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Optimization and Modelling of Process Parameters Involved in Ultrasonic Machining of Glass Using Design of Experiments and Regression Approach

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Abstract Glass is an ideal material for parts with micro-holes and has been widely used in automotive, aerospace and woodworking industries due to its superior wear and corrosion resistance. In this research paper, the statistical analysis of the ultrasonic machining of glass using design of experiments and regression approach has been done. The performance characteristics such as material removal rate of machined samples using ultrasonic machining process have been presented. The experimental conditions were designed by using the design of experiments approach. The analysis of results has been done using the MINITAB 14.0 software and results obtained are validated by conducting the confirmation experiments. The F-test and P-value has been applied to determine the significant parameters.

Keywords: *design of experiments, analysis, regression, modelling, statistics, validation*

1. Introduction

The optimum parameters for multi-performance characteristics in drilling using grey relational analysis were determined [1]. The design optimization of cutting parameters for side milling operations with multiple performance characteristics was done [2]. The statistical analysis of experimental parameters in ultrasonic machining of tungsten carbide using taguchi approach has been done [3].The robust design of flank milling parameters based on grey-taguchi method was reported [4]. The effects of the Nd: YAG laser welding parameters on the bead formation on the neuro-stimulator were analysed by [5]. The effects of magnetic force on EDM machining characteristics were explored using L_{18} orthogonal array based on taguchi method and statistically evaluated the experimental data by analysis of variance (ANOVA). The MRR of magnetic force assisted EDM was almost three times as large as the value of standard EDM and the REWR was improved from 1.03% to 0.33% as determined [6]. The optimization of compensation cutting for eliminating the residual form error of an aspheric surface using the taguchi method was performed and the experimental trials based on the $L_9(33)$ orthogonal array were carried out. Based on the results of analysis of variance, the most significant factor was compensation ratio having a percentage contribution of 49.37% as concluded by [7]. The refrigerants R22 and R404A five of their binary mixtures which contain about 0%, 25%, 50%, 75% and 100% mass fractions of R404A were tested. The collected data were analyzed by using ANOVA. This work was done [8]. The influences of various surface treatments on indium-tin-oxide (ITO) anodes on the performance of OLED devices were investigated by applying the taguchi Method. The chemical treatment producing ultra-smooth ITO film surfaces does not provide the highest efficiency and luminescence as investigated by [9]. The contribution percentages of the rotational speed, feed, depth of cut, and pulsed frequency to the LBM performance was determined as 42.68%, 22.58%, 20.73% and 14.01%, respectively [10].

