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Machining of Al6061/10%Al_2O_3Composite using Abrasive Waterjet

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Abstract: Abrasive waterjet machining is a non-traditional machining process whose capabilities to compete with laser machining process has widened its industrial applications and drawn a good degree of research attention. The present work investigates the quality characteristics of surface machined by using an abrasive waterjet (AWJ). The work sample taken for study is Al6061/10%Al_2O_3 composite, whose machining is always associated with a degree of difficulty. Taguchi's L_9 array is used for experimentation and the cutting trials are performed by varying the AWJ cutting parameters like abrasive flow rate, water pressure and feed rate at three levels. Surface finish and kerf width are observed as the quality characteristics. A new approach of desirability based simulated annealing (DSA) is disclosed to predict the optimal cutting condition for Al6061/10%Al_2O_3 composite. The results are validated through confirmation experiment and the effect of water pressure is observed to be noteworthy in influencing the responses.
Keywords: Al6061/10%Al_2O_3; Composite; Abrasive waterjet; Desirability analysis; Simulated annealing; optimization.

1 Introduction

The abrasive waterjet (AWJ) cutting can be employed to cut almost all known materials like inconel, steel and titanium. The merit of the process includes its eco-friendly nature and absence of thermal distortion, compared to machining by using lasers and plasma. The AWJ machining process employs the conversion of high pressure of water into huge magnitude of kinetic energy, which is focussed at supersonic speeds to perform machining. The process variants include pure waterjet or waterjet mixed with abrasives to improve the machining capabilities of the jet. The strength of the process lies in generating a machined surface without any heat affected zone compared to the traditional machining techniques. The abrasives mixed with waterjet moves out of the focussing tube or nozzle to perform the desired operation on the work material. The flow rate of abrasives and cutting speed was found to influence the characteristics of the machined surface [1]. While machining aluminium alloys, it was observed that cutting speed was more influential on the kerf characteristics and surface finish [2, 3]. The similar observations were made while machining aramid fibre reinforced plastics as well [4]. The cut surface roughness and kerf were found to increase with the traverse speed while cutting Inconel 718, a difficult to cut super alloy [5]. Hence AWJ cutting was a multi-input, multi-output process requiring identification of optimal operating condition to produce better responses. The AWJ cutting parameters like water pressure, abrasive flow rate and feed rate were found to influence the quality characteristics of cut surface [1-5].

Methods employed to solve problems involving multi-inputs and multi-outputs include the grey relational analysis (GRA), principal component analysis (PCA), response surface methodology (RSM), meta-heuristic methods and desirability analysis [6]. RSM employs a statistical procedure to form a model and perform subsequent optimization using desirability analysis [7]. Taguchi technique combined with meta-heuristic algorithm was also employed for parameter design in a different manufacturing scenario, but these methods were powerful only in single response optimization [8]. Genetic algorithm was employed to optimize the mathematical model formed using neural networks and the results were validated using confirmation test [9]. However training of neural networks was observed to be tedious and difficult. The grey theory coupled with PCA and desirability analysis on different occasions of manufacturing, properly supplemented by ANOVA was observed to be effective in multi response optimization [10, 11]. These hybrid methods were found to utilize the merits of different techniques followed to conclude at an optimal level. The desirability analysis either in pure form or in an integrated format with other methodologies was observed to be better in identifying the optimal operating condition [12-16]. The grey theory based analysis using the S/N ratio for studied quality characteristics was identified to perform better in various manufacturing processes [17, 18]. The experimental design based on the orthogonal array and further analysis using RSM was observed to be economical, as there was a considerable reduction in number of trials [19-23].

From the literature, it was studied that work done in the area of AWJ cutting of Al6061/10%Al_2O_3 composite was scarce. Hence an approach of desirability based simulated annealing (DSA) was revealed to arrive at the optimal cutting condition for Al6061/10%Al_2O_3 composite.

2 Experimental Setup and Observations

The material used in study was Al6061 aluminium alloy. It was reinforced with 10% weight fraction of Al_2O_3 (alumina) particles by using the method of two stage stir casting. The alumina particles were pre-heated to remove moisture and enhance wettability. These particles were added to liquid aluminium alloy and the cast Al6061/10%Al_2O_3 composite plates of thickness 10 mm was subjected to radiography to identify the defects. The selected plates were subjected to experimentation using a L_9 orthogonal array with two replications.

