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ORIGINAL ARTICLE

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Surface quality evaluation in ultrasonic drilling through the Taguchi technique

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Abstract Ultrasonic drilling of commercially pure titanium and titanium alloy (Ti-6Al-4v) was investigated in this study. During the experiments, process parameters such as work piece, grit size, slurry concentration, power rating and tools were changed to explore their effect on the surface roughness. Taguchi's technique was applied to obtain an optimal setting of ultrasonic drilling (USD) process parameters. Average surface roughness (Ra) was measured by using the Optical Profiling System. Two-dimensional and three-dimensional contour plots were obtained from the profiling system to quantify and visualize the surface roughness. From the experimental results and further analysis, it is concluded that the effect of slurry concentration and grit size have a significant effect on surface roughness more than other parameters. In addition, the surface roughness is apparently similar in two and three dimensions as visualized from contour plots. Ultrasonic drilling is established as a material removal process with good surface quality.

Keywords Ultrasonic drilling · Ultrasonic machining · Taguchi method · Titanium

1 Introduction

Ultrasonic drilling (USD) is an abrasive process that utilizes the ultrasonic (~20 kHz) vibration of a tool and material removal is purely mechanical. The process equipment consists of a vibrational horn, a tool part, an abrasive paste, and the working material.

Titanium is a relatively lightweight metal whose density is approximately 60% of steel's and 50% of nickel and copper alloys. It provides excellent corrosion resistance, a high strength-to-weight ratio, and good high-temperature properties. Titanium and its alloys are classified as difficult-to-machine materials. Machining of titanium is generally done by the conventional processes of machining keeping very low feed to guarantee that during machining there are the least structural changes. The machining characteristics for titanium and its alloys with conventional machining processes are summarized below [9]:

– Titanium and its alloys are poor thermal conductors. As a result, the heat generated when machining titanium cannot dissipate quickly; rather, most of the heat is concentrated on the cutting edge and tool face.
– During machining, titanium alloys exhibit thermal plastic instability that leads to unique characteristics of chip formation. The shear strains in the chip are not uniform; rather, they are localized in a narrow band that forms serrated chips.
– The contact length between the chip and the tool is extremely short (less than one-third the contact length of steel with the same feed rate and depth of cut). This implies that the high cutting temperature and the high stress are simultaneously concentrated near the cutting edge (within 0.5 mm).
– Serrated chips create fluctuations in the cutting force; this situation is further promoted when alpha-beta alloys are machined. The vibrational force, together with the high temperature, exerts a micro-fatigue loading on the cutting tool, which is believed to be partially responsible for severe flank wear.
– The surface finish achieved by a single machining process (no finishing operations) is very poor.

With advances in machining technologies, many difficult-to-machine materials are machined at higher metal removal rates with better surface finish. None of these machining processes, however, seems to be effective in machining titanium because of inherent chemical reactivity of titanium. Al_2O_3 coating has a lower thermal conductivity than the tungsten carbide insert, which prevents heat dissipation from extremely concentrated high stress and high temperature at the cutting point.

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Titanium carbide and titanium nitride coatings are not suitable for machining titanium alloys because of their chemical affinities [9].

Most cryogenic machining studies on titanium and its alloys have documented improved machinability when freezing the workpiece or cooling the tool using a cryogenic coolant. However, inherent weaknesses exist in these approaches [9].

Non-conventional methods of machining like electro discharge machining (EDM) and laser beam machining (LBM) are also used for machining of titanium. EDM with its inherent advantages for machining work pieces with special shape, regardless of material strength or hardness but EDM also has low machining efficiency as compared to traditional machining process. In addition, the recast layer with micro-pits and cracks, caused by rapid cooling gives both worse surface accuracy and shorter tool life. LBM being a thermal process produces thermal stress and a heat affected zone in the material. Also, LBM usually result in holes with a funnel or pear-like shape: holes with straight profiles are difficult to obtain. Ultrasonic drilling rarely causes such a concern. USD can be suitable for machining of titanium and its alloys due to following characteristics [13]:

- Titanium and its alloys have low thermal conductivity and in ultrasonic machining (USM) there is a thinner zone affected by machining, generous quantity of cutting fluid is used resulting in better heat dissipation, efficient slurry flow can be maintained, depth of cut can be maintained due to rigidity of tool fixed in tool holder, and chemically active medium can be used to transfer heat efficiently and reduce cutting forces between the tool and workpiece.
- Titanium and its alloys have a tendency to react with cutting tools, which contributes to seizing, galling, abrasion, and pick up on cutting edges and faces and in USM there is no tool work contact preventing all the above-mentioned side effects.
- USM is superior to hybrid processes in terms of simplicity, economic and provides a better control.

