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Pulsed CO_2 Laser Cutting of Al/SiCp Composite sheets

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Abstract: Metal matrix composites (MMCs) are widely used in aerospace and automotive industries. Attaining a decent surface texture while cutting these advanced materials is challenging and hence the research attention is focused towards the application of pulsed CO_2 laser cutting process on Al/SiCp composite. The process parameters in laser cutting like power, frequency, cutting speed and gas pressure affect the quality of cut surface. Surface finish and kerf width are observed as the quality characteristics for various combinations of input parameters with the experimental trials planned as per Taguchi's L_9 orthogonal array. A combined technique of grey desirability analysis (GDA) is presented for multi response optimization. Significant improvements in the responses are observed with the optimal setting of parameters permitting the usage of GDA technique in experimental welding optimization. Laser power and pulsing frequency are found to significantly affect the quality characteristics studied in the process.
Keywords: Grey relational analysis; Desirability analysis; Laser cutting; Optimization; Al/SiCp composite.

1 Introduction

Aluminium and its alloys are the widely used materials, next to steel in automotive and maritime applications. Ceramic reinforced aluminium exhibit good strength-to-weight ratio and wear resistance. Aluminium and its alloys can be cut by traditional methods but ceramic reinforcement in MMC was found to create tool wear in conventional machining.

Wide spread industrial applications are impossible without solution to stringent design requirements and problems associated with cutting. Laser beam (non-contact mode) was generally employed to generate complex cut profiles faster than other methods. However the material properties govern the selection of laser system [1]. Pulsed CO_2 laser beam can be employed to cut materials like metals, ceramic, plastics and composites [2]. The mechanism of metal removal by lasers involves melting, vaporizing and degrading. The vaporized material was removed by the assisting gas producing no mechanically induced damage to the work material. Investigations with CO_2 lasers while handling aluminium had indicated the presence of heat affected zone in the cut surface [3]. While cutting polymers, it was observed that cutting speed plays an important role in determining the dimensional accuracy and finish of cut surface, while the relationship between speed of cutting and surface finish was observed to be non-linear [4]. Nitrogen was found to produce smooth cut surface with smaller kerf, when used as an assist gas on austenitic stainless steels [5]. From the literature it was found that the cutting parameters play a vital role in deciding the quality characteristics of the surface machined [1-5].

Artificial neural network (ANN), grey relational analysis (GRA), principal component analysis (PCA), response surface methodology (RSM), simulated annealing (SA), fuzzy logic, technique for order of preference by similarity to ideal solution (TOPSIS) and genetic algorithm (GA) were generally employed to solve multi response optimization problems [6-12]. The tool wear was found to be more in traditional machining processes, while handling stronger and advanced materials like metal matrix composites. The increased tool wear was a major concern as it could spoil the finish of the cut surface [13, 14]. The quality of machined surfaces was utmost essential to reduce further processing and time. The selection of proper input parameters was important in obtaining a good machined surface [15, 16].

The technique of GRA was employed to compute the grey relational grade as the performance index. The grade values could be used to sort out the near optimal parameter setting. The GRA was found to be very effective in an integrated format along with PCA and RSM [17-20]. The desirability analysis involving simple computational efforts, when compared to techniques like PCA, TOPSIS, ANN, SA was also found to yield optimal solutions in various manufacturing processes. The desirability method was integrated with RSM and Taguchi techniques to improve its effectiveness [21-24].

From the available literature, it was understood that not enough work was carried out in laser cutting of aluminium based composite. Hence the present work was focussed towards developing a new methodology (GDA), which combines the merits of grey theory and desirability analysis to predict the optimal set of machining parameters in pulsed CO_2 laser cutting process.

2 Experimental Trial Design and Observations

2.1. Material

The work material used for experimentation was Al/SiCp composite. The matrix material (Al6061-aluminium alloy) was reinforced with fine particles (10 µ) of silicon carbide (SiC) in weight fraction of 20%. The reinforcing particles were dispersed in the liquid matrix using the process of two stage stir casting to produce a composite plate of dimension 12 cm × 12 cm × 4 mm, which was subjected to X-ray radiography to endorse the lack of defects. A scanning electron microscope (SEM) image of Al/SiCp composite used as work material (Fig. 1) is displayed to show the uniform distribution of SiC particles in the matrix.

