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Optimization of Process Parameters in Plasma Arc Cutting of EN 31 Steel Based on MRR and Multiple Roughness Characteristics Using Grey Relational Analysis

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Abstract

This paper investigates the effects and parametric optimization of process parameters for plasma arc cutting (PAC) of EN31 steel using grey relation analysis. Three process parameters viz. gas pressure, arc current and torch height are considered and experiments are conducted based on L_{27} orthogonal array (OA). Process responses viz. material removal rate (MRR) and surface roughness parameters (centre line average roughness: R_a, root mean square: R_q, skewness: R_{sk}, kurtosis: R_{sk} and mean line peak spacing: R_{sm}) of the machined surface are measured for every experimental runs. For maximum MRR and minimum surface roughness characteristics process parameters are optimized based on Taguchi method coupled with grey relational analysis. Analysis of variance (ANOVA) is performed to get the contribution of each process parameters on the performance characteristics and it is observed that gas pressure is significant process parameter that affects the responses. Confirmation test using optimal setting shows good agreement to the predicted value. This indicates utility of the grey-Taguchi technique as a multi-objective optimizer in the field of PAC. Finally, using scanning electron microscopy, the surface morphology is studied.

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Keywords: Plasma arc cutting; Material removal rate; Surface roughness characteristics; Taguchi grey analysis; ANOVA

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1. Introduction

Nowadays, a wide range of thermal cutting techniques has been applied for shaping materials in different fields of mechanical engineering, shipbuilding, and process technology. Plasma arc cutting (PAC) is a very important thermal cutting process and has been used successfully in the cutting of stainless steel, high hardness metals, high melting point metals, and other difficult to machine alloys (Willett, 1996; Ian, 1997). In this cutting process, an inert gas is blown with high speed out of a nozzle; at the same time, an electrical arc is formed through that gas from the nozzle to the surface, being cut turning some of that gas to the plasma. The plasma melts the material being cut and swiftly moves blowing molten metal away from the cutting zone (Vasil'ev, 2003). Plasma arc current, torch geometry, gas type, flow rate, and cutting speed factors have important effects on the cutting quality. It is possible to find multiple studies of the influence of plasma cutting parameters on machinability. The focus on this paper is to obtain an optimum condition (setting) to obtain maximum MRR and minimum surface roughness. From the economic point of view, it is obvious that material removal rate should be the maximum in any industrial purpose. Also, surface roughness plays an important role in determining how a real objective will interact with its environment. It has large impact on the mechanical properties like fatigue behavior, corrosion resistance, creep life etc. It also affects other functional attributes of machine components like friction, wear, light reflection, heat transmission, lubrication, electrical conductivity etc.

There are many researchers who have studied PAC process in many aspects. Bhuvenesh et al. (2012) have optimized the process parameters namely air pressure, cutting current, cutting speed and arc gap with consideration of multiple performance characteristics including MRR and surface roughness using Taguchi technique in plasma arc cutting of AISI 1017 steel. Moarrefzadeh (2011)has investigated the thermal effect of plasma arc cutting, which depends on the plasma, gas type and temperature field of it in work piece and simulated the process parameters using ANSYS. Also, it can be optimized the process parameters.Ismail and Taha (2012) have employed Taguchi method to optimize the machining process parameters in the plasma arc surface hardening ASSAB618 and ASSABDF3 steel considering arc current, scanning velocity and carbon content of steel as the process parameters. Chen et al. (2009) have optimized the plasma arc cutting process (tip size, feed rate, voltage and current) with multiple performance characteristics viz. bevel magnitude and smallest diameter deviation of the hole using Taguchi technique. Ozek et al. (2011) have successfully applied fuzzy algorithm for prediction of surface roughness in PACAISI 4140 steel. Salonitis and Vatousianos (2012) have studied the influence of machining parameters, viz., cutting speed, cutting current, plasma gas pressure and torch height on the surface roughness, heat effected zone and conicity of the cut geometry in plasma arc cutting of S235 mild steel and also developed a regression model. Radovanovic et al. (2011) have developed an artificial neural network (ANN) model using cutting current, plate thickness and cutting speed as three input neurons, to predict the output neuron-surface roughness R_z values for PAC operation of stainless steel, aluminum and nickel.Bahram (2009)has optimized arc current, cutting speed and torch height with considering performance characteristics including flatness, clean cut and bevel angle using RSM in automated plasma cutting process of stainless steel sheet metal and also validation is performed on the optimum setting. Yang(2001) has maximized depth of the hardened zone in steel specimens is significant with the optimization of plasma arc cutting process.