The AWJ parameters used in the study were water pressure (WP), abrasive flow rate (AF) and feed rate (F). The parameters were chosen based on the available literature [1-5] and their levels (three) were identified based on the pilot trials. The experiments were conducted at random to avoid the extraneous effects. The roughness of cut surface was a direct measure of its texture, while material removed was indicated by kerf. Hence surface roughness (SR) and kerf width (KW) were observed as the process responses. The SR was measured using a contact stylus surface roughness tester (surfcoder: SE3500), at the middle of the depth for a cut-off length of 0.8 mm. The kerf width was measured by using a video measuring system as the average of top and bottom kerf. The responses are listed in Table 1 and a sample specimen is shown in Figure 1. A button-hole cut made in the work material was used to measure KW.

Table 1 Cutting parameter combination and observed responses

Trial	Control parameters			Responses	
	AF (g/min)	F (mm/min)	WP (bar)	SR (µm)	KW (mm)
1	200	100	2000	6.522	1.055
2	200	150	2500	4.842	1.013
3	200	200	3000	5.135	0.965
4	400	100	2500	5.385	0.781
5	400	150	3000	5.093	0.858
6	400	200	2000	5.927	1.151
7	600	100	3000	4.915	0.954
8	600	150	2000	5.044	0.851
9	600	200	2500	4.894	0.768

Figure 1 Photograph of specimen cut using AWJ

3 Parameter Design using Desirability based Simulated Annealing (DSA) Algorithm

The method employs the desirability function to calculate the individual desirability values for the responses [12]. The weights for individual responses were generated using simulated annealing (SA) algorithm and used in the desirability analysis to find the optimal setting of AWJ cutting parameters. The steps in DSA algorithm was disclosed below.

Step 1:Calculate the individual desirability (d_{ij}) value for the observed responses using the *smaller-the-better* desirability function [12] shown in Equations (1-3). The *Smaller-the-better* desirability function was used, as both the quality characteristics observed in the process require minimization.

$$d_{ij} = 1, if y_{ij} > T_i \quad (1)$$

$$d_{ij} = \left(\frac{y_{ij} - U_i}{T_i - U_i}\right)^s, if T_i \le y_{ij} \le L_i \quad (2)$$

$$d_{ij} = 0, if y_{ij} > U_i \quad (3)$$

Where $T_i$is the target value of a response and $U_i$is the maximum value of a response.

*Step 2:*Simulated annealing is an analogous method expressed in terms of thermodynamics for estimating the fitness value of a wide search space. Temperature acts as a main parameter in the SA algorithm to determine the annealing schedule. The algorithm starts on at high temperature and ends at a low temperature. The number of iterations required in finding out the optimal point is also determined by the range of temperature and the cooling rate. The algorithm approaches the optimal value when the temperature is reduced slowly. Generate the optimal weights using SA algorithm to find the individual weighted desirability value (WDV). The objective function value for the problem was indicated by Equation(4).

Maximize

$$f(x) = \sum_{i=1}^{n}\sum_{j=1}^{m} W_j Z_{ij} \quad (4)$$

Subject to $W_j \le 1$ and $\sum_{i=1}^{n} W_i = 1;$

Where *f(x)* is the total weighted desirability value and W_j is the weight for each response.

The operation parameters of the SA algorithm were chosen by conducting a pilot study. The initialization of algorithm was carried out by generating initial set of weights to the responses randomly. The neighborhood weights are generated using the technique by pair wise exchange of a small amount of weights between two weights within a seed.

Step 3: Obtain the best seed which maximizes the objective function from the SA algorithm and use the generated weights to calculate the WDV using Equation (5).

$$WDV_j = \sum_{i=1}^{n} W_i Z_{ij} \quad (5)$$

where $j = 1,2,3,...,m$.

Step 4: Determine the main effect (α_i) of cutting parameters using Equation (6) to find the optimal level.

$$\alpha_i = \max\left(\overline{WDV}_{ij}\right) - \min\left(\overline{WDV}_{ij}\right) \quad (6)$$

Where $\overline{WDV}_{ij}$ is the average WDV value of i_{th} factor at j_{th} level. The best level j^* of the factor 'i' is selected by $j^* = \max\left(\overline{WDV}_{ij}\right)$.