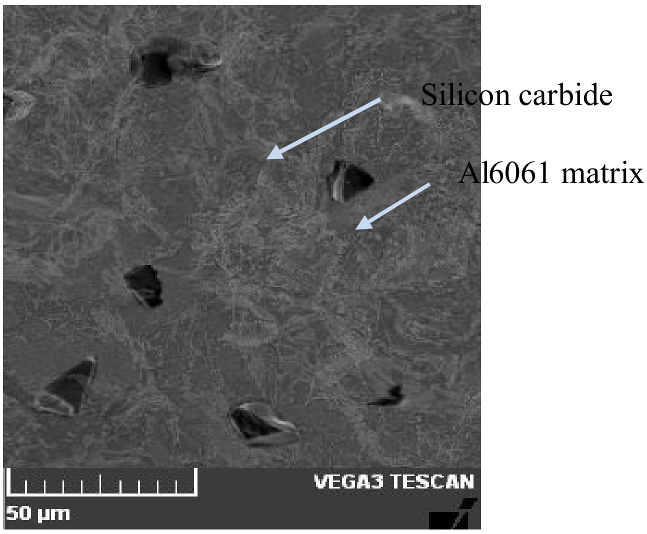

Figure 1 SEM image of parent material showing uniform distribution of reinforcement

2.2. Machine

The CO_2 lasers are most frequently used in machine shops to cut aluminium alloys [10]. The trial cuts were performed using pulsed CO_2 laser cutting machine, capable of generating a peak power of 3.8 KW in pulsed mode. The set-up employs a PLC based system for varying the cutting speed and pulsing frequency. Nitrogen was used as the assist gas and the laser beam was focused using a lens of 127 mm focal length on to a spot of diameter 0.2 mm on the work material. The nozzle-work piece stand-off was maintained at 1 mm during experimentation and the laser beam impact was kept at right angles during the trials.

2.3. Experimentation

The dominant cutting parameters like cutting velocity, laser beam power, assist gas pressure and pulsing frequency were found to affect the quality of the cut surface [1-3]. Preliminary cutting trials were performed to identify the acceptable upper and lower bounds of parameters for which the quality of cut surface remained within acceptable limits without dross and burning effect. These cutting parameters were varied at three levels and Taguchi's L_9 orthogonal array was used to design the cutting trials. The various levels of input parameters chosen for the laser cutting trials are shown in Table 1.

Table 1 Chosen levels of cutting parameters

Symbol	Input Parameters	Level 1	Level 2	Level 3
P	Laser power (W)	1800	2000	2200
F	Pulse frequency (Hz)	5	10	15
V	Cutting velocity (mm/sec)	4	8	12

Two (repetitions) square samples of dimension 20 mm x 20 mm x 4 mm were cut for different combinations of parameters and the trials were performed at random to reduce the effects of extraneous factors [9]. A button-hole cut was also made in each sample for measuring the kerf width. The responses measured include the surface roughness (SR) and kerf width (KW), which require minimization during cutting trials. The cut surfaces of a few samples cut are shown in Fig. 2. A contact stylus surface roughness tester was used to measure the surface roughness and the measurements were taken at the middle of depth on all four cut sides along the direction of cut. The kerf width was measured using a video measuring system equipped with high resolution CCD camera and a maximum possible magnification of 190X. Kerf width was measured as the average of top and bottom kerf from the button-hole cut made in each sample. The responses obtained for various cutting trials are shown in Table 2.

Figure 3 Cut surfaces of a few samples

Table 2 Quality characteristics observed during various trials

Trial	**Input**			**Responses**	
	A	**B**	**C**	**Ra (µm)**	**KW (mm)**
1	1	1	1	7.012	0.602
2	1	2	2	6.211	0.572
3	1	3	3	7.825	0.527
4	2	1	2	6.775	0.598
5	2	2	3	7.183	0.575
6	2	3	1	6.817	0.588
7	3	1	3	5.505	0.586
8	3	2	1	7.334	0.508
9	3	3	2	6.979	0.525

3 Multi Response Optimization Using Grey Desirability Analysis (GDA)

The demand for good surface finish (requiring little post processing) poses a huge challenge to metal cutting industries. The grey theory used in finding the optimal operating condition compensates the drawback of regression analysis by identifying the link between parameters based on the amount of difference or similarity of trends among those elements [13]. Generally the Taguchi techniques use signal-to-noise (S/N) ratio to compare the responses. The GDA method involves following steps.

Step 1: Calculate the S/N ratio (y_{ij}) for both the responses treated as the *lower-the-better* characteristic using Equation (1). The *lower-the-better* analysis tends to minimize the responses, improving them significantly [3].

$$S/N\ Ratio(\eta_{ij}) = -10\log_{10}\left(\frac{1}{r}\cdot\sum_{i=1}^{n}(y_{ij})_k^2\right) \quad (1)$$

Where r = number of replications; m = number of trials; y_{ij} = observed response values; i = 1,2,3..r and j = 1,2,…m.

