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Analysis in plasma arc cutting of 21Cr ferritic stainless steel

H.Ravi kumar and S.Thileepan

Department of Mechanical Engineering, Saveetha Engineering College, Chennai-602105, Tamilnadu, India

Abstract: Plasma arc cutting (PAC) is thermal cutting process capable of handling various materials at higher speeds. The economic aspects of the process and its less polluting nature makes it comparable with laser cutting process. Metal cutting industries face stiff challenge in obtaining a good quality cut surface. In plasma cutting, the dominant parameters affecting the quality characteristics of the cut surface include arc current, cutting speed, stand-off distance and gas pressure. The objective of the research work is focussed towards assessing the quality of cut surface (surface roughness and bevel angle of cut) obtained with 21Cr ferritic stainless steel. Taguchi's L_9 orthogonal array was employed to design the cutting trials and grey based technique for order of preference by similarity to ideal solution (TOPSIS) analysis (GTA) was presented for designing the cutting parameters. The GTA was found to enhance the responses observed in PAC process permitting its usage in experimental cutting optimization.
Keywords: 21Cr ferritic stainless steel; Grey theory; TOPSIS; Plasma arc cutting; surface finish; parameter design.

1 Introduction

Modern day metal cutting industries face rigid competition for producing high quality cut surface requiring minimal or zero further processing. Plasma arc cutting (PAC) is an unconventional metal removal process utilizing an elevated temperature, high velocity arc through a plasma gas between the electrode and workpiece. The intense heat content and momentum of the plasma vaporizes the work material [1]. The extreme power density of the plasma can vaporize all solid materials allowing the process to cut high speed steel, stainless steel, cast iron and hardened alloys. Oxygen, nitrogen, hydrogen, argon or air can be used as plasma gas either individually or in combined form [2]. 21Cr ferritic stainless steel has good mechanical properties and better corrosion resistance. It is used in beverage and chemical processing equipment. The traditional cutting processes like gas cutting was found to produce a poor surface finish in stainless steels [3].

The kerf width and surface roughness along with the taper angle were identified as important indicators of quality in PAC process. The plasma gas was found to diverge as it interacts with the atmosphere, hence the nozzle stand-off could affect the quality of cut surface. The cutting height and arc current were sorted out as the significant factors affecting the process responses [4]. Arc voltage was also observed to have considerable effect on the kerf [5]. The plasma gas pressure and its flow rate along with the cutting speed were also identified to play a crucial role in establishing the stability of arc, which becomes essential to obtain good responses [6]. The heat load on the nozzle while handling titanium alloys was found to decrease its service life. However the quality characteristics were observed to be better with oxygen as plasma gas than nitrogen [7]. The decreased level of arc current was observed to minimize the kerf width and taper angle allowing the usage of higher cutting speeds [8].

The PAC is basically a multi-input multi-output process requiring a proper design of the operating parameters to get a good quality cut surface. The dominant cutting parameters affecting the responses were identified as the cutting current, cutting speed, torch stand-off, pressure and flow of the plasma gas [4-8]. The optimization problems can be handled by employing various techniques including grey relational analysis (GRA), technique for order of preference by similarity to ideal solution (TOPSIS), Principal component analysis (PCA), data envelopment analysis, artificial neural networks (ANN), response surface methodology (RSM) and fuzzy logic [9]. In GRA, the S/N ratio was used as quality index whose values were maximized irrespective of the nature of responses. The method using S/N ratio was found to be effective in predicting the optimal condition [10]. RSM based desirability analysis could be employed to forecast the optimal cutting condition for cutting composite material. However the analysis was performed for single response optimization [11].