Commercially pure titanium (American Society for Testing and Materials - Grade 2) and titanium alloy (Ti-6%Al-4%V (American Society for Testing and Materials - Grade 5) are considered workhorses of the titanium family. Most of the applications of commercially pure titanium (ASTM - Gr. 2) and Ti-6%Al-4%V (ASTM - Gr. 5) are common. These are:

- Surgical implants (biomedical implants, dental prosthesis)
- Jet engines, airframe components, aircraft ducting, hydraulics, tubing, etc
- Automotive components
- Consumer goods
- Hydrometallurgical extraction
- Chemical processing plants
- Marine applications

Statistical experimental design methods provide a systematic and efficient plan for experimentation to achieve certain goals so that many control factors can be simultaneously studied. Frequently applied experimental design methods include the simplex method [4, 18], evolutionary operation [1, 25], response surface methodology [4, 9, 22] and the Taguchi method [5, 7, 23]. In contrast to the traditional 'one-factor at a time' approach, these methods can be used to examine and optimize the operational variables while considering the interactive effects among the control factors. Studying the effects of experimental parameters requires many experiments, much time and some certain statistical techniques for quantitative evaluation of the effects. Various design-of-experiment (DOE) methods are widely used to reduce this problem. DOE methods set up the efficient experimental schedule and produce a statistical analysis to indicate quickly and easily what parameters are important for the final results. In particular, the Taguchi method is one of the most powerful DOE methods for experiments.

The advantages of using the Taguchi method are that many more factors can be optimized simultaneously and quantitative information can be extracted by only a few experimental trials. Therefore, this method has been extensively applied in industry [2].

The approach, quality by design, developed by Taguchi has produced a unique and powerful quality improvement discipline that differs from traditional practices. The Taguchi method of quality engineering encompasses all stages of product/process development. However, the key element for achieving high quality and low cost is parameter design. Through parameter design, optimal levels of product and process parameters can be determined.

Taguchi's approach provides the designer with a systematic and efficient approach for conducting experimentation to determine near optimum settings of design parameters for performance and cost. The method emphasizes pushing quality back to the design stage, seeking to design a product/process, which is insensitive to quality problems. The Taguchi method utilizes orthogonal arrays to study a large number of variables with a small number of experiments and analyzes data easily and effectively with the signal-to-noise (S/N) ratio. Using orthogonal arrays significantly reduces the number of experimental configurations to be studied. The conclusions drawn from small-scale experiments are valid over the entire experimental region spanned by the control factors and their settings. This method can reduce research-and-development costs by simultaneously studying a large number of parameters. The S/N ratio takes both the mean and the variability into account. The S/N equation depends on the criterion for the quality characteristic to be optimized. In general, we get a better signal when the noise is smaller, so that a larger S/N ratio yields better final results. Increasing the S/N ratio makes the final results more desirable. This means the divergence of the final results becomes smaller. This is the most important feature of the S/N ratio and the Taguchi method. After performing the statistical analysis of the S/N ratio, an analysis of variance (ANOVA) needs to be employed for estimating error variance and for determining the relative importance of various factors.

Using the Taguchi method for parameter design, the predicted optimum setting need not correspond to one of the rows of the matrix experiment. Therefore, an experimental confirmation is run using the predicted optimum levels for the control parameters being studied. The purpose is to verify that the optimum conditions suggested by the matrix experiments do indeed give the projected improvement. This approach presents a scope of its applications to the ultrasonic drilling of titanium alloys in order to achieve minimum possible surface roughness.

2 Materials and methods

The experiments of ultrasonic drilling were conducted on an AP-500 (240 V) model Sonic-Mill Ultrasound Machine, with a maximum power output of 500 W. The frequency of the machine is 20 kHz. Automatic feed of the tool was employed.

2.1 Process parameters

Before designing the experiments, an exhaustive evaluation of the factors that could influence the optimization of the quality characteristic was carried out. The main factors can be divided into two categories: control factors and noise factors. The control factors are those factors that can be controlled during the measurement. In order to identify the process parameters of the USD process that may affect the surface roughness in titanium work pieces, an Ishikawa cause-effect diagram was constructed [10]. The Ishikawa diagram (Fig. 1) depicts that the following parameters may affect the quality characteristics in USD. The process parameters whose effects are investigated in this study are:

1. Workpiece
2. Grit size
3. Slurry concentration
4. Power rating
5. Tool material

The parameters depending on machine setting (except power rating) and trunk design were not considered for experimentation purpose due to limitations of machine setup.

Two types of noise factors can be distinguished. First, the noise factors that cannot be controlled: environmental conditions, human errors (operator), history of the transducer, etc; second, those factors which can be controlled, but controlling these factors would excessively complicate the experiments. Thus noise factors were not considered for experimentation.

Commercially pure titanium [(ASTM Gr. 2) (C 0.006%, H 0.0007%, N 0.014%, O 0.140%, Fe 0.03% and balance Ti)] and titanium alloy [(ASTM Gr. 5) (C 0.019%, H 0.0011, N 0.007%, O 0.138%, Fe 0.05%, V 4.04% and balance Ti)] were selected as workpiece materials with deferring hardness but approximately similar properties viz. melting range, specific heat, thermal coefficient, fatigue limit, and density. A pilot experimentation was conducted with selected process parameters at different values using the one-factor-at-a-time approach taking surface finish as response characteristic. It has been observed that surface roughness decreases from slurry concentration at 30% from 25% and then again increases at 35% for both the workpieces. The machine on which experiments are conducted has a 500-W maximum power rating. It can be worked safely with 10 to 90% of power rating, i.e., from 50 to 450 W. In this study, power ratings at 40, 60, and 80% were selected i.e., 200, 300, and 400 W. With power rating as the factor under consideration, the lowest range selected was based on the trial-and-error method [21], starting from the lowest power rating at which first satisfactory machining rate was observed. This came out to be 200 W; below this very poor MRR was observed. When the power rating was increased from 400 W in case of hard tool it caused crack on tip especially in case of high carbon steel and tungsten carbide tools resulting in uneven surface roughness and moreover tool failure. Thus, the power rating was limited to 80% (400 W) as the high limit. Surface roughness increases from 40 to 60% of the power rating and then decreases at 80% of power rating. Similarly, with grit size as the control factor, surface roughness decreases at #320 and is at higher values with #220 and