Step 2: Calculate the normalized S/N ratio (Z_{ij}) using Equation (2) to decrease the effect of variability among S/N ratio [6]. The normalized S/N ratio varies between 0 and 1.

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, j = 1,2,.....,m)}{\max(y_{ij}, j = 1,2,.....,m) - \min(y_{ij}, j = 1,2,.....,m)} \quad (2)$$

Step 3: Compute the grey relational coefficient (GRC (γ)) for normalized S/N ratio values [13] using Equation (3).

$$\gamma_i^j = \frac{\Delta\min + \xi\Delta\max}{\Delta_{oj}(i) + \xi\Delta\max} \quad (3)$$

Where $\Delta_{oj} = \|z_o(i) - z_j(i)\|$; $z_o(i)$ is the referential sequence; $z_j(i)$ is the comparative sequence; $\Delta\min = \min_{\forall j\in i}\min_{\forall i}\|z_o(i) - z_j(i)\|$ and $\Delta\max = \max_{\forall j\in i}\max_{\forall i}\|z_o(i) - z_j(i)\|$. ξ is the distinguishing coefficient whose value is chosen as 0.5.

Step 4: Compute the individual grey desirability (d_{ij}) value for the quality characteristics [7, 11], using the desirability function (*larger-the-better type*) represented by Equation (4).

$$d_{ij} = \left(\frac{y_{ij} - L_i}{LT_i - L_i}\right)^S, if\ L_i \le y_{ij} \le T_i \quad (4)$$

L_i and T_i are the lower and target values of the responses respectively.

Step 5: Calculate the composite performance measure (CPM) by taking the geometric mean of individual desirability values using Equation (5). The CPM value lies between 0 and 1.

$$CGDI_j = \{\prod_{i=1}^{n} d_{ij}\}^{\frac{1}{n}} \quad (5)$$

Step 6: Find the main effect (ε_i) of various parameters using Equation (6) to identify the optimal level.

$$\varepsilon_i = max(\overline{CPM}_{ij}) - min(\overline{CPM}_{ij}) \quad (6)$$

Step 7: Calculate the predicted S/N ratio $(\overline{\eta})$ at the selected optimal level [6, 11], using Equation (7) and perform ANOVA to find the contribution of individual parameters.

$$\overline{\eta} = \eta_m + \sum_{i=1}^{f}(\overline{\eta_i} - \eta_m). \quad (7)$$

η_m = Average S/N ratio and $\overline{\eta_i}$= Average S/N ratio corresponding to the i^{th} factor at the f^{th} level

Step 8: Conduct confirmation test for validation.

4. Results and Discussion

4.1 Implementation of GDA method

The grey generating technique was applied to transform the disordered raw data to regular series useful for measuring the relationship between different data elements [13]. The target for *lower-the-better* characteristic is zero and a linear normalization of the observed data was performed to find the normalized S/N ratio values. The GRC and individual desirability values along with the CPM values are listed in Table 3. The CPM values offer the single representation for the two responses and a larger value of CPM is preferred irrespective of the nature of responses. The CPM value plotted for different cutting trials is shown in Fig. 3. The noteworthy variations in the computed CPM values signify the selected levels of different cutting parameters. The peak value of CPM was obtained for the seventh trial and hence the operating condition corresponding to that trial could be closer to the optimum parameter setting and would offer better responses.

Table 3 Data pre-processing and CPM values

Trial	S/N ratio		Normalized S/N ratio		Grey relational coefficient		Individual grey desirability		CPM
	SR	KW	SR	KW	SR	KW	SR	KW	
1	-16.97	4.408	0.312	0.000	0.421	0.333	0.131	0.000	0.000
2	-15.83	4.852	0.657	0.301	0.593	0.417	0.390	0.126	0.221
3	-17.80	5.564	0.000	0.784	0.333	0.698	0.000	0.547	0.000
4	-16.68	4.466	0.410	0.039	0.459	0.342	0.188	0.013	0.050
5	-17.16	4.807	0.243	0.270	0.398	0.407	0.097	0.110	0.103
6	-16.62	4.612	0.392	0.139	0.451	0.367	0.177	0.051	0.095
7	-14.85	4.642	1.000	0.159	1.000	0.373	1.000	0.059	0.243
8	-17.37	5.883	0.184	1.000	0.380	1.000	0.070	1.000	0.265
9	-16.86	5.597	0.325	0.806	0.426	0.721	0.138	0.581	0.284