Taguchi technique was employed for optimization in surface treatment using plasma torch. But with limited orthogonal array design which when selected wrongly, this technique would fail to deal with important interaction effects [12]. The results obtained with a combined format of GRA and PCA was observed to be effective in multi response optimization [13]. RSM is used for mapping decision variables with the quality characteristics and it was observed to perform better when the number of responses is limited to a maximum of three [14]. The statistical regression method requires a prior functional relationship and the solutions were valid only within the defined domain of the experimental data. ANN on the other hand, requires a larger data and tedious training. The method was characterized by an uncertainty in finite convergence, while the fuzzy logic rules may not be easily amendable to dynamic changes of the cutting processes. Taguchi based desirability analysis was used successfully in predicting the best operating condition. This method was found to involve a lesser number of trials to arrive at the conclusion [15]. An integrated method using two different techniques (GRA and PCA) was also found to take the merits of both the techniques for optimizing multiple responses [16]. TOPSIS is a multi-attribute decision making technique employed to rank the responses [17, 18]. Taguchi method of experimentation followed by the desirability analysis could identify the near optimal operating conditions in different manufacturing processes and optimization using simulated annealing approach was found to be effective within the experimental domain [19-22]. Taguchi based grey theory and RSM was more advantageous than CCD and Box-Behnken based experimentations. The methods were economically superior as well [23-25].

From the literature review, it was observed that research work in the area of parameter design in plasma arc cutting of 21Cr ferritic stainless steel was scarce. Hence the work is focussed towards disclosing an integrated method of grey based TOPSIS analysis (GTA) for predicting the optimal cutting condition.

2 Experimental Design

The ferritic stainless steel is widely used for architectural moulding, chemical and pharmaceutical processing industries. Two ferritic stainless steel sheets, each of dimension 300 mm x 300 mm x 5 mm were used for the cutting trials. The MC-1 plasma cutter (bridge type) equipped with numerical control and inbuilt CAM-DUCT software was used for taking the designed cuts. The servo assisted and numerically controlled plasma torch can be moved in all three directions with acceptable precision. The torch uses an air cooled, swirl copper nozzle with an orifice diameter of 1.5 mm. A hafnium bar inserted in the electrode tip acts as the cathode. The compressed air is blown out of the arc converting some portion of it to high energy plasma. The PAC machine employed for cutting is shown in Figure 1(a). The dominant process parameters chosen for study were the air pressure, arc current, cutting speed and stand-off distance [4-8]. A considerable number of pilot cuts were taken to confirm the range of cutting parameters for full kerf separation and minimum bottom dross. These parameters were varied at three levels and Taguchi's L_9 orthogonal array was used for performing the cutting trials with two replications. The bevel angle of cut (BA) and surface roughness (SR) were observed after each trial. BA was measured using video measuring system. SR was measured using a contact stylus surface roughness tester (surfcoder SE3500) for a cut-off length of 0.8 mm on all sides and the average value was taken for analysis. The levels of different cutting parameters chosen for various trials are listed in Table 1.

Table 1 Cutting parameters and their levels

Symbols	Input Parameters	Level 1	Level 2	Level 3
A	Air pressure (bar)	5	5.5	6
B	Cutting speed (mm/min)	1000	1500	2000
C	Arc current (A)	50	60	70
D	Stand-off distance (mm)	1	1.5	2

The photograph of cut profile is shown in Figure 1(b). The trials were performed at random to minimize the effects of extraneous factors [9]. Trapezoidal profiles were cut allowing a sufficient time and distance between the cuts to avoid thermal effects. The responses for various trials are listed in Table 2.

Figure 1 (a) plasma arc cutter and (b) cut profile

Table 2 L_9 array displaying the combination of cutting parameters and the observed responses

Trial	Input Parameters				Responses	
	A	B	C	D	SR (µm)	BA (deg)
1	1	1	1	1	4.164	4.154
2	1	2	2	2	5.012	3.769
3	1	3	3	3	6.319	4.329
4	2	1	2	3	4.615	3.597
5	2	2	3	1	4.411	4.292
6	2	3	1	2	4.793	4.436
7	3	1	3	2	4.949	3.927
8	3	2	1	3	5.202	4.596
9	3	3	2	1	5.763	3.779

3 Methodology of Grey TOPSIS Analysis (GTA)

The parameter design is a desired offline quality control approach, offering more viable solutions to the severe competition for producing quality parts [14]. In multi response optimization using GRA, a grey system represents the level of data between the black (incomplete information) and white (complete information) states. The grey relational grade indicates the correlation between the two states [10]. The strength of grey theory lies in transforming a disorderly raw data into a regular series by applying the grey generating technique. The '*signal-to-noise*' ratio (S/N ratio) is considered as the performance measure in grey theory. The algorithm for the GTA is disclosed in two phases (section 3.1 and section 3.2).