The experimental studies for WEDM were conducted under varying pulse duration, open circuit voltage, wire speed and dielectric flushing pressure. The settings of machining parameters were determined by using Taguchi experimental design method. The level of importance of the machining parameters on the cutting kerf and MRR was determined using analysis of variance (ANOVA) [11] .The implementation and selection of cutting path strategies with appropriate cutting parameters had significant effect on surface roughness as found by [12]. Reciprocating wear process parameters were optimized for minimum weight loss and friction based on mixed L16 Taguchi orthogonal design with three process parameters, sliding velocity, applied load and oil type. The experimental results were in good agreement with the values from the theoretical model. The optimal combination of parameters is found to be highest level of sliding velocity, lowest level of load and lowest level of oil type as determined [13]. Electro deposition of thin copper layer was carried out on titanium wires in acidic sulphate bath. The influence of titanium surface preparation, cathodic current density, copper sulphate and sulphuric acid concentrations, electrical charge density and stirring of the solution on the adhesion of the electrodeposits was studied using the taguchi statistical method [14]. The ANOVA results illustrated the influence of each V-ring indenter parameter on the smooth shear surface and cracks of the fine-blanked surface, together with their calculated percentage contributions as found [15]. A taguchi design investigation was made for the relationship between the micro porosity and process variables in a sand cast A360 aluminium alloy [16]. The effect of cutting speed, feed rate and drill point geometry on the residual tensile strength of the drilled unidirectional glass fibre reinforced epoxy composite were determined using the taguchi method [17]. The optimal setting of the process parameters on the electro-discharge machining (EDM) of carbon–carbon composites were determined using experiments planned, conducted and analysed applying the Taguchi method. It was found that the electrode wear rate reduces substantially as concluded [18] .The influence of pinholes on the chip on film (COF) in screen-printing was studied. The process parameters such as ink capacity, origin control distance, angle of the squeezer, method of mixing, freshness of ink, speed of printing, and speed of scraper were considered to improve the pinholes as studied [19]. The influence of the cutting parameters, such as cutting speed, feed rate and point angle on delamination produced during drilling a GFRP composite was studied. The point angle of 118° drill produced less damage on the entrance of GFRP composite than the point angle of 135° drill as observed [20]. The optimization of injection molding process for friction properties of fiber-reinforced polybutylene terephthalate was done using taguchi method and principal component analysis [21]. The combined quality function deployment (QFD) and the taguchi method to analyze the produced quality characteristics and to optimize the process parameters was applied [22]. The CO_2 continuous laser welding process was successfully applied and optimized for joining a dissimilar AISI 316 stainless-steel and AISI 1009 low carbon steel plates [23]. The use of an Nd:YAG laser for thin plate magnesium alloy butt welding was optimized using the taguchi analytical methodology. The optimal result was confirmed with a superior ultimate tension stress of 169 MPa, 2.5 times larger to that from original set for laser welding as determined [24]. An experimental investigation into the effects of cutting speed, feed rate, depth of cut, nose radius and cutting environment in CNC turning of AISI P-20 tool steel was done. Design of experiment techniques, i.e. response surface methodology (RSM) and Taguchi's technique was used to accomplish the objective of the experimental study [25].

2 Materials and Method

Taguchi's method of experimental design provides a simple, efficient and systematic approach to determine optimal machining parameters. Taguchi has recommended orthogonal arrays (OA) for the designing of experiments. In taguchi method, the results of experiments are analyzed to achieve one or more of the objectives as to establish the best or the optimum condition for a product or process. Analysis of variance (ANOVA) is the statistical treatment applied to the results of the experiments in determining the percent contribution of each parameter against a stated level of confidence. The study of ANOVA table for a given analysis helps to determine which of the parameters need control and which do not. Taguchi suggested two different routes to carry out the complete analysis. First, the standard approach; where the results of a single run or the average of repetitive runs are processed through main effect and analysis of variance. The second approach, which taguchi strongly recommends for multiple runs, is to use signal-to-noise (S/N) ratio for the same steps in the analysis. The S/N ratio is a concurrent quality metric linked to the loss function. Design of experiment (DOE) methods results in an efficient experimental schedule and produce a statistical analysis to determine easily as to which parameters have the most significant effects on the final results. The use of signal-to-noise (S/N) ratio in system analysis provides a quantitative value for response variation comparison. The requirement to test multiple factors means that a full factorial experimental design that describes all possible conditions would result in a large number of experiments. There are several S/N ratios available depending on the types of characteristics; lower is better (LB), nominal is best (NB), and higher is better (HB).

Lower-the-better type problem

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

where (S/N) is the inspection index, defined as the signal-to-noise ratio (unit:dB), n is the number of repetitions for each trial, independent of the values assigned to noise factors, and y_i is the value of the response obtained in the i^{th} repetition of the trial.