Moreover, an extensive review of literature on roughness studies of PAC surfaces reveals the fact that the centreline average roughness (R_a) has been the focus of most of the investigations. However, a surface generated by machining is composed of a large number of length scales of superimposed roughness (Sahoo, 2005) and generally characterized by three different types of parameters, viz., amplitude parameters, spacing parameters and hybrid parameters. Amplitude parameters are the measures of the vertical characteristics of the surface deviations and examples of such parameters are centre line average roughness, root mean square roughness, skewness, kurtosis, peak-to-valley height etc. Spacing parameters are the measures of the horizontal characteristics of the surface deviations and examples of such parameters are mean line peak spacing, high spot count, peak count etc. On the other hand, hybrid parameters are a combination of both the vertical and horizontal characteristics of surface deviations and example of such parameters are root mean square slope of profile, root mean square wavelength, core roughnessdepth, reduced peak height, valley depth, peak area, valley area etc. Thus consideration of only one parameter like centre line average roughness is not sufficient to describe the surface quality though it is the most commonly used roughness parameter. The present study aims at consideration of five different roughness parameters, viz., centre line average roughness (R_a), root mean square roughness (R_q), skewness (R_{sk}), kurtosis (R_{ku}) and mean line peak spacing (R_{sm}) for the surface texture generated in PAC of EN 31steel.

The objectives of this study are to determine the effects and optimization of three process parameters viz., gas pressure, arc current and torch height on material removal rate and surface roughness characteristics in PAC of EN 31 steel using grey relational analysis coupled with Taguchi method. Analysis of variance (ANOVA) is performed to get percentage of contribution of each parameter on the performance characteristics. Confirmation testis conducted to check the validity of optimal process parameters.3D surface plots are generated to study the effects of input parameters on responses. Surface morphology is also studied with the help of SEM images.

2. Experimental procedure

2.1. Experimental setup

Experiments are conducted on the CNC plasma arc cutting (EPP-450, 380 V and 50/60 Hz) with PT-36 (Torch) supplied by ESAB. Air is used for the cutting gas when special electrodes made from water-cooled copper withinserts of metals such as hafnium are used. Mechanized torches can be mounted on a computer-controlled cutting machine. Usually a standoff is maintained between the torch tip and work piece for best-cut quality. In this study, the experimental plan has three controllable variables, namely, gas pressure, arc current and torch height. The response variables considered in the present study are: material removal rate (MRR) and surface roughness characteristics (R_a, R_q, R_{sk}, R_{ku} and R_{sm}).MRR is expressed as the ratio of weight difference of the work piece before and after machining to the machining time and in the present study it is measured by weight loss of the material and expressed by gm/sec.Roughness measurement is done using a stylus-type profilometer, *Talysurf* (Taylor Hobson, Surtronic 3+).In the machining parameter design, three levels with equal spacing of the cutting parameters are selected as shown in Table 1.