3.1. Phase I: Grey Relational Analysis

Step 1: Calculate the S/N ratio (y_{ij}) for the responses treating them as the *smaller-the-better* characteristics using Eq. (1). The target for *smaller-the-better* characteristic is zero [16].

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

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

Step 2: Compute the normalized S/N ratio (Z_{ij}) values, as a part of data pre-processing using Eq. (2), to avoid the effect of variability among the S/N ratio [13, 14].

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

Step 3: Compute the grey relational coefficient (GRC (x)) to express the relationship between the best and actual normalized experimental results from the normalised S/N ratio using Eq. (3) [10, 12].

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

$\Delta_{oj} = \left\| z_o(i) - z_j(i) \right\|$ is the absolute value of the difference between $z_o(i)$ and $z_j(i)$, $z_o(i)$ is the reference sequence ($z_o(i)$=1; i=1,2,…,n), $z_j(i)$ is the specific comparison sequence, $\Delta\min = \min_{\forall j \in i}\min_{\forall i}\left\| z_o(i) - z_j(i) \right\|$ is the smallest value of $z_j(i)$, $\Delta\max = \max_{\forall j \in i}\max_{\forall i}\left\| z_o(i) - z_j(i) \right\|$ is the largest value of $z_j(i)$ and ξ is the distinguishing coefficient.

3.2. Phase II: Topsis

TOPSIS is a proven ranking technique requiring a restricted experimental input [17, 18]. The merit of TOPSIS lies in its ability to identify the best alternative faster. The decision making matrix is formed with the grey coefficients and is subjected to further analysis as follows.

Step 4: Establish the multiple attribute decision making matrix [A].

$$[A] \dagger \begin{vmatrix} x_1^1 & x_2^1 & .. & .. & x_n^1 \\ x_1^2 & x_2^2 & .. & .. & x_n^1 \\ .. & .. & .. & .. & .. \\ .. & .. & .. & .. & .. \\ x_1^m & x_1^m & .. & .. & x_n^m \end{vmatrix}$$

Where n is the number of variables and x_i^j is the value of GRC.

Step 5: Compute the distance of the j_{th} alternative from ideal solution (separation measure I) and from the negative-ideal solution (separation measure II) using Eq. (4) and Eq. (5) respectively.

$$d_j^+ = \sqrt{\sum_{i=1}^{n}\left(x_i^j - x_i^+\right)^2}\text{, for } i=1, 2\ldots n \quad (4)$$

$$d_j^- = \sqrt{\sum_{i=1}^{n}\left(x_i^j - x_i^-\right)^2}\text{, for } i=1, 2\ldots n \quad (5)$$

Where

$$x_i^+ = \max\left\{x_i^j, \text{for } j = 1,2,..., m\right\}\ \forall x_i^j\left(i = 1,2,..., n, j = 1,2,..., m\right)$$

$$x_i^- = \min\left\{x_i^j, \text{for } j = 1,2,..., m\right\}\ \forall x_i^j\left(i = 1,2,..., n, j = 1,2,..., m\right)$$

Step 6: Calculate the relative closeness of various alternatives to the ideal solution [17, 18] using Eq. (6). It is considered as the grey TOPSIS index (GTI).

$$GTI_j = \frac{d_j^-}{d_j^+ + d_j^-} \quad (6)$$

Step 7: Find the optimal cutting condition based on GTI. The main effect (ε_i) of the parameters is calculated using Eq. (7) to determine the optimal level.

$$\varepsilon_i = \max\left(\overline{GTI}_{ij}\right) - \min\left(\overline{GTI}_{ij}\right) \tag{7}$$

The best level $j*$ of any factor 'i' is selected as $j *= \max\left(\overline{GTI}_{ij}\right)$

Step 8: Compute the predicted S/N ratio ($\bar{\eta}$) at the selected optimal levels [13, 16] using Eq. (8).

$$\bar{\eta} = \eta_m + \sum_{i=1}^{f}\left(\bar{\eta}_i - \eta_m\right) \tag{8}$$

Where η_m= average S/N ratio, f = number of control factors and $\bar{\eta}_m$= average S/N ratio corresponding to the i_{th} factor at f_{th} level.