Higher-the-better type problem

In this type of problem, the quality characteristic is again continuous and non-negative and it is to be made as large as possible. There is no adjustment factor to be used in this case as well and one is interested in maximizing the objective function expressed as:

$$\eta = -10\log_{10}\left\{\frac{1}{n}.\sum_{1}^{n}\frac{1}{y_i^2}\right\} \tag{2}$$

Nominal-the-best type problem

In the nominal-the-best type problem, the quality characteristic is continuous and non-negative, but its target value is non zero and **assumes** some finite value. For these types of problems, if the mean becomes zero the variance also tends to become zero. A scaling factor can be used as an adjustment factor to shift the mean closer to the target for such type of problems. The objective function that is to be maximized can be expressed as:

$$\eta = 10\log_{10}\left(\mu^2/\sigma^2\right) \tag{3}$$

$$\mu = \frac{1}{n}.\sum_{1}^{n} y_i^2 \tag{4}$$

$$\sigma = \frac{1}{(n-1).\sum_{1}^{n}(y_i-\mu)^2} \tag{5}$$

The values of SS', DOF, MS, F and P as shown in ANOVA tables are calculated using MINITAB14.0 Software.

3. Results and Discussion

The orthogonal array based on the taguchi concept was utilized to arrange the discrete variables and robust solutions for unconstrained optimization problems were found. In this investigation, the four machining parameters, abrasive slurry, slurry concentration, grit size and power rating were taken. The two levels of slurry concentration and others each of three different levels were taken. According to taguchi, the samples could be organized into only 18 groups and if they were to be considered separately still it yield results with the same confidence. The S/N ratios of MRR and surface roughness in single quality optimization according to the arrangement of the samples into 18 groups; L_{18} according to taguchi is shown in Table 1.

Table 1. Results of MRR

Trail No:	Slurry Concentration (%)	Abrasive	Power Rating (%)	Grit Size (Sieve no.)	MRR mm^3/min	S/N Ratio	Mean
1	20	Al_2O_3	20	280	27.956	28.9295	27.956
2	20	Al_2O_3	40	400	23.821	27.5392	23.821
3	20	Al_2O_3	60	600	22.689	27.1163	22.689
4	20	SiC	20	280	31.899	30.0755	31.899
5	20	SiC	40	400	28.998	29.2474	28.998
6	20	SiC	60	600	25.569	28.1543	25.569
7	20	Mixture	20	400	27.638	28.8301	27.638
8	20	Mixture	40	600	23.256	27.3307	23.256
9	20	Mixture	60	280	29.754	29.4709	29.754
10	30	Al_2O_3	20	600	24.268	27.7007	24.268
11	30	Al_2O_3	40	280	30.195	29.5987	30.195
12	30	Al_2O_3	60	400	26.985	28.6224	26.985
13	30	SiC	20	400	34.052	30.6429	34.052
14	30	SiC	40	600	31.032	29.8362	31.032
15	30	SiC	60	280	36.506	31.2473	36.506
16	30	Mixture	20	600	21.469	26.6362	21.469
17	30	Mixture	40	280	29.654	29.4417	29.654
18	30	Mixture	60	400	34.654	30.7951	34.654

The knowledge of the contribution of individual factors is critically important for the control of the final response. The parameters sum of squares (SS), pure sum of squares (SS'), degree of freedom (DOF), Mean sum of squares (MS), F-ratio, P-value and percentage of each factor were calculated.

The Sum of Squares (SS) is a measure of the deviation of the experimental data from the mean value of the data.

Let '*A*' be a factor under investigation

$$SS_T = \sum_{i=1}^{N} \left(y_i - T\right)^2 \tag{6}$$

Where N = Number of response observations, T is the mean of all observations y_i is the i th response

Factor Sum of Squares (SS_A) - Squared deviations of factor (A) averages from overall average

$$SS_A = \left[\sum_{i=1}^{k_a}\left(\frac{A_i^2}{n_{Ai}}\right)\right] - T^2 / N \tag{7}$$

Average of all observations under A_i level = A_i/n_{Ai}, T = sum of all observations, n_{Ai} =Number of observation under A_i level

Error Sum of Squares (SS_e) - Squared deviations of observations from factor (A) averages

$$SS_e = \sum_{j=1}^{k_A}\sum_{i=1}^{n_{Ai}}\left(y_i - A_j\right)^2 \tag{8}$$

Sum of Squares (SS_{AxB}) for interactions

$$SS_{AxB} = \left[\sum_{i=1}^{c}\left(AxB\right)_i^2 / n_{(AxB)i}\right] - T^2/N - SS_A - SS_B \tag{9}$$