Step 5: Supplement the DSA by performing analysis of variance (ANOVA) to predict the significant factors and their contribution in influencing the observed quality characteristics

Step 6: Conduct confirmation test for validation.

3. Results and Discussion

4.1 Implementation of DSA method

The simulated annealing algorithm was used to obtain the optimal weights for the responses as 0.9784 and 0.0216 respectively. The WDV calculated using the generated weights are listed in Table 2. The trial with higher value of WDV indicates a better AWJ cutting condition. The WDV plotted for various trials is shown in Figure 2. The significant variations in WDV values justify the levels of the AWJ cutting parameters chosen for study. The WDV value was observed to be at its peak for the trial number 2, indicating the proximity of the cutting condition to near optimal setting of parameters.

Table 2Weighted desirability values

Trials	Individual desirability		Weighted individual desirability		WDV
	SR	KW	SR	KW	
1	0.0000	0.0834	0.0000	0.0018	0.0009
2	0.2576	0.1199	0.2520	0.0026	0.1273
3	0.2127	0.1616	0.2081	0.0035	0.1058
4	0.1743	0.3215	0.1706	0.0069	0.0888
5	0.2191	0.2546	0.2144	0.0055	0.1099
6	0.0912	0.0000	0.0893	0.0000	0.0446
7	0.2464	0.1712	0.2411	0.0037	0.1224
8	0.2266	0.2606	0.2217	0.0056	0.1137
9	0.2496	0.3328	0.2442	0.0072	0.1257

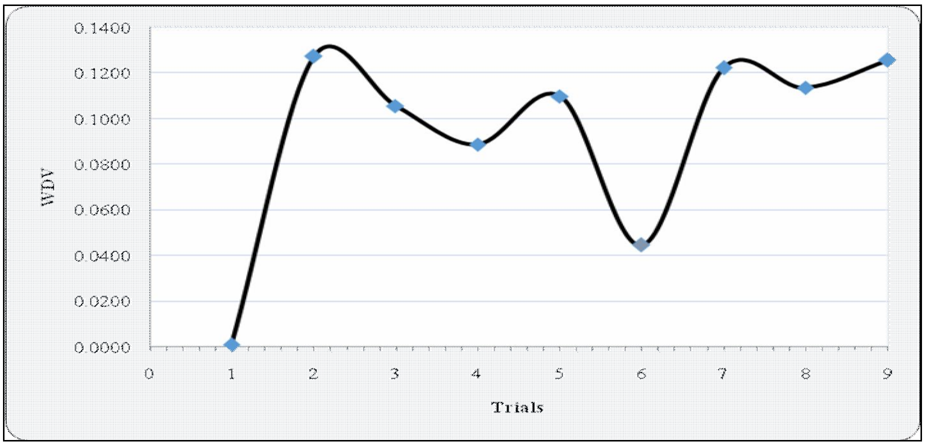

Figure 2 Variation of WDV for various trials

4.2. Optimal Level Selection and ANOVA

The key effect of cutting parameters on WDV was computed for each level and shown in Table 3. The finest level of each control factor was identified as the one with the peak value of WDV. The optimal parameter level was found out as $AF_3F_2WP_2$. The result of ANOVA on WSN is listed in Table 4 and it was used to find the degree of influence of various process parameters in affecting the responses. The contribution of various factors could also be sorted out using ANOVA.

Table 3Main effect of parameters on WDV values

Parameters	Level 1	Level 2	Level 3	Max-Min
AF	0.0780	0.0811	0.1206	0.0426
F	0.0707	0.1170	0.0920	0.0463
WP	0.0531	0.1139	0.1127	0.0609

Table 4ANOVA on WDV values

Source of variance	Sum of squares	Degrees of freedom	Mean sum of square	F-ratio	% Contribution
AF	0.0034	2	0.0017	3.512	22.81
F	0.0032	2	0.0016	3.344	21.72
WP	0.0073	2	0.0036	7.539	48.97
Error	0.0010	2	0.0005		6.50
Total	0.0148	8			100

4.3 Confirmation experiment

The confirmatory test was essential to validate the adopted approach of DSA. Hence the responses obtained with DSA parameter setting (optimal) were compared with those obtained with the initial setting of parameters ($AF_1F_2WP_2$) and listed in Table 5. The confirmation test had shown substantial improvements in the responses. The macro view of cut surfaces for initial and optimal setting of parameters is shown in Figure 3(a) and Figure 3(b) respectively. Further the P-profile plots obtained for the cut surfaces generated using the initial and optimal setting of parameters are also displayed in Figure 3. The unfiltered P-profile graphs were used to study the SR. It was evident that the cut surface obtained with the optimal setting of cutting parameters reveal a good surface texture, compared to the one generated using the initial setting of process parameters.