Step 9: Perform ANOVA to supplement the GTA method and conduct the confirmation test for validation.

4. Results and Discussion

4.1 Data pre-processing

A linear normalization of the responses (SR and BA) was performed and the GRCs were calculated and listed in Table 3. The SR and BA were treated as the *smaller-the-better* responses with the target for them remaining at zero. The S/N ratio was preferred over standard deviation in the grey theory and a larger value of S/N ratio was desired irrespective of the quality characteristics [16].

Table 3 Data pre-processing and GRC of responses.

Trial	S/N ratio		Normalized S/N ratio		GRC	
	SR	BA	SR	BA	SR	BA
1	-12.390	-12.369	1.000	0.413	1.000	0.460
2	-14.000	-11.525	0.556	0.809	0.529	0.724
3	-16.013	-12.728	0.000	0.244	0.333	0.398
4	-13.283	-11.119	0.753	1.000	0.670	1.000
5	-12.891	-12.653	0.862	0.279	0.784	0.410
6	-13.612	-12.940	0.663	0.145	0.597	0.369
7	-13.890	-11.881	0.586	0.642	0.547	0.583
8	-14.323	-13.248	0.466	0.000	0.484	0.333
9	-15.213	-11.548	0.221	0.799	0.391	0.713

4.2. Effect of parameters on responses

After calculating the S/N ratio for various responses, the effect of a parameter at a particular level can be found out by taking the mean of S/N ratios at that level. A pictorial representation of the effect of various process parameters at different levels is shown in Figure 2. The level corresponding to maximum average S/N ratio for a parameter could produce better responses [13]. It was seen from Figure 2, that moderate values of air pressure and arc current produce better responses, while lesser values of cutting speed and stand-off can improve the quality characteristics observed in the process.