Table 2. ANOVA for MRR

Source	DOF	Seq SS	Adj MS	F	P	SS'	% Contribution	Status
Concentration,A	1	37.66	37.657	10.26	0.013	36.551	9.148	Significant
Abrasive, B	2	94.03	47.015	12.82	0.003	91.812	22.979	Significant
Power Rate, C	2	35.88	17.940	4.89	0.041	33.662	8.205	Significant
Grit Size, D	2	191.54	79.691	21.72	0.001	189.322	47.381	Significant
A x C	2	11.09	5.544	1.51	0.278	8.872	2.2205	Insignificant
Residual Error	8	29.35	3.669	--	--	--	---	---
Total	17	399.54	--	--	--	--	---	---
e-Pooled	10	11.09	1.109	--	--	--	12.283	---

3.1 Analysis of Variance for MRR

The result of MRR was analyzed using ANOVA for identifying the significant factor affecting the performance measure. The analysis of variance (ANOVA) for the mean MRR at 95% confidence interval is given in Table 2.

The P-value determines that if the P- value is less than 0.05 that factors or interactions are significant. From the ANOVA Table 2 it was observed that the P values for slurry concentration, type of abrasive, power rating and grit size are 0.013, 0.003, 0.041 and 0.001 respectively. All these factors are significant but as the p-value for the interaction between slurry concentration and Power rating is more than 0.05, it is insignificant. The Table 3 presents the ranks for the process parameters.

Table 3. Response table for means of MRR

Level	Concentration	Abrasive	Power Rate	Grit Size
1	27.06	25.49	28.79	31.75
2	29.96	31.01	26.66	29.73
3	---	29.04	30.08	24.05
Delta	2.89	5.52	3.42	7.70
Rank	4	2	3	1

The ascending order of ranks is given as grit size, type of abrasive, power rating and slurry concentration. The grit size is most significant parameter and slurry concentration is the least significant parameter and having minimum contribution to the MRR. From Figure 1, it was observed that the MRR is more using 30% concentration as compared to 20% concentration.

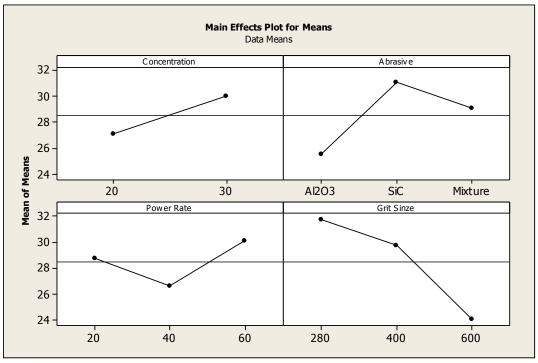

Figure 1. Main effects plot of MRR for means

It was also observed that the silicon carbide have more effect on MRR as compared to using the mixture (aluminium oxide + silicon carbide).

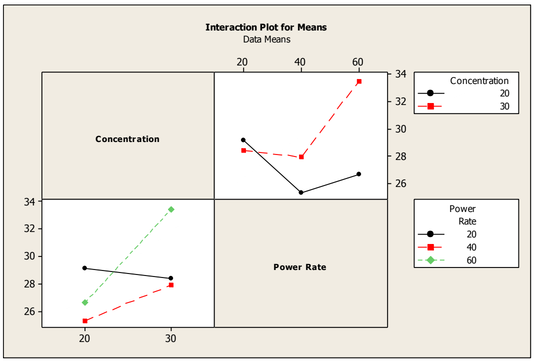

Figure 2. Interaction plot for MRR

The aluminium oxide has the least effect on MRR. This may be due to that silicon carbide is harder than aluminium oxide. The 60% power rating resulted in maximum MRR as compared to 20% and 40%. This may be due to that more power rating will result in more erosion of the work. The grit size of 280 resulted in maximum MRR as compared to the 400 and 600.