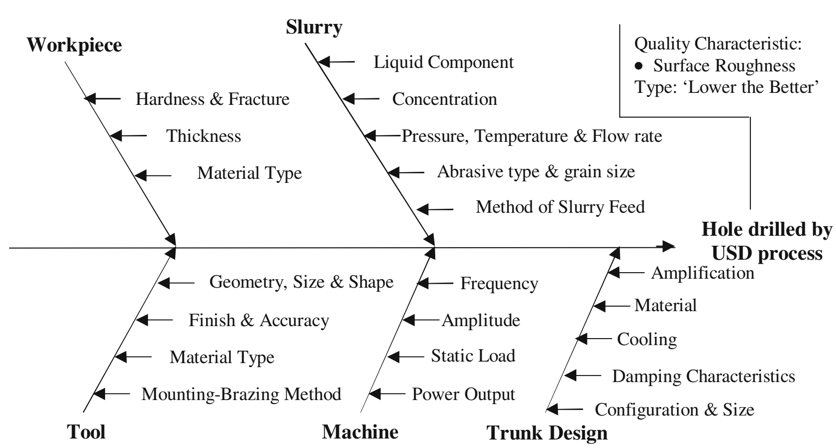


Fig. 1 Ishikawa diagram

#500 grit sizes, respectively. Solid tools of 5.0-mm diameter with different materials were used. The tool materials selected were high-speed steel [T1 (0.75 C, 4.25 Cr, 18 W, 1.2 V)], Tungsten Carbide [C2 (92– 98% WC -2–8%Co)] and high carbon steel [(1–1.3%C)]. The T1-type high-speed tool steels with a high carbon content have high wear resistance and very high hardness. This class of tool material has a substantial amount of wear-resistant carbides in a very high heat resistant matrix. High-carbon steels are extremely strong yet more brittle. They offer better responses to heat treatment and longer service life than medium-carbon steels. High-carbon steels typically have high wear resistance due to their superior surface hardness. Tungsten carbide is actually grains of tungsten carbide in a matrix generally in a cobalt matrix (the carbon form carbides and the cobalt does not). Thus the tungsten forms very hard grains for wear resistance and the cobalt stays relatively soft for impact resistance. Thus, five controllable parameters and their chosen levels are given in Table 1. It is decided to study four of five selected parameters at three levels, because non-linear behavior of the parameters of a process can only be determined if more than two levels are used.

The average surface roughness (R_a) is typically used to describe the roughness of machined surfaces. It is well established and understood, literature and standards are available to explain its parameters, and, most importantly, historical part data is based upon it. It is the main height as calculated over the entire measured length or area. The average surface roughness (R_a) in a direction parallel to the tool axis was measured on the Optical Profiling System and three measurements were taken for each specimen.

2.2 Selection of an orthogonal array (OA)

In the present study, five parameters were selected in which one of the parameters is at two levels and the rest of the parameters are at three levels each; the design becomes a mixed level design. Thus L_{18} OA was chosen for experimentation. In addition, the two-level parameter has 1 degree of freedom (No. of levels-1), and four three-level parameters have 2 degrees of freedom, i.e., the total degree of freedom (DOF) required will be 9[=(1*1)+(4*2)]. Thus the most appropriate array in this case $L_{18}(2^1*3^7)$ OA with 17[=18−1] DOF was selected for experimentation [3]. The L_{18} array is given in Table 2. The assignment of parameters to the columns of the L_{18} OA is also given in Table 2. The L_{18} specifies 18 runs to be conducted.

Table 1 Definition and trial levels of factors in Taguchi's orthogonal array experiment

Process parameter designation	Process parameters	Level 1	Level 2	Level 3
A	Workpiece	ASTM Gr.2	ASTM Gr. 5	*
B	Grit size	220	320	500
C	Slurry concentration	25%	30%	35%
D	Power rating	40%	60%	80%
E	Tool	HCS	HSS	WC

3 Measurement and analysis

A standard orthogonal array $L_{18}(2^1*/3^7)$ [24] was used to examine this five-factor system, which is proven less affected by interaction of design parameters. L and subscript 18 denote the Latin square and the number of the experimental runs, respectively. A run involved the corresponding combination of levels to which the factors in the experiment were set. The 18 experiments were conducted on the trial conditions given in Table 2. For each trial, experiments were repeated three times and the surface roughness was measured. The average surface roughness (R_a) values are also given in Table 2. The signal-to-noise (S/N) ratios were computed for each of the 18 trial conditions and the values are recorded in Table 2. Although data from a designed experiment are traditionally used to analyze the mean response, however, in addition to emphasizing that the variability in the quality of the product should be reduced, the Taguchi method uses the signal-to-noise (S/N) ratio, which is directly transformed from the quadratic quality loss function as a measure to determine the robustness of a process. Thus, optimizing process parameters by the Taguchi method is an attempt not only to bring the average quality closer to the target value but also to simultaneously minimize the variation in quality. Whenever an experiment involves repeated observations at each of the trial conditions, the S/N ratio analysis proves to be effective [19]. The quality characteristic for surface roughness is of lower-the-better type. So, the S/N ratio for the 'lower-the-better' type of response is used and computed as:

$$(\mathrm{S/N})_{\mathrm{LB}} = -10\ \log\left[\frac{1}{\boldsymbol{R}}\sum_{i=1}^{R} y_i^2\right] \tag{1}$$

where R is the number of all data points and y_i is the value of the ith data point.

