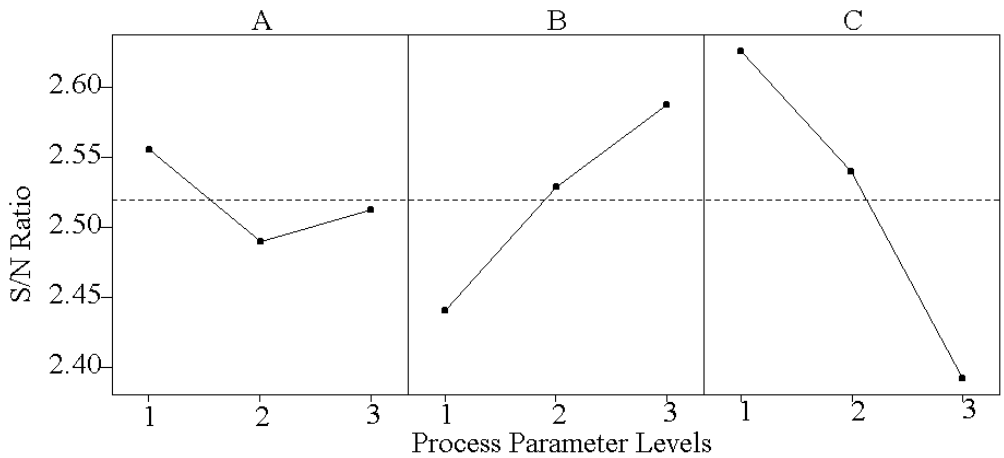
Level	Aluminium			Brass			Mild steel		
	A	*B*	*C*	*A*	*B*	*C*	*A*	*B*	*C*
1	2.8628	2.9177	3.0765	2.9940	2.9485	3.1324	2.5559	2.4404	2.6262
2	2.7102	2.8086	2.6756	2.6868	2.7526	2.9115	2.4894	2.5290	2.5397
3	2.7187	2.5654	2.5397	2.8294	2.8091	2.4662	2.5122	2.5881	2.3916
Delta	0.1526	0.3523	0.5368	0.3072	0.1959	0.6662	0.0666	0.1477	0.2346
Rank	3	2	1	2	3	1	3	2	1



2(a)



2(b)



2(c)

Figure 2: Main effect plots for mean S/N ratios for aluminium (a), brass (b), mild steel (c).

Table IV: Result of ANOVA for aluminium surfaces.

Source	DF	SS	MS	F	% Contribution	P
A	2	0.003195	0.001597	0.48	3.17	0.635
B	2	0.01475	0.007375	2.22	14.62	0.171
C	2	0.035828	0.017914	5.39	35.52	0.033
A*B	4	0.008883	0.002221	0.67	8.81	0.632
A*C	4	0.005751	0.001438	0.43	5.70	0.782
B*C	4	0.005891	0.001473	0.44	5.84	0.775
Error	8	0.02658	0.003322		26.34	
Total	26	0.100878			100	

Table V: Result of confirmation experiment for aluminium surfaces.

	Initial machining parameter	Optimal machining parameters	
		Prediction	Experiment
Level	*A*2*B*2*C*2	*A*1*B*1*C*1	*A*1*B*1*C*1
Fractal Dimension, *D*	1.4125		1.4375
S/N ratio(dB)	2.9998	3.3292	3.1521
Improvement of S/N ratio = 0.1523			

5.2 Results and Discussion for Brass

Table II contains the experimental results for fractal dimension of brass surfaces and the corresponding S/N ratios. The mean S/N ratio for each level of the factors *A*, *B* and *C* is summarized in Table III. The corresponding main effects plots are shown in Fig. 2 (b). Table VI shows the ANOVA result for fractal dimension of brass surfaces. Here also it is seen that parameter *C* (feed rate) has got the greatest influence at the confidence level of 95% while *A* has some contribution. The two-way interactions of parameters have also got some influence on fractal dimension of brass surfaces. The optimal machining parameter combination for maximum fractal dimension in this case is found to be *A*1*B*1*C*1. Table VII shows the comparison of the estimated S/N ratio with the actual S/N ratio using the optimal parameters in case of brass. It may be noted that there is good agreement between the estimated and actual S/N ratios observed. The increase of the S/N ratio from the initial machining parameters to the optimal machining parameters is 0.5174dB, which means the fractal dimension is improved by about 18%. In other words, the experimental results confirm the prior design and analysis for optimizing the machining process parameters.