Table 1. Design factors and their levels

Design factors	Unit	Notation	Levels		
			1	2	3
Gas pressure	bar	A	5	6	7
Arc current	amp	B	180	190	200
Torch height	mm	C	2	4	6

2.2. Selection of work piece material

Rectangular block of 80 mm X 15 mm and 10 mm height made of EN 31 steel which is a high carbon alloy steel with high degree of hardness, compressive strength and abrasion resistance is selected as work piece. It is popularly used in automotive type applications like axle, bearings, spindle beading rolls, punches and dies etc.The tensile test has been done at room temperature by using a UTM (Instron) with 100 KN grip capacity, and 8810 controller; in displacement controlled mode. The test is controlled from command computer using 'Blue Hill' software. Mechanical and chemical properties of EN 31 steel are shown in Table 2.

Table 2.Mechanical and chemical properties of EN 31 steel

Work-piece material	Mechanical property	Chemical composition (wt%)
EN 31 tool steel	Modulus of Elasticity-197.37 GPa, Yield Strength (2% Strain Offset)-528.97 MPa, Ultimate Tensile Strength-615.40 Mpa and Poisson's Ratio-0.294	1.07% C, 0.57% Mn, 0.32% Si, 0.04% P, 0.03% S, 1.13% Cr and 96.84% Fe

2.3. Design of experiment (DOE)

Design of experiments (DOE) technique is used to obtain and organize the maximum amount of conclusive information from the minimum amount of experimental run, time, energy, money, or other limited resource. By applying this technique, it is possible to reduce the required time and number of experiments significantly for experimental investigations. In Taguchi method, an orthogonal array (OA) is employed to reduce the number of experiments for determining the optimal machining process parameters. An OA requires the minimum number of experimental trials to determine the main effect as well as interaction effects of parameters simultaneously. The choice of a suitable OA design depends on the total degrees of freedom (DOF) required for studying the main and interaction effects. DOF refers to the number of fair and independent comparisons that can be made from a set of observations. In present study, to check the DOFs in the experimental design, for the three-level test, the three main factors take 6 [3 X (3 − 1)] DOFs. The DOF for three second order interactions (A X B, A X C, B X C) is 12 [3 X (3 −1) X (3 − 1)] and the total DOFs required is 18 (6+12). Here the L_{27} OA (DOFs 26) has been selected because as per Taguchi method, the total DOFs of selected OA must be greater than or equal to the total DOFs required for the experiment.

3. Result and discussion

The experimental results for MRR and surface roughness are included in Table 3. Surface roughness parameters and MRR are optimized in this study and this is a multi-response optimization problem. Taguchi technique (Taguchi, 1990) is suitable for single response optimization, but optimization of multiple performance characteristics is different from of a single performance characteristics. For multi-response optimization, grey relational analysis (Deng, 1989) coupled with Taguchi method is employed in this study.

3.1. Grey analysis

The experimental results obtained from MRR and surface roughness tests are presented in Table 3. The final response needed for processing with Taguchi analysis is the grey relational grade which is obtained through the following set of calculations.

3.1.1. Grey relational generation

The first step in grey relational analysis is to perform the grey relational generation in which the results of the experiments are normalized in the range of 0 to 1. For normalization of MRR data, higher-the-better (HB) criterion (Eq. 1) and for surface roughness parameters, lower-the-better (LB) criterion (Eq. 2) are used as MRR is to be maximized and surface roughness is to be minimized.

$$X_i(k) = \frac{y_i(k) - min\, y_i(k)}{max\, y_i(k) - min\, y_i(k)} \tag{1}$$

$$X_i(k) = \frac{max\, y_i(k) - y_i(k)}{max\, y_i(k) - min\, y_i(k)} \tag{2}$$

where $x_i(k)$ is the value after grey relational generation, min $y_i(k)$ is the smallest value of $y_i(k)$ for the k^{th}response, and max $y_i(k)$ is the largest value of $y_i(k)$ for the k^{th} response. An ideal sequence is $x_0(k)(k=1,2,3,\ldots\ldots,27)$ for the response.The processed data after grey relational generation is given in Table 4. Larger normalized results correspond to the better performance and the best normalized result should be equal to 1.