The mean response refers to the average values of the performance characteristics for each parameter at different levels. The average values of surface roughness for the workpiece at two levels and the rest of the parameters at three levels were obtained and are given in Table 3. These values are plotted in Fig. 2. The main effects of the various parameters when they are changed form the lower level are also given in Table 3.

The average values of the S/N ratios of various parameters at different levels are given in Table 4 and plotted in Fig. 2. The main effects of the parameters in terms of S/N data are also given in Table 4. The average effect of each parameter on the surface roughness (S/N ratio) can be visualized from Fig. 2, when parameters changes from one level to another. It is clear from Fig. 2

Table 2 Design and experimental results of the L_{18} orthogonal array experiment

Trial no.	Process parameters								Surface roughness (R_a)			
	A	B	-	-	C	D	E	-	R1	R2	R3	S/N ratio
	Columns											
	1	2	3	4	5	6	7	8				
	Trial conditions											
1	1	1	1	1	1	1	1	1	1.88	2.00	1.90	−5.70
2	1	1	2	2	2	2	2	2	2.42	2.54	2.44	−7.84
3	1	1	3	3	3	3	3	3	2.70	2.82	2.72	−8.78
4	1	2	1	1	2	2	3	3	1.09	1.21	1.11	−1.12
5	1	2	2	2	3	3	1	1	1.80	1.92	1.82	−5.33
6	1	2	3	3	1	1	2	2	0.96	1.08	0.98	−0.04
7	1	3	1	2	1	3	2	3	1.77	1.89	1.79	−5.19
8	1	3	2	3	2	1	3	1	1.87	1.99	1.89	−5.65
9	1	3	3	1	3	2	1	2	1.88	2.00	1.90	−5.70
10	2	1	1	3	3	2	2	1	3.30	3.40	3.21	−10.38
11	2	1	2	1	1	3	3	2	1.35	1.45	1.26	−2.64
12	2	1	3	2	2	1	1	3	1.58	1.68	1.49	−4.00
13	2	2	1	2	3	1	3	2	2.10	2.20	2.01	−6.46
14	2	2	2	3	1	2	1	3	0.84	0.94	0.75	1.44
15	2	2	3	1	2	3	2	1	1.32	1.42	1.23	−2.45
16	2	3	1	3	2	3	1	2	2.03	2.13	1.94	−6.17
17	2	3	2	1	3	1	2	3	2.28	2.38	2.19	−7.18
18	2	3	3	2	1	2	3	1	1.69	1.79	1.60	−4.58
Total									32.86	34.84	32.23	−87.78

$\overline{T}$ is the grand average of surface roughness of =(32.86+34.84+32.23)/18=1.85

R1, R2, R3 - Average surface roughness for three repetitions of each trial

that parameters B and C have more effect on surface roughness than the rest of the parameters. Level B_2 and C_1 appear to be the best choice in terms of both mean response and variation. The S/N ratios for parameters suggest that levels A_2, D_1 and E_1 are better than any other levels of the parameters A, D, and E, respectively.

After completing the experimenter's log given in Table 1, the next step in data analysis is to estimate the optimum level of each control factor and to perform analysis of variance (ANOVA). The pooled ANOVA for raw data, i.e., the measured value of surface roughness (R_a) is given in Table 5. The ANOVA was also performed for S/N data and the pooled version is given in Table 6. The analysis of variance of raw data indicates that grit size, slurry concentration, and tool parameters significantly affect the mean values of the surface roughness. The percentage contribution of significant parameters indicates that the influence of grit size (B: 33.90%) and slurry concentration (C: 40.38%) is much higher than influence of tool (E: 4.57%) as seen from Table 5. It is clear that surface roughness is at minimum value at the second level of workpiece (A_2) and second level of grit size (B_2), first level of slurry concentration (C_1), first level of power rating (D_1), and tool (E_1) when mean values are considered.

Table 3 Average values and main effects (raw data)

Process parameter designation	Level 1	Level 2	Level 3	(L_2-L_1)	(L_3-L_2)
A	1.87	1.84	-	−0.03	-
B	2.23	1.38	1.95	−0.85	0.57
C	1.44	1.74	2.37	0.30	0.63
D	1.80	1.90	1.85	0.1	−0.04
E	1.69	2.03	1.83	0.34	−0.2