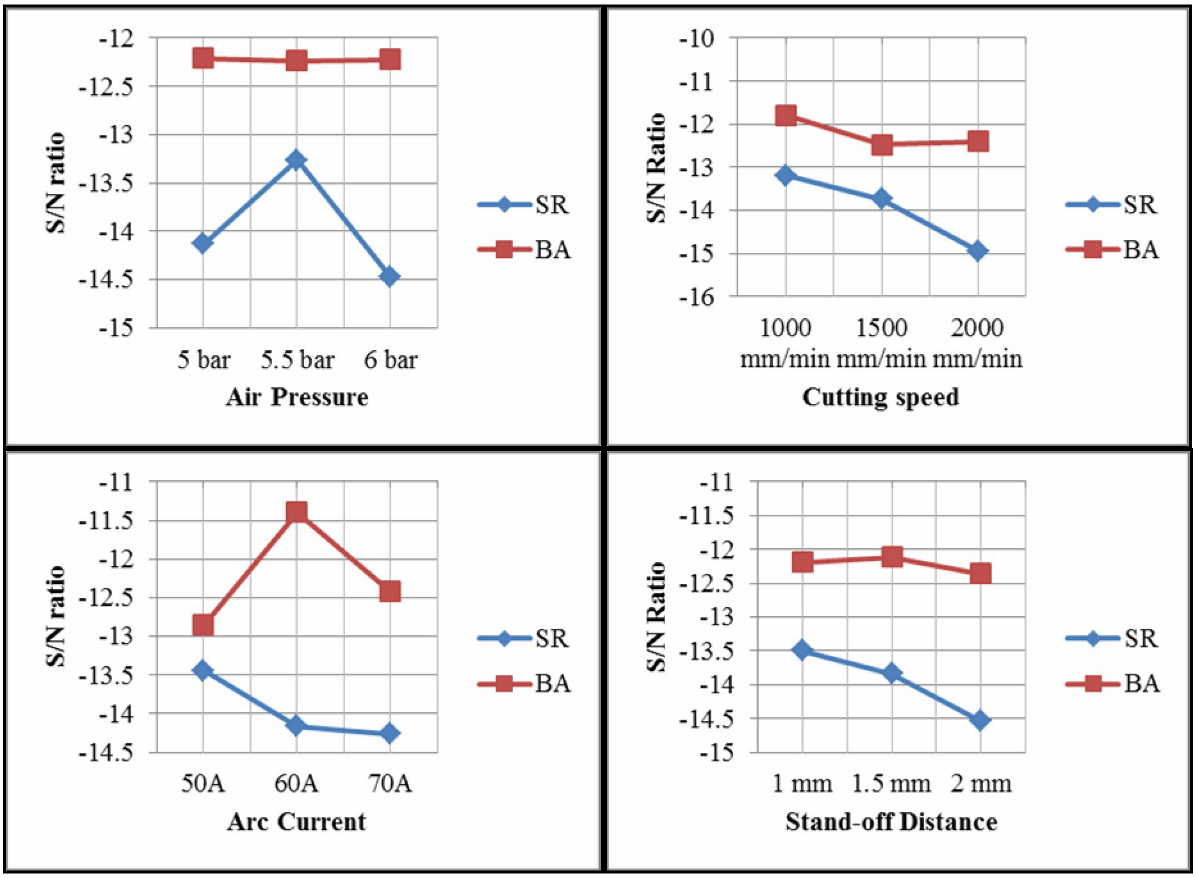

Figure 2 Effect of parameters on the responses

4.3 Calculation of GTI

The normalized matrix and the separation measures (I and II) were found out along with the relative closeness of various alternatives to ideal solution. The GTI values are listed in Table 4. The GTI values were representatives of the overall quality measure for the two responses. The variation of GTI values for the nine trials is indicated in Figure 3. The larger values of GTI indicate better responses. The factor combination corresponding to the trial number 4 was found to have a higher GTI value (Figure 3). However the effect of factor levels on the GTI values should be analyzed before arriving at the optimal setting (Figure 4). The main effect of the cutting parameters on GTI was calculated and listed in Table 5. The best levels of parameters were identified as the ones having the maximum value of average GTI among the different levels. From Figure 3 and Table 5 the optimal parameter level was identified as $A_2B_1C_2D_1$.