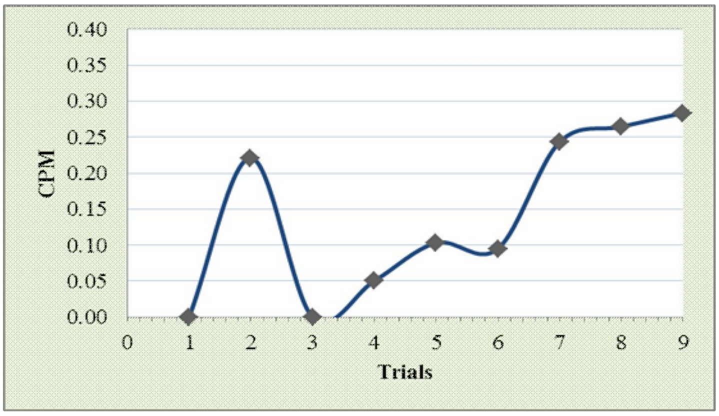

Figure 3 Variation of CPM for various trials

4.2. Optimal Laser Cutting Parameters and Analysis of Variance

The main effect of the laser cutting parameters on the CPM was calculated for each level and listed in Table 4, from which the optimal parameter level was found as $A_3B_2C_2$. The result of pooled ANOVA on CPM is listed in Table 5, which could be used to identify the contribution of various cutting parameters in affecting the responses. Generally aluminium alloys are difficult to cut by lasers due to their high reflectivity and high power requirements in continuous wave mode of operation. Hence a pulsed laser beam using nitrogen as assist gas was employed to cut the material. Generally a higher degree of melting was found at the top surface of work material than at the bottom surface. A higher level of pulse frequency improves the value of CPM. This was due to the fact that high instantaneous energy in pulses at high frequency results in quicker melting and blow-off resulting in improved responses. A higher level of laser power was found to increase the energy content of the beam, which was essential to melt the matrix to be ejected by gas pressure removing a portion of reinforcements along with it.

Table 4 Main effect of parameters on CPM

Parameters	Level 1	Level 2	Level 3	Max-Min
P	0.074	0.083	0.264	0.190
F	0.098	0.196	0.126	0.099
V	0.120	0.185	0.115	0.070

Table 5 Result of ANOVA on CPM

Source of variance	Sum of squares	Degrees of freedom	Mean sum of square	F-ratio	% Contribution
P	0.0690	2	0.0345	6.5601	66.31
F	0.0154	2	0.0077	1.4669	14.83
V	0.0091	2	0.0046	0.8658	8.75
Error	0.0105	2	0.0053		10.11
Total	0.1040	8			100

4.3 Confirmation Experiment

A confirmation test becomes essential to authorize the methodology of GDA for optimization. The responses observed for the initial parameter setting were compared those obtained with the optimal parameter setting predicted by the GDA method (Table 6). It was found that GDA approach had improved the responses significantly.

Table 6 Comparison of the responses obtained for the initial and optimal parameter setting

Responses	Initial parameter setting		Optimal Setting using GDA		% Improvements	
	Calculated S/N ratio	Response Value	Predicted S/N ratio	Response Value	S/N ratio	Response Value
SR (μm)	-16.5767	6.846	-15.2029	5.5365	1.3738	1.3095
KW (mm)	5.6408	0.531	5.3613	0.487	0.2795	0.044
Parameter settings	$A_3 B_3 C_2$		$\mathbf{A_3 B_2 C_2}$			

5 Conclusion and Future Research

In the present work Al/SiCp composite plates of thickness 4 mm were cut using the pulsed CO_2 laser cutting process and a combined approach (GDA) was revealed for predicting the optimal cutting condition. The following conclusions were drawn.

- The hybrid technique of GDA was found to be proficient in predicting the optimal setting of laser cutting parameters for Al/SiCp composite as: laser power = 3200 W, cutting velocity = 5 mm/sec, gas pressure = 1 MPa and pulsing frequency = 14 Hz.

- The cutting parameters investigated in the laser cutting process were found to be significant in affecting the observed responses. The contribution of laser power was observed to be maximum, followed by the pulsing frequency.
- The uncertainty handling abilities of grey theory was combined with the merits of desirability analysis to predict the optimal cutting parameters. The application of GDA method for multi response optimization in various areas of manufacturing is also possible.

The investigation findings will offer the necessary guideline and database for cutting Al/SiCp composite plates using pulsed CO_2 laser cutting process, hence widening the scope of application of the MMCs.

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