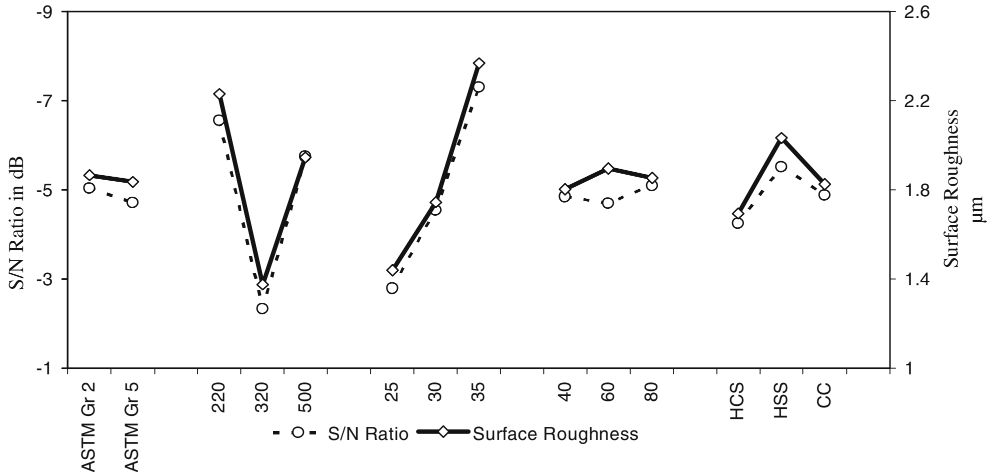
L_2-L_1 is the average main effect when the corresponding parameter changes from level 1 to level 2

L_3-L_2 is the average main effect when the corresponding parameter changes from level 2 to level 3

The S/N ratio analysis suggests for minimum average surface roughness, the optimum parameters are second level of grit size (B_2) and first level of slurry concentration as seen from Table 6. In addition, workpiece, power rating, and tool are insignificant as process parameters with respect to there effect on variation on surface roughness. Based on this analysis, the process parameters can be classified as given in Table 7.

Since parameters A and D are insignificant, any levels for these parameters can be selected. In the present study, levels, A_1 and D_1 are selected based on the material removal rate and economical factors, respectively. The

Fig. 2 Response curves showing the effects of parameters



selected levels of parameters (optimum) are A_1, B_2, C_1, D_1, and E_2.

L_{18} is an especially designed array with an interaction inbuilt between first two columns. Thus, in order to see whether interaction exists between A and B, the average values of these parameters combined at various levels were calculated and these are given in Table 8. The data from Table 8 are plotted in Fig. 3. The interaction between grit size and workpiece has a severity index value of approximately 19% for raw data (the severity index 'SI' is expressed in percentage, ranging between 0 and 100, which corresponds to the angle between the lines between 0 and 90 degrees. Thus 100% SI will mean a 90-degree angle between the lines and indicate the strongest presence of interaction and 0% SI will indicate parallel lines and non-existence of the same). In addition, an interaction plot between these parameters suggests that for factors A and B, levels A_1 and B_2 are better. Nevertheless, based on previous analysis, these levels of the factors are already included in the optimum condition.

3.1 Estimation of optimum surface roughness

The optimum value of surface roughness ($\overline{\mu}$) is predicted at the selected levels of significant parameters. The significant factors with optimum levels are already selected as B_2 and C_1:

$$\begin{aligned}\overline{\mu}_{B_2C_1} &= \overline{T} + (\overline{B}_2 - \overline{T}) + (\overline{C}_1 - \overline{T}) \\ &= 1.44 + 1.38 - 1.85 \\ &= 0.97\ \mu\text{m}\end{aligned} \tag{2}$$

where $\overline{T} = 1.85\ \mu m$ (Table 2) and B_2 and C_1 are the average values of surface roughness (Table 3).

The confidence interval (CI) for the predicted result can be calculated from Eq. (19):

$$\text{CI} = \sqrt{F_\alpha(1, f_e)V_e\left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \tag{3}$$

Where $F_\alpha(1, f_e)$ = The F-ratio at a confidence level of (1-α) against DOF 1 and error DOF f_e and V_e=error variance, n_{eff} is the effective number of replications:

$$n_{eff} = \frac{N}{1 + [\text{Total DOF in the estimation of mean}]}$$

N=total number of results (18*3=54)
R=sample size for confirmation experiment.
Using the following values:
V_e=0.08 (Table 5)

Table 4 Average values and main effects (S/N data)

Process parameter designation	Level 1	Level 2	Level 3	(L_2-L_1)	(L_3-L_2)
A	−5.04	−4.71	-	0.33	-
B	−6.56	−2.33	−5.75	4.23	−3.42
C	−2.78	−4.54	−7.31	−1.76	−2.76
D	−4.84	−4.70	−5.09	0.14	−0.40
E	−4.24	−5.51	−4.87	−1.27	0.64

L_2-L_1 is the average main effect when the corresponding parameter changes from level 1 to level 2
L_3-L_2 is the average main effect when the corresponding parameter changes from level 2 to level 3

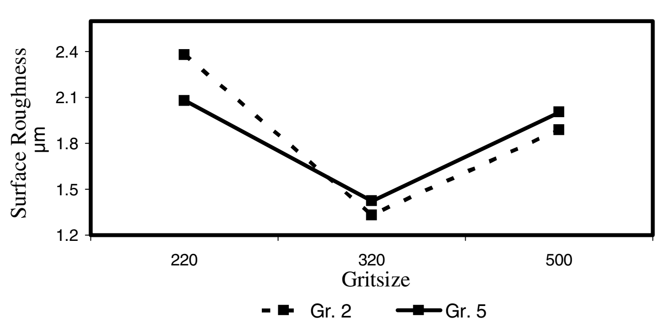


Fig. 3 Interaction size between grit size and workpiece

Table 5 Pooled ANOVA (raw data)