5.3 Results and Discussion for Mild Steel

Table II includes the experimental results for fractal dimension of mild steel surfaces and the corresponding S/N ratios. The mean S/N ratio for each level of the factors *A*, *B* and *C* is also summarized in Table III. The corresponding main effects plots are shown in Fig 2(C). The optimal machining parameter combination for maximum fractal dimension in this case is found to be *A*1*B*3*C*1. Table VIII shows the ANOVA result for fractal dimension of mild steel surfaces. It is seen that parameters C has got the most significant influence at the confidence level of 95% while *B* has some contribution in controlling the fractal dimension of mild steel surfaces. The interactions of parameters *B* x *C* and *A* x *C* have got some influence as well. Table IX shows the comparison of the estimated S/N ratio with the actual S/N ratio using the optimal parameters in case of tungsten carbide. It may be noted that there is good agreement between the estimated and actual S/N ratios observed. The increase of the S/N ratio from the initial machining parameters to the optimal machining parameters is 0.016dB, which means the fractal dimension is improved marginally in this case.

Table VI: Result of ANOVA for brass surfaces.

Source	DF	SS	MS	F	% Contribution	P
A	2	0.011135	0.005567	7.08	11.76	0.017
B	2	0.004826	0.002413	3.07	5.09	0.103
C	2	0.051806	0.025903	32.94	54.72	0.000
A*B	4	0.007847	0.001962	2.49	8.29	0.126
A*C	4	0.008181	0.002045	2.60	8.64	0.116
B*C	4	0.004589	0.001147	1.46	4.85	0.300
Error	8	0.006292	0.000787		6.65	
Total	26	0.094675			100	

Table VII: Result of confirmation experiment for brass surfaces.

	Initial machining parameter	Optimal machining parameters	
		Prediction	Experiment
Level	*A*2*B*2*C*2	*A*1*B*1*C*1	*A*1*B*1*C*1
Fractal Dimension, *D*	1.3850		1.4700
S/N ratio(dB)	2.8290	3.40	3.3464
Improvement of S/N ratio = 0.5174			

Table VIII: Result of ANOVA for mild steel surfaces.

Source	DF	SS	MS	F	% Contribution	P
A	2	0.000462	0.000231	0.50	2.18	0.625
B	2	0.002357	0.001179	2.55	11.14	0.139
C	2	0.005920	0.002960	6.40	27.96	0.022
A*B	4	0.001370	0.000343	0.74	6.47	0.590
A*C	4	0.003408	0.000852	1.84	16.09	0.214
B*C	4	0.003954	0.000988	2.14	18.67	0.168
Error	8	0.003702	0.000463		17.49	
Total	26	0.021173			100	

Table IX: Result of the confirmation experiment for mild steel surfaces.

	Initial machining Parameter	Optimal machining parameters	
		Prediction	Experiment
Level	*A*2*B*2*C*2	*A*1*B*3*C*1	*A*1*B*3*C*1
Fractal Dimension, *D*	1.3550		1.3575
S/N ratio(dB)	2.6388	2.6437	2.6548
Improvement of S/N ratio = 0.016			

A comparison of the optimization results for fractal dimension in different materials reveals the fact that these are material specific. It has been observed that feed rate has got the most significant influence in controlling fractal dimension characteristics of surface profile for all the three materials. In addition, spindle speed has got some influence in case of mild steel and aluminium while depth of cut has some significant influence in case of brass. In case of mild steel, higher spindle speed yields higher fractal dimension while the reverse is true for aluminium. In case of brass, the variation is not monotonic; fractal dimension decreases with spindle speed initially and then increases. The reason for such behaviour may probably be attributed to the difference in mechanical properties of the materials. The interactions between the machining parameters have also got some influence in controlling the fractal dimension of surface profile produced. Accordingly, optimum machining parameter combinations for maximum fractal dimension depend greatly on the workpiece material within the experimental domain. However, it is possible to select a combination of depth of cut, spindle speed and feed rate for achieving the surface topography with optimum (maximum) fractal dimension within the constraints of the available machine. The application of the present approach to obtain optimal machining conditions may be quite useful in computer aided process planning. This type of analysis is not available in the literature and will be useful with an objective of optimum fractal dimension within the particular range of machining parameters.

6. CONCLUSIONS

Taguchi orthogonal array is employed to optimize the machining parameters with respect to fractal dimension of the surface topography produced in CNC turning of three different materials. It has been observed that feed rate (*C*) has got the most significant influence in controlling fractal dimension characteristics of surface profile for all the three materials. In addition, spindle speed (*B*) has got some influence in case of mild steel and aluminium while depth of cut (*A*) has some significant influence in case of brass. The interactions between the machining parameters have also got some influence in controlling the fractal dimension of surface profile produced in CNC turning. The optimal machining parameter combination for maximum fractal dimension is found to be *A*1*B*1*C*1 in case of aluminium and brass, and *A*1*B*3*C*1 in case of mild steel. Thus optimum machining parameter combinations for maximum fractal dimension depend greatly on the workpiece material within the experimental domain. However, it is possible to select a combination of depth of cut, spindle speed and feed rate for achieving the surface topography with optimum (maximum) fractal dimension.

7. ACKNOWLEDGEMENTS

The first author gratefully acknowledges the financial assistance of Department of Science and Technology, GOI through a SERC Fast Track Project for young scientists vide Ref. No. SR/FTP/ETA-11/2004 dated 28.06.2004.

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