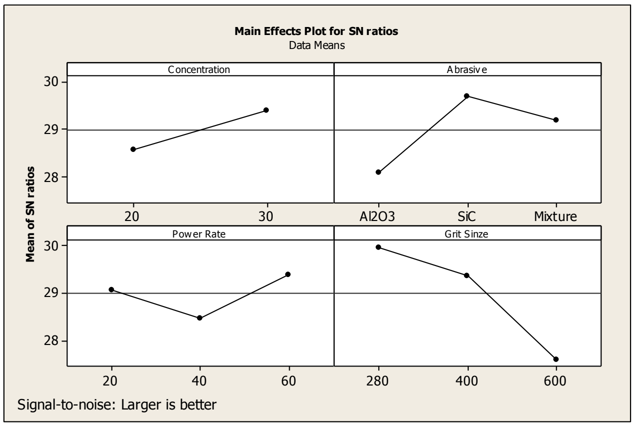

Figure 3. Main effects plot of MRR for S/N ratio

This may be due to that coarse grit size provides the more impact on work as compared to medium and fine grit size. The S/N ratio consolidates several repetitions into one value and is an indication of the amount of variation present. The S/N ratios were calculated to identify the major contributing factors and interactions that cause variation in the MRR.

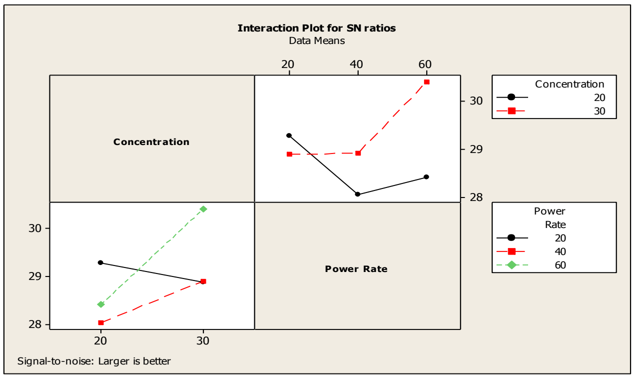

Figure 4. Interaction plot for MRR of S/N ratio

Table 4 presents the ANOVA results for S/N ratio of MRR at 95% confidence interval.

Table 4. ANOVA for S/N Ratio of MRR

Source	DOF	Seq SS	Adj MS	F	P	SS,	% Contribution	Status
Concentration,A	1	3.0354	3.0354	11.46	0.010	2.7694	7.9091	Significant
Abrasive, B	2	8.2160	4.1080	15.51	0.002	7.6720	21.957	Significant
Power Rate, C	2	2.6901	1.3450	5.08	0.038	2.1461	6.1423	Significant
Grit Size, D	2	18.2781	7.3070	27.59	0.000	17.7341	50.756	Significant
A x C	2	0.6012	0.3006	1.13	0.368	0.0572	0.1637	Insignificant
Residual Error	8	2.1189	0.2649	--	--	--	---	---
Total	17	34.9396	--	--	--	--	---	---
e-Pooled	10	2.7201	0.2720	--	--	--	13.2353	---

From the ANOVA Table 4 it was observed that the P values for slurry concentration, type of abrasive, power rating and grit size are 0.010, 0.002, 0.038 and 0.000 respectively. All these factors are significant but as the p-value for the interaction between slurry concentration and Power rating is more than 0.05, it is insignificant. The Table 5 presents the ranks for the process parameters.

Table 5. Response table for S/N ratio of MRR

Level	Concentration	Abrasive	Power Rate	Grit Size
1	28.58	28.08	29.08	29.98
2	29.40	29.70	28.47	29.37
3	--	29.18	29.40	27.61
Delta	0.82	1.62	0.93	2.38
Rank	4	2	3	1

The ascending order of ranks is given as grit size, type of abrasive, power rating and slurry concentration. The grit size is most significant parameter and slurry concentration is the least significant parameter and having minimum contribution to the MRR.