Table 3. Design of Experiment and experimental for response parameters

Exp. No.	MRR (gm/sec)	R_a (μm)	R_q (μm)	R_{sk}	R_{ku}	R_{sm} (mm)	Exp. No.	MRR (gm/sec)	R_a (μm)	R_q (μm)	R_{sk}	R_{ku}	R_{sm} (mm)
1	1.850	1.85	2.38	0.299	3.888	0.111	15	1.427	1.81	2.14	0.225	3.640	0.113
2	1.333	2.02	2.49	0.750	4.010	0.124	16	2.210	1.62	2.19	0.273	3.330	0.100
3	1.425	1.97	2.45	0.219	3.806	0.141	17	1.760	1.78	2.16	0.219	3.870	0.125
4	1.001	3.74	4.49	0.051	3.650	0.204	18	2.145	1.45	1.83	0.843	3.680	0.100
5	1.672	1.99	2.51	0.232	3.989	0.138	19	1.895	1.78	1.67	0.328	3.943	0.091
6	1.044	3.11	4.00	0.341	3.623	0.205	20	2.065	1.81	2.35	0.485	4.398	0.101
7	1.703	1.99	2.55	0.211	3.845	0.117	21	1.616	1.91	2.35	0.299	4.326	0.115
8	1.175	1.70	2.14	0.369	4.266	0.115	22	1.4233	1.93	2.43	0.469	3.937	0.127
9	1.500	1.84	2.21	0.143	4.130	0.127	23	1.899	1.69	2.17	0.245	3.670	0.107
10	1.632	3.00	3.65	0.523	3.510	0.214	24	1.696	1.56	2.03	0.173	3.587	0.117
11	1.780	1.87	2.38	0.288	4.088	0.128	25	1.483	1.83	2.58	0.245	3.637	0.099
12	2.793	1.52	1.93	0.177	3.354	0.090	26	1.980	1.71	2.11	0.195	3.801	0.115
13	1.859	1.86	2.48	0.289	3.880	0.110	27	1.470	1.69	2.00	0.018	3.798	0.116
14	1.732	1.89	2.44	0.225	4.188	0.118							

3.1.2. Grey relational coefficient

Grey relational coefficients are calculated to express the relationship between the ideal (best = 1) and the actual experimental results. The grey relational coefficient $\xi_i(k)$ (k) can be calculated as:

$$\xi_i(k) = \frac{\Delta_{min} + \Psi\Delta_{max}}{\Delta_{0i}(k) + \Psi\Delta_{max}} \tag{3}$$

where $\Delta_{0i} = ||x_0(k) - x_i(k)||$ is difference of the absolute value between $x_0(k)$and $x_i(k)$, Δ_{min} and Δ_{max} are respectively the minimum and maximum values of the absolute differences (Δ_{0i}) of all comparing sequences. $\Psi$is a distinguishing coefficient, $0 \le \psi \le 1$, the purpose of which is to weaken the effect of Δ_{max} when it gets too big, and thus enlarges the difference significance of the relational coefficient. The suggested value of the distinguishing coefficient, Ψ, is 0.5, due to the moderate distinguishing effects and good stability of outcomes. Therefore, Ψ is adopted as 0.5 for further analysis in the present study. The grey relation coefficient of each performance characteristic is shown in Table 4.

3.1.3. Grey relational grade and grey relational ordering

The grey relational grade is treated as the overall response of the process instead of the multi response of MRR and surface roughness. The grey relational coefficients are calculated for the experimental data using $\Psi = 0.5$. The grey relational grade γ_i is obtained by averaging the grey relational coefficient as follows:

$$\gamma_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k) \tag{4}$$

where n is the number of process responses. Higher value of grey relational grade implies stronger relational degree between the ideal sequence $x_0(k)$ and the given sequence $x_i(k)$.Table 5 shows the experimental results for the grey relational grade and their orders. Thus multi-response optimization problem can be converted into single response optimization problem.