Source	SS	DOF	V	F-ratio	SS'	P (%)
A	(0.01)	(1)	Pooled	-	-	-
B	6.81	2	3.40	43.48*	6.65	33.90
C	8.08	2	4.04	51.59*	7.92	40.38
D	(0.08)	(2)	Pooled	-	-	-
E	1.05	2	0.53	6.73*	0.9	4.57
e (pooled)	3.68	47	0.08	-	4.15	21.15
Total	19.62	53	-	-	19.62	100

SS Sum of squares, *DOF* Degree of freedom
V Variance, *SS'* Pure sum of squares
*Significant at 95% confidence level

Total DOF in estimation of mean=6 (i.e., DOF of unpooled process parameters from Table 5)

n_{eff}=7.71 (calculated)

R=3(since three confirmation experiments were conducted)

$F_{0.05}$ (1, 47)=4.056 (tabulated)

The confidence interval CI=±0.205

The 95% confidence interval of the predicted optimum surface roughness is

$$\left[\overline{\mu}_{B_2C_1} - \text{C.I.}\right] < \overline{\mu}_{\mathrm{B_2C_1}} < \left[\overline{\mu}_{\mathrm{B_2C_1}} - \text{C.I.}\right]$$

$$0.765 < \overline{\mu}_{B_2C_1} < 1.175$$

3.2 Confirmation experiments

Three confirmation experiments were conducted at the optimum levels of the process parameters. The average surface roughness at the optimal setting of the process parameters of the USD process was found to be at the mean value of 1.11 μm, which was within the confidence interval of the predicted optima of surface roughness.

4 Discussion

From Fig. 2, it is clear that surface roughness is more for commercially pure titanium (ASTM Grade 2) and less for alloy titanium (ASTM Grade 5). ASTM Grade 5 is harder than CP titanium and there is a negative relation between the amount of metal removed and the hardness of material in case of titanium and its alloys [8, 14, 15]. Most productive materials give the greatest roughness and vice versa [6, 15, 16].

A decrease in the grit size decreases the average surface roughness (R_a) material removal rate form first level (220) to the second level (320), and then increases at the third level (500) of the grit sizes, respectively. An initial improvement in the surface roughness was observed with an increase in the grit size but it deteriorated with further increase in grit size. In general, surface finish improves with decreasing grit size. Past research has shown that surface roughness decreases with abrasive particle size [12, 15]. In theory, smaller grains chip off smaller microscopic flakes, resulting in a smoother surface. In the present investigation, the resultant surface drilled at level 1 (220) and level 2 (320) agree with this perception; however, a surface machined with the #500 silicon carbide (SiC) abrasive grit yielded a higher average surface roughness than with the larger #220 SiC grit. One explanation for this is that smaller particles are not as effective as larger particles in terms of material removal. The grains may have been disintegrating instead of cutting, reducing the average grain size and consequently increasing the time needed for drilling. It has been shown that prolonged drilling can have an adverse effect on the surface finish due to continued contact between the workpiece surface and the tool with non-uniform slurry flow [11, 17].

Table 6 Pooled ANOVA (S/N data)

Source	SS	DOF	V	F-ratio	SS'	P (%)
A	(0.48)	(1)	Pooled	-	-	-
B	60.52	2	30.26	12.12*	12.12*	35.75
C	62.33	2	31.16	12.48*	12.48*	36.92
D	(0.48)	(2)	Pooled	-	-	-
E	(4.83)	(2)	Pooled	-	-	-
e (pooled)	32.45	13	2.49	-	-	27.33
Total	155.3	17	-	-	-	100

SS Sum of squares, *DOF* Degree of freedom
V Variance, *SS'* Pure sum of squares
*Significant at 95% confidence level

Table 7 Classification of process parameters

Control parameters*	Signal parameter #
B: Grit size	E: Tool
C: Slurry concentration	

*These control the variation and mean
#This has an effect only on mean

Table 8 Averages of parameter combinations (raw data)

Parameters with levels	B_1	B_2	B_3
A_1	2.38	1.33	1.89
A_2	2.08	1.42	2.00

A_1B_1=Average value when both A and B are at level 1
A_1B_2=Average value when parameter A is at level 1 and B at level 2, and so on

Surface roughness increases with an increase in abrasive slurry concentration from level 1 (25%) to level 2 (30%) and again from level 2 to level 3 (35%) [20].

Surface roughness is almost the same at all the three levels of power rating, although it can be seen from Fig. 2 that it is lowest at level 1 (40%), highest at second level (60%), and lowers slightly at the third level (80%) of the power rating. The reason for this behavior is at level two of the power rating, material removal also follows the same pattern, thus resulting in increased surface roughness [6, 15, 16]. A high-speed tool gives maximum surface roughness when compared to cemented carbide and high-carbon steel. In this case, a high-speed tool is also giving the maximum material removal rate with maximum tool wear. Also from the ANOVA table, it was seen that among the significant factors, grit size and slurry concentration played a more major role than did the tool. In addition, the effect of the tool was only on the mean values.