Table 6. Significant factor and interaction

Factor	Affecting Mean		Affecting Variation	
	Contribution	Best Level	Contribution	Best Level
Concentration, A	Significant	Level-2(30%)	Significant	Level-2(30%)
Abrasive, B	Significant	Level-2(SiO)	Significant	Level-2(SiO)
Power Rate, C	Significant	Level-3(60)	Significant	Level-3(60)
Grit Size, D	Significant	Level-1(280)	Significant	Level-1(280)
A x C	Insignificant	---	Insignificant	---

From Figure 2, Figure 3 and Figure 4, it was observed that the MRR is more using 30% concentration as compared to 20% concentration.

3.2. Confidence interval around the estimated mean for MRR

Mean Value for MRR,

$$\mu A_2 B_2 C_3 D_1 = A_2 + B_2 + C_3 + D_1 - 4T \quad (10)$$

$= 29.96 + 29.04 + 30.08 + 31.75 - 3 \times 28.35 = 35.78$ mm^3/min

The confidence interval is a maximum and minimum value between which the true average should fall at some stated percentage of confidence. The estimate of the mean μ is only a point estimate based on the averages of results obtained from the experiment. Statistically this provides a 50% chance of the true averages being greater than μ and a 50% chance of the true average being less than μ .

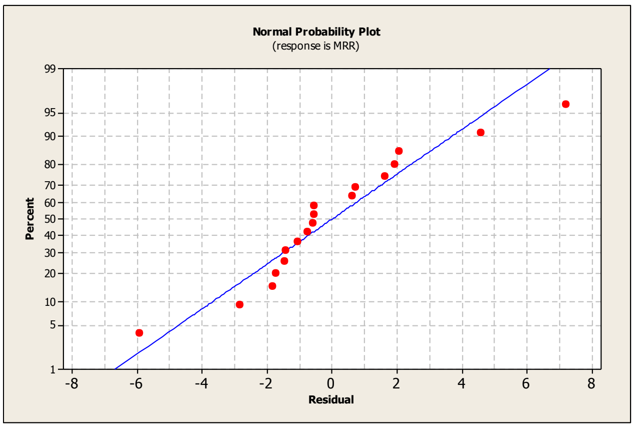

Figure 5. Normal Probability plot for MRR

Confidence Interval around the estimated MRR mean

$$CI_1 = \sqrt{\left(F_{\alpha, V_1, V_2} V_e\right) / n_{eff}} \quad (11)$$

Where $F \alpha\ V_1 V_2$= F ratio, α = Risk (0.01) Confidence = 1- α, V_1 = DOF for mean which is always = 1, V_2 = DOF for error = Ve, η_{eff} = Number of tests under that condition using the participating factors

η_{eff}= (N/ 1+ $DOF_{A2B2C3D1}$) = 18/ 1+1+2+2+2 = 2.25

$$CI_1 = \sqrt{(4.512 \times 5.54)/2.25} = 1.5$$

So the confidence interval around the MRR is given by 35.78 ± 1.5 mm^3/min.

Conclusions

In this research paper, the statistical analysis of the ultrasonic machining of glass using design of experiments and regression approach has been done. The performance characteristic such as material removal rate of machined samples using ultrasonic machining process has been presented. The ascending order of ranks for the material removal rate is given as grit size, type of abrasive, power rating and slurry concentration. The grit size is most significant parameter and slurry concentration is the least significant parameter and having minimum contribution to the MRRIt was also observed that the silicon carbide have more effect on MRR as compared to using the mixture (aluminium oxide + silicon carbide). The 60% power rating resulted in maximum MRR as compared to 20% and 40 %. This may be due to that more power rating will result in more erosion of the work. The grit size of 280 resulted in maximum MRR as compared to the 400 and 600. The confidence interval around the MRR is given by 35.78 ± 1.5 mm^3/min.

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