Table 4 Grey relational analysis

Exp. No.	Normalized of experimental data						Grey relational coefficient					
	MRR	Ra	Rq	Rsk	Rku	Rsm	MRR	Ra	Rq	Rsk	Rku	Rsm
1	0.4737	0.827	0.750	0.659	0.478	0.832	0.4872	0.743	0.667	0.595	0.489	0.749
2	0.1854	0.753	0.709	0.113	0.363	0.728	0.3803	0.669	0.632	0.360	0.439	0.648
3	0.2369	0.775	0.721	0.757	0.554	0.591	0.3959	0.690	0.642	0.673	0.529	0.549
4	0.0000	0.000	0.000	0.959	0.700	0.081	0.3333	0.333	0.333	0.924	0.625	0.352
5	0.3743	0.762	0.702	0.741	0.383	0.615	0.4442	0.677	0.627	0.658	0.448	0.565
6	0.0239	0.276	0.173	0.608	0.725	0.073	0.3388	0.409	0.377	0.560	0.645	0.350
7	0.3919	0.767	0.689	0.765	0.518	0.785	0.4512	0.682	0.617	0.681	0.509	0.699
8	0.0971	0.890	0.835	0.575	0.124	0.801	0.3564	0.819	0.752	0.540	0.363	0.715
9	0.2784	0.831	0.808	0.849	0.251	0.704	0.4093	0.747	0.722	0.768	0.400	0.628
10	0.3521	0.324	0.297	0.388	0.832	0.000	0.4355	0.425	0.415	0.449	0.748	0.333
11	0.4346	0.818	0.748	0.672	0.291	0.696	0.4693	0.734	0.665	0.604	0.414	0.622
12	1.0000	0.969	0.909	0.807	0.978	1.000	1.0000	0.943	0.847	0.722	0.957	1.000
13	0.4785	0.820	0.715	0.672	0.485	0.841	0.4895	0.735	0.637	0.604	0.493	0.759
14	0.4078	0.806	0.727	0.748	0.197	0.777	0.4578	0.721	0.647	0.665	0.384	0.692
15	0.2375	0.843	0.833	0.748	0.709	0.817	0.396	0.761	0.75	0.665	0.633	0.733
16	0.6745	0.927	0.815	0.691	1.000	0.923	0.6057	0.872	0.729	0.618	1.000	0.865
17	0.4235	0.855	0.825	0.756	0.494	0.720	0.4645	0.775	0.741	0.672	0.497	0.641
18	0.6383	1.000	0.944	0.000	0.672	0.923	0.5802	1.000	0.899	0.333	0.604	0.865
19	0.4991	0.857	1.000	0.624	0.425	0.995	0.4995	0.777	1.000	0.571	0.465	0.991
20	0.5936	0.845	0.759	0.433	0.000	0.915	0.5517	0.764	0.675	0.469	0.333	0.854
21	0.3431	0.800	0.757	0.658	0.067	0.801	0.4322	0.714	0.673	0.594	0.349	0.715
22	0.2356	0.793	0.732	0.453	0.432	0.704	0.3955	0.707	0.651	0.478	0.468	0.628
23	0.5009	0.898	0.823	0.724	0.682	0.865	0.5005	0.830	0.739	0.644	0.611	0.789
24	0.3878	0.951	0.872	0.812	0.759	0.785	0.4495	0.911	0.797	0.726	0.675	0.699
25	0.2691	0.834	0.679	0.724	0.713	0.927	0.4062	0.750	0.609	0.644	0.635	0.872
26	0.5462	0.887	0.846	0.785	0.559	0.801	0.5242	0.816	0.765	0.699	0.531	0.715
27	0.2617	0.896	0.883	1.000	0.562	0.793	0.4038	0.828	0.810	1.000	0.533	0.707

3.2. Analysis of Signal-to-Noise (S/N) ratio

To capture the variability of the results, signal to noise (S/N) ratio analysis is done taking the grey relational grade as the performance index. As grey relational grade is to be maximized, the S/N ratio for overall grey relational grade is calculated using higher-the-better (HB) criterion and is given by:

$$S / N ratio = -10 \log\left(\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right) \tag{5}$$

where y is the observed data and n is the number of observations.