The contour plots of surface roughness for both the work materials and trials with the best and worst surface roughness are presented in Figs. 4, 5, 6, 7 to quantify and visualize surface roughness. A visual inspection shows that there is not much difference between the surface roughness shown by two-dimensional and three-dimensional plots. Thus, it can be inferred from these plots that the effect of process parameters on roughness is same in both two and three dimensions. In addition, the maximum and minimum values for average surface roughness are 0.96–2.82 μm and 0.75–3.10 μm for commercially pure

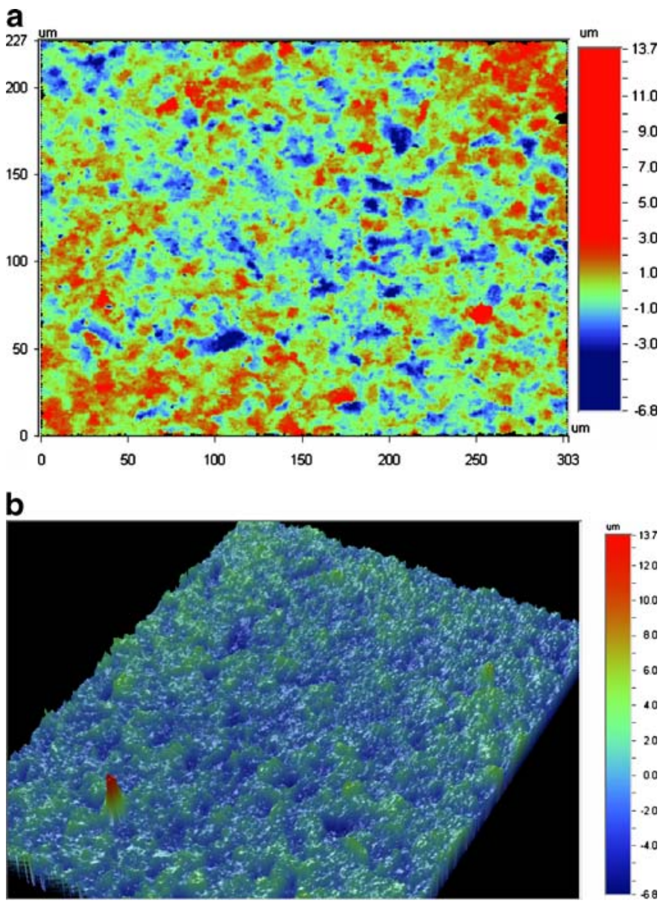


Fig. 4 **a** Two dimensional contour plot (R1-6). **b** Three-dimensional contour plot (R1-6). Total surface area=0.068 mm^2. Array size=640*480. Ra=0.96 μm

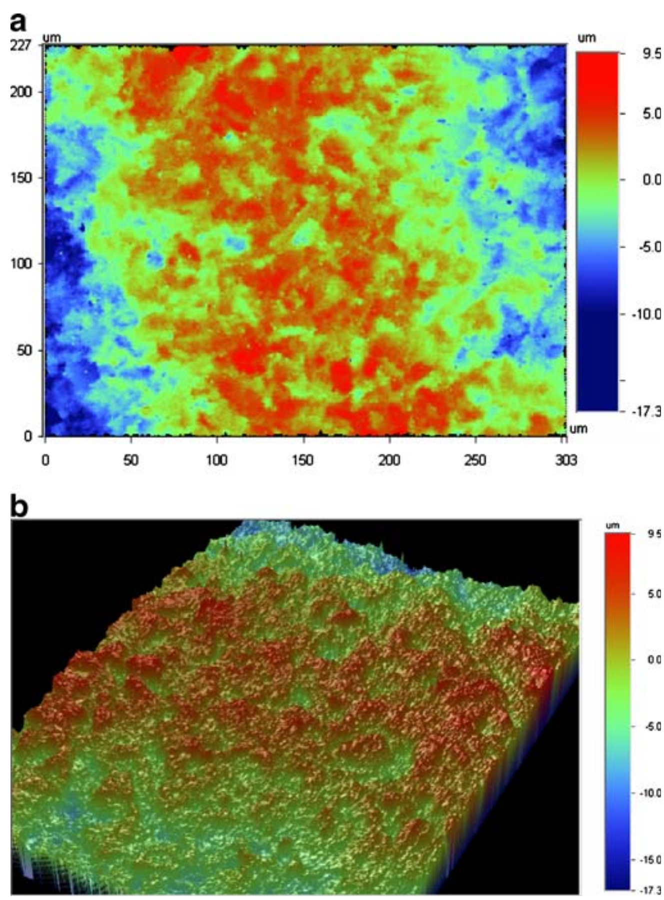


Fig. 5 **a** Two-dimensional contour plot (R2-3). **b** Three-dimensional contour plot (R2-3). Total surface area=0.068 mm^2. Array size=640*480. R_a=2.82 μm

titanium (ASTM Gr. 2) and alloy titanium (ASTM Gr.5), respectively.

The results from this study will be far better than other material processing methods like EDM and LBM. USD is a mechanical process with no recast layer, no cracks caused by rapid cooling, and holes with straight profiles can be drilled.

In the present work, only five process parameters viz. workpiece, tool, slurry concentration, power rating, and grit size were investigated. Study of other process parameters like type of abrasive, temperature of abrasive slurry, and different tool materials can be done. Although the effect of the power rating has been established in this study in terms of machinability, it can be further investigated with different combinations of process parameters on high-power machines. The effect of interaction parameters in terms of severity index was found to be very poor in this study, so experiments can be further designed by considering other possible interactions. The effect of process parameters on titanium workpieces with dimensional accuracy (oversize) and form accuracy (out-or-roundness and conicity) as a quality characteristic is to be further investigated. An economic evaluation of the process vis-à-vis other processes, both quantity and quality wise is further needed. The combination of processes like EDM with USM can also be investigated regarding the surface quality of titanium as the work material.