Table 5 Quality characteristics obtained with initial and optimal parameter setting

Parameter Settings	WDV	Responses	
		SR (µm)	KW (mm)
Initial Setting ($AF_1F_2WP_2$)	0.1273	4.842	1.013
Optimal Setting ($AF_3F_2WP_2$)	0.1855	4.202	0.729
Improvement	0.0582	0.64	0.284
% Improvement	45.72%	13.22%	28.04%

(a)

(b)

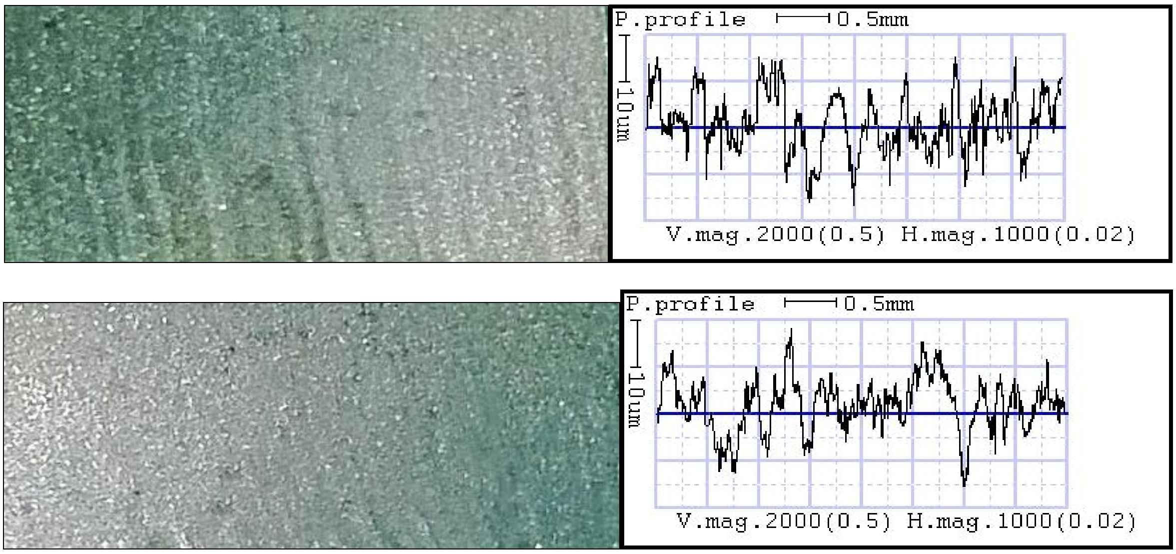

Figure 3 Macro view of cut surface and P-profile plots obtained with (a) initial setting of parameters (b) optimal setting of parameters

5 Conclusions

The modern day industries are stringent in their quality requirements related to the cut surfaces. Quality cut surfaces reduce further processing, cost and time. This investigation reveals an informative report on AWJ cutting of Al6061/10%Al_2O_3 composite. SR and KW were studied as the quality characteristics and an integrated algorithm of DSA was revealed to predict the optimal AWJ cutting condition. The following conclusions were drawn.

- The merits of desirability analysis and SA algorithm were combined to form an integrated approach of DSA and identify the optimal AWJ cutting condition as:water pressure- 2500 bar, feed rate- 150 mm/s and abrasive flow rate- 600 g/min.
- The WDV values offer the single representation for both quality characteristics, hence converting a multi response optimization problem into single response optimization.
- The ANOVA results on WDV had revealed the contribution of abrasive flow rate (22.81%), feed rate (21.72%) and water pressure (48.97%) in influencing the responses.

The report offers informative database for cutting Al6061/10%Al_2O_3 composite using AWJ process and will contribute to enhance the applications of these advanced materials.

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