The results may be expressed in terms of either the S/N ratio or the mean. The response table for the mean of grey relational grade is shown in Table 6.The response table compares the relative magnitude of the effects which includes ranks based on Delta statistics. The Delta statistic is the highest average for each factor minus the lowest average for the same. Ranks are assigned on the basis of Delta values.

Table 5.Grey relational grade and their order

Exp. No.	Grade	Order	Exp. No.	Grade	Order	Exp. No	Grade	Order
1	0.62159	12	10	0.46787	26	19	0.71736	3
2	0.52159	24	11	0.58455	19	20	0.60772	15
3	0.5799	20	12	0.91146	1	21	0.57961	21
4	0.48366	25	13	0.61961	13	22	0.55462	23
5	0.56983	22	14	0.59424	17	23	0.68557	7
6	0.4467	27	15	0.65617	9	24	0.70968	6
7	0.60653	16	16	0.78197	2	25	0.65275	10
8	0.5913	18	17	0.63198	11	26	0.67518	8
9	0.61247	14	18	0.71381	4	27	0.71374	5

Table 6.Response table for the grey relational grade

Level	A	B	C
1	0.5593	0.6213	0.6118
2	0.6624	0.5911	0.6069
3	0.6551	0.6644	0.6582
Delta	0.1031	0.0733	0.0513
Rank	1	2	3

3.3. Factor effects

Fig. 1 shows the main effects plot. In the main effects plot, if the line for a particular parameter is near horizontal, then the parameter has no significant effect. On the other hand, a parameter for which the line has the highest inclination will have the most significant effect. It is very much clear from the main effects plot that parameter A (gas pressure) is the most significant parameter, while B (arc current) also has a quite significant effect on the response. But parameter C (torch-height) has almost no effect. Since higher grey relational grade indicates that the system tends optimality, the optimal condition for each parameter is taken at those points where the mean grey relational grade is found to be the maximum. Hence the optimal process parameter combination for maximum material removal rate and minimum roughness characteristics of PAC is given as A2B3C3 (middle level of gas pressure, highest level of arc current and highest level of torch height).

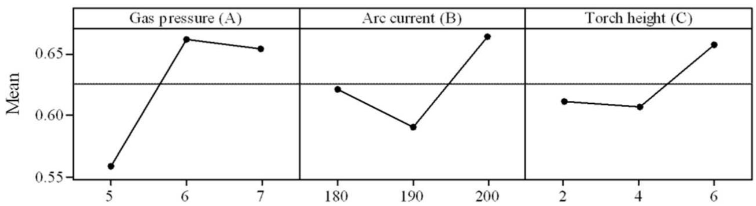

Fig. 1. Main effects plot for mean of grey relational grade

3.4. Effect of process parameters on responses

Fig. 2 shows the estimated three-dimensional surface as well as contour plots for MRR and roughness parameters as function of the independent machining parameters. In all these figures, one of the three independent variables is held constant at centre level. Fig 2(a, b) shows that MRR increases with an increase of gas pressure and MRR is minimum at centre level of arc current. However, with increase in torch height, MRR remains constant. A higher plasma gas flow rate leads to an increase in the mean arc voltage and its fluctuations. Therefore, more heat is transferred into the work piece on MRR increasing and consequently, roughnessvalue reduces (Bhuvenesh et al., 2012). It is seen from Fig. 2(c, d) that R_a decreases with an increaseof gas pressure and torch height and R_a increases