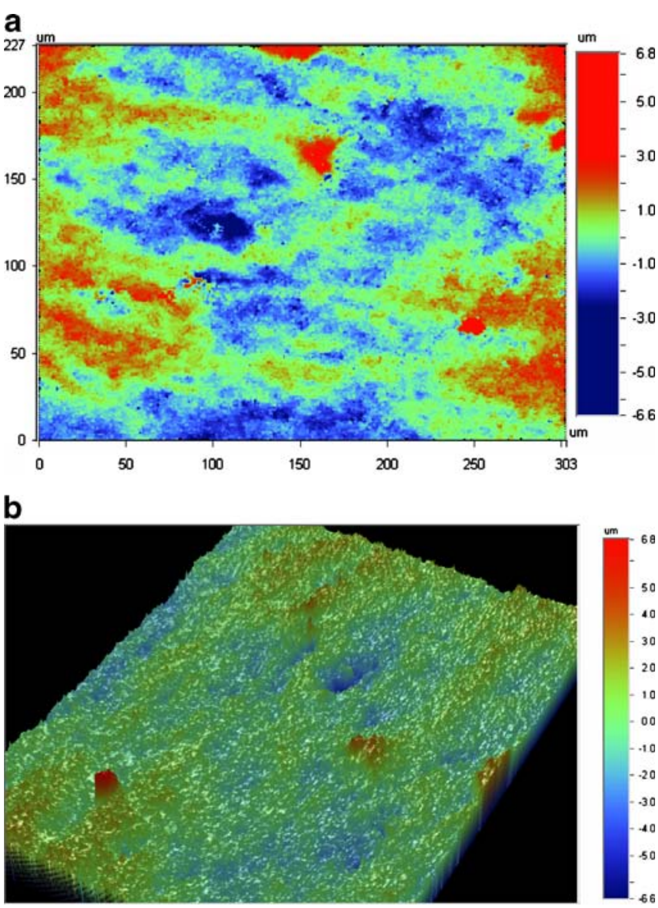


Fig. 6 **a** Two-dimensional contour plot (R3-14). **b** Three-dimensional contour plot (R3-14). Total surface area=0.068 mm^2. Array size=640*480. R_a=0.75 µm

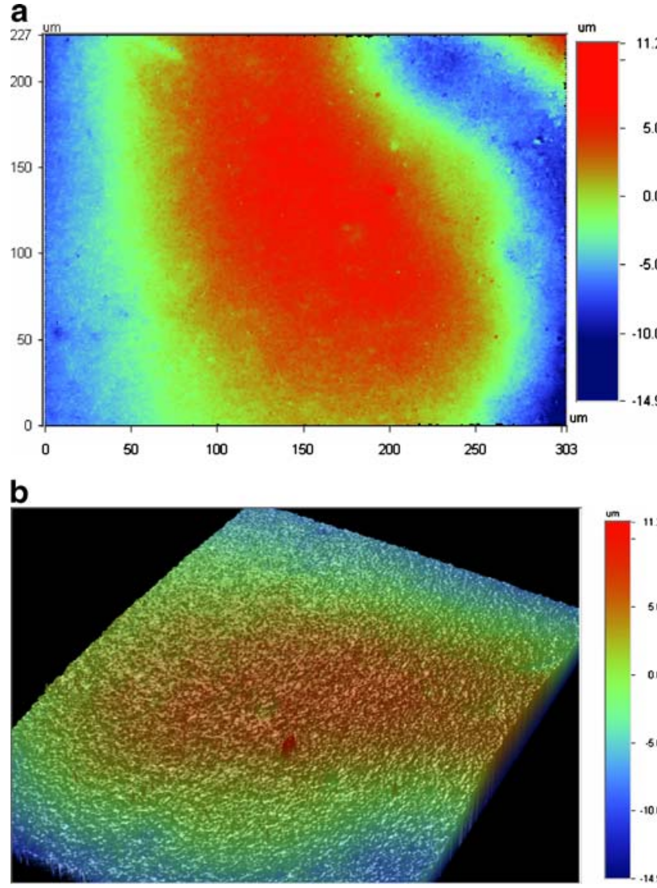


Fig. 7 **a** Two-dimensional contour plot (R2-10). **b** Three-dimensional contour plot (R2-10). Total surface area=0.068 mm^2. Array size=640*480. R_a=3.40 µm

5 Conclusions

The purpose of this paper is to establish a new efficient method for ultrasonic drilling in titanium alloys through the Taguchi method. Some generalized conclusions are as follows:

- A robust design is presented for improving surface finish during ultrasonic drilling in titanium alloys so that high-quality products can be produced quality wise by a simple and economical process compared to other material processing methods.
- The orthogonal array technique was used for experimental design as it reduces the number of experiments required to investigate a set of parameters and to minimize time and cost.
- White light interferometry is a suitable technique to characterize surface roughness in any material-removal process.

– The predicted optimal range of surface roughness at 95% confidence level was $0.765 < \overline{\mu}_{B_2C_1} < 1.175$. The optimal result obtained was validated by conducting confirmation experiments.

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