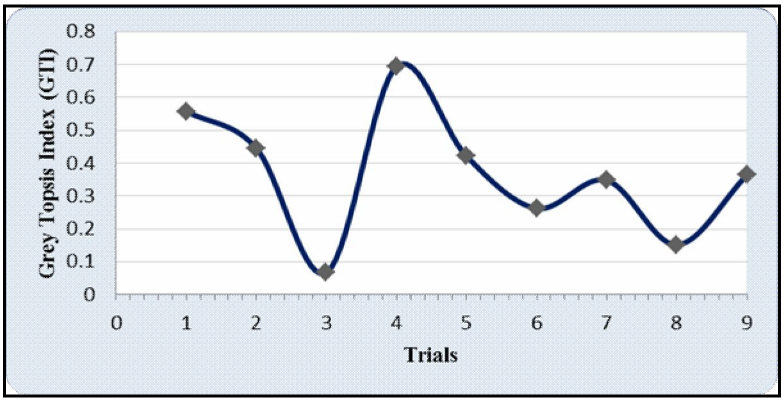

Figure 3 Variation of GTI values for various trials

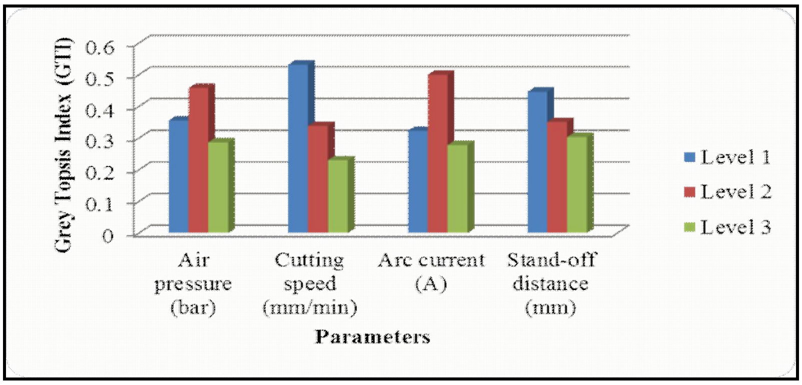

Figure 4 Effect of parameter levels on GTI

Table 4 Separation measure (I and II) and GTI values

Trial	Separation measure I	II	GTI
	d_j^+	d_j^-	
1	0.5402	0.6786	0.5568
2	0.5455	0.4371	0.4449
3	0.8981	0.0648	0.0673
4	0.3303	0.7467	0.6934
5	0.6289	0.4566	0.4206
6	0.7487	0.2662	0.2623
7	0.6159	0.3283	0.3477
8	0.8432	0.1504	0.1514
9	0.6734	0.3839	0.3631

Table 5 Effect of parameter levels on GTI

Parameters	Level 1	Level 2	Level 3	Max-Min
A	0.3563	**0.4588**	0.2874	0.1714
B	**0.5326**	0.3390	0.2309	0.3017
C	0.3235	**0.5004**	0.2786	0.2219
D	**0.4468**	0.3516	0.3040	0.1428

4.4 ANOVA and Confirmation test

The analysis of variance (ANOVA) was performed to supplement the GTA method and the significant cutting parameters (percentage contribution) influencing the quality characteristics was found out. ANOVA was performed on the GTI and the results are listed in Table 6.

Table 6 Result of the ANOVA on GTI

Source of variation	Sum of square	Degrees of freedom	Mean sum of square	F-ratio	% Contribution
A	0.0446	2	0.0223	1.4063	14.92
B	0.1402	2	0.0701	4.4195	46.88
C	0.0826	2	0.0413	2.6022	27.60
D	0.0317	2	0.0159		10.61
Total	0.2991	8			100

After obtaining the optimal level of cutting parameters using the GTA method, the confirmation test was carried out for verifying the improvements in performance characteristics. The results of the confirmation experiment conducted with the optimal parameter setting were compared with those obtained with initial setting of parameters (trial 4) and listed in Table 7. The confirmatory test gave satisfactory results and a significant improvement in the response values was observed.

Table 7 Comparison of the responses obtained with initial parameter setting and GTA setting

Parameter Settings	S/N ratio		Responses	
	SR (μm)	BA (deg)	SR (μm)	BA (deg)
Initial setting ($A_2B_1C_2D_3$)	-13.28	-11.11	4.615	3.597
Optimal setting using GTA ($A_2B_1C_2D_1$)	-12.24	-10.94	4.019	3.474
Improvement	1.04	0.17	0.5957	0.1232
% Improvement	7.84%	1.57%	12.91%	3.43%

5 Conclusions

Solving a multi response optimization problem is a challenging task. In this work, 21Cr ferritic stainless steel was cut by using the PAC process and grey based technique for order of preference by similarity to ideal solution (TOPSIS) analysis (GTA) was presented for identifying the optimal combination of cutting parameters. The following conclusions were drawn.

- The GTA method was efficient in designing the optimal setting of cutting parameters for 21Cr ferritic stainless steel as - air pressure: 5.5 bar, cutting speed: 1000 mm/min, arc current: 60 A and stand-off distance: 1 mm using PAC process. This operating condition had significantly improved the S/N ratio, thereby enhancing the performance characteristics.
- The GTA approach had combined the merits of both GRA and TOPSIS. The uncertainty handling capabilities of GRA was integrated with the more realistic ranking method of TOPSIS, requiring a relatively simple computational effort in handling multi response problems.
- ANOVA was performed on GTI to reveal the major cutting parameters affecting the responses as cutting speed (46.88%), followed by the arc current (27.60%) and air pressure (14.92%).

The research findings offer the required guidelines for cutting 21Cr ferritic stainless steel using PAC process. The results will offer good cutting database for the textile, chemical and pharmaceutical processing industries.

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