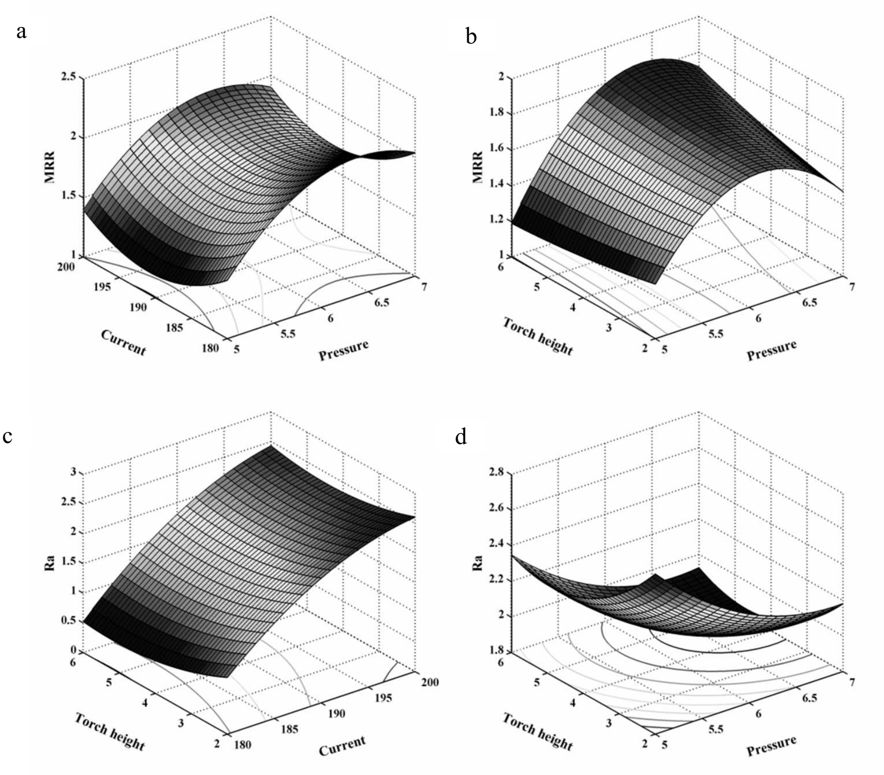

Fig. 2. 3D surface plots: a) MRR with current and pressure, b) MRR with torch height and pressure, c) R_a with torch height and current d) R_a with torch height and pressure

with increase of arc current. Minimum torch height results in over melting of the processing area that can not be removed and re-solidifies within the cutting area. This re-solidification is in the form of striations increasing thus the surface roughness. Also, surface roughness increases as the plasma arc current increases. This is due to the fact that amount of the molten metal which can be flashed away by the shielding gas is constant. Therefore, more heat is transferred into the sample, higher plasma arc current occurs, the shielding gas is increasingly unable to clear away the molten material, and so it builds up upon the surface of the parent material (Ozek et al., 2011).The variations of other roughness parameters are same as R_a though for the brevity of the paper, the plots are omitted.

3.5. Analysis of variance (ANOVA)

ANOVA is a statistical technique that can infer some important conclusions on the basis of analysis of the experimental data. The method is very useful for revealing the level of significance of influence of factor(s) or interaction of factors on a particular response. In the present study, ANOVA is performed using Minitab (Minitab, 2001). Table 7 shows the ANOVA result for overall grey relational grade of MRR and roughness parameters. ANOVA calculations are based on the F-ratio, which is the ratio between the regression mean square and the mean square error. The F-ratio, also called the variance ratio, is the ratio of variance due to the effect of a factor and variance due to the error term. This ratio is used to measure the significance of the parameters under investigation with respect to the variance of all the terms included in the error term at the desired significance level, α. If the calculated value of F-ratio is higher than its tabulated value, then the factor is significant at the desired α level. In general, when the F-value increases, the significance of the parameter also increases. ANOVA table shows the percentage contribution of each parameter. It is clear from the ANOVA table that parameter A (gas pressure) has got the most significant influence on MRR and roughness, which is about 24% contribution.

Table 7. Results of ANOVA for grey relational grade

Source of variation	Degrees of freedom	Sum of square	Mean square	F-ratio	% Contribution
A	2	0.05962	0.02981	2.56	23.8556338
B	2	0.02442	0.01221	1.05	9.771126761
C	2	0.01442	0.00721	0.62	5.769846351
A*B	4	0.00722	0.0018	0.16	2.888924456
A*C	4	0.03136	0.00784	0.67	12.54801536
B*C	4	0.01985	0.00496	0.43	7.942541613
Error	8	0.09304	0.01163		
Total	26	0.24992			

3.6. Confirmation test

After the optimal level of process parameters has been found out, a verification test needs to be carried out in order to check the accuracy of the analysis. Table 8 shows the comparison of the estimated grey relational grade with the actual grey relational grade obtained in the experiment using the optimal test parameters. It may be noted that there is good agreement between the estimated and actual grey relational grade. The improvement of grey relational grade from initial to optimal condition is 0.12391 which is about 21% improvement from the initial conditions.

Table 8.Results of confirmation test

Level	Initial parameter combination	Optimal parameter combination	
	A2B2C2	A2B3C3	
		Prediction	Experimental
MRR	1.732		2.145
R_a	1.896		1.4522
R_q	2.442		1.83
R_{sk}	0.2255		0.843
R_{ku}	4.187		3.68
R_{sm}	0.118		0.1
Grade	0.594278	0.6624	0.713811
Improvement of grey relational grade=0.12391 (21%)			

3.7. Surface morphology study

The surface morphology of before and after machining (Fig. 3) is studied with the help of scanning electron microscopy (SEM). Before machining, the work piece surface is nearly smooth and there is no globular spot and after machining the work surface becomes rougher and contains plenty of globules which are unevenly distributed due to grain coarsening near the cutting surface and it can be attributed to the very high temperatures and slow cooling. In PAC process, the material is heated to its melting point and cooled in the air after cutting. High heating and slow cooling could lead to temper conditions. This grain coarsening will decrease the hardness of the machined surface and make the surface less resistant to the wear or other environmental conditions.

4. Conclusion

This paper presents an investigation on the optimization and the effect of machining parameters on MRR and surface roughness characteristics in plasma arc cutting (PAC) of EN31 steel using Taguchi OA with grey relational analysis. The optimal combination of process parameters is obtained as A2B3C3 (middle level of gas pressure, highest level of arc current and highest level of torch height). Based on ANOVA, the highly effective parameters is gas pressure, whereas arc current and torch height are less effective factors within the specific test range. To check the validity of the analysis a confirmation test is carried out. There is an improvement of grey relational grade from initial to optimal process parameter by about 21%. Three dimensional contour and surface plots are studied, in which MRR is proportional to gas pressure and surface roughness is proportional to arc current.Finally, surface morphology of the surfaces is also studied using SEM images.

a b

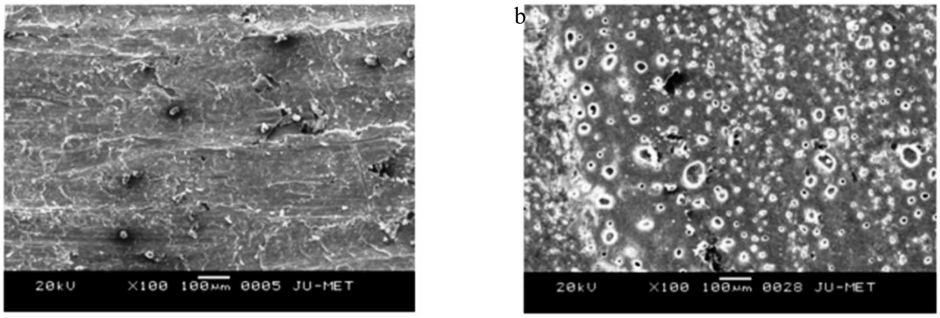

Fig. 3. SEM images (a) before machining; (b) after machining

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