

Optimisation of heat affected zone by partial swarm optimisation in air plasma cutting operation

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This paper presents development of mathematical model for prediction of heat affected zone (HAZ) and optimised parameters for air plasma cutting operation on AISI 6061 aluminium alloy. Experimental and predictive values from RSM are found of same trend. Partial swarm optimisation (PSO) was employed to optimise cutting parameters. Deviation of HAZ obtained by optimised HAZ model is 2.72%. Optimum cutting parameters for minimum HAZ are: output current, 100 A; stand-off gap, 1 mm and pressure, 620.52 kPa.

Keywords: Air plasma cutting, Heat affected zone, Partial swarm optimization (PSO)

Introduction

Plasma arc cutting is well suited for applications where speed and excellent cut quality are important. Because of intense heat of plasma arc (22,000°C) compared to gases (3150°C), cut is very clean with little or no dross. Plasma technology for industrial processes essentially uses thermal plasmas, which are produced at high pressures by means of direct or alternating current (dc-ac) or radiofrequency (RF) or microwave sources. Plasma technology based processes have been demonstrated on laboratory scale to generate value added materials (metals, ceramics, composites, etc.). Thermal plasmas (temp, 2000-20,000 K; charged particle density, 10^9 - 10^{21} m⁻³) offer unlimited scope for materials processing for a variety of applications¹⁻⁷. This study presents optimisation of welding parameters to obtain a better heat affected zone (HAZ).

Experimental Section

Response Surface Method (RSM)

In modelling of manufacturing processes using RSM, sufficient data is collected through designed experimentation. In general, a second order regression model is developed because of first order models often

give lack off fit⁸. The study uses Box-Behnken design (BBD) in optimization of experiments using RSM to understand effect of important parameters. BBD has fewer design points hence less expensive to run than central composite designs (CCD) with same number of factors. BBD ensures that all factors are never set at their high levels simultaneously⁹⁻¹¹. Proposed linear model correlating responses and independent variables can be represented as¹¹

$$y = m \times \text{output current} + n \times \text{stand-off gap} + p \times \text{air pressure} + C \quad \dots(1)$$

where y is response; C , m , n , p and q are constants.

Second-order model can be expressed as

$$y'' = \beta_0 x_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_{11} x_1^2 + \beta_{22} x_2^2 + \beta_{33} x_3^2 + \beta_{11} x_1 x_2 + \beta_{12} x_1 x_3 + \beta_{14} x_2 x_3 \quad \dots(2)$$

Experimental Setup

Air plasma stand-off method was used to weld aluminium alloy (AA6061-T6). Experiments were carried out on Cutmaster 101 air plasma model having following specifications: thermal dynamics, 20-80 A; input-output current, 1ph 200/230 V, 3ph 400V, 3ph 400 V CE, 3ph 415 V, 1/3 ph 460 V, 3ph 600V; duty cycle, 40% @ 80A, 100% @ 45A; 1Torch SL 100 @ with built in ATC quick; non HF

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Table 1—Design parameters

Output current A	Stand-off gap mm	Pressure kPa	HAZ mm
80	3	551	2.0296
60	3	482	1.8794
40	3	551	1.751
60	3	620	1.865
60	2	551	1.8264
40	2	482	1.4586
60	2	551	1.7906
40	2	620	1.471
80	2	482	2.3132
60	2	551	1.738
80	2	620	2.027
40	1	551	1.4422
60	1	482	1.6084
60	1	620	1.7992
80	1	551	2.083

(high frequency) start; and auto pilot restart for cutting expanded metal. Experiments were done with standoff cutting method, which normally cut metal (thickness > 4.8 mm) at current > 40 A. Normally, single-piece shield cup is used in 'standoff' cutting with torch tip (3.175-6.35 mm) from workpiece. Shield cup body together with deflector extends parts life and improves resistance to reflected heat. This combination provides cutting results similar to single piece shield cup, as well as easy changeover to gouging or drag shield cutting. Total 15 experiments were carried out accordingly to design of experiments (Table 1). A hole was made for each experiment since it is easy to measure HAZ. Each experiment was stopped after cutter penetrates workpiece. HAZ was measured with 2D microscope. Each experiment was repeated three times to obtain accurate readings of HAZ. Chemical composition of aluminium alloys workpiece is as follows: Al, 95.8-98.6; Cr, 0.04-0.35; Cu, 0.15-0.40; Fe, 0.7; Mg, 0.8-1.2; Mn, 0.15; Si, 0.4-0.8; Ti, 0.15; Zn, 0.25% (by wt).

Partial Swarm Optimisation (PSO)

PSO algorithm is similar to that of evolutionary computation techniques, in which a population of potential solutions to optimal problem under consideration is used to probe search space. Each potential solution is also assigned a randomized velocity, and potential solutions, called particles, correspond to individuals. Each particle in PSO flies in D -dimensional problem space with a velocity dynamically adjusted according to flying

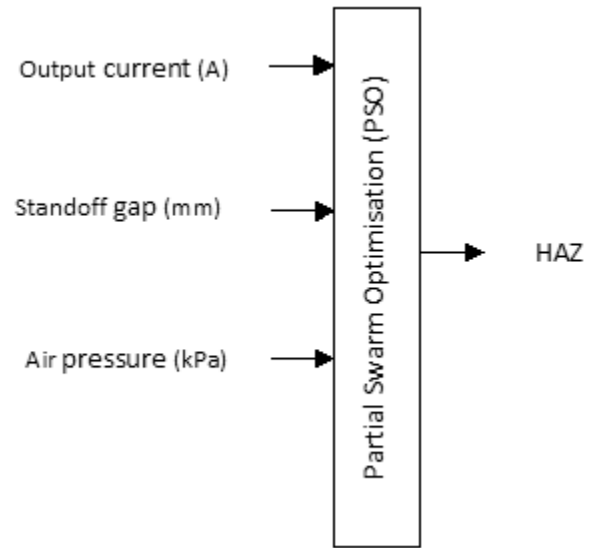


Fig. 1—PSO for paddle cantilever

experiences of its individuals and their colleagues. Location of i th particle is represented as $X_i = [x_{i1}, x_{i2}, \dots, x_{iD}]$, where $x_{id} \in [I_d, U_d]$, $d \in [1, D]$, I_d and U_d are lower and upper bounds for d th dimension, respectively. Best previous position (which gives best fitness value) of i th particle is recorded and represented as $P_i = [p_{i1}, p_{i2}, \dots, p_{iD}]$, which is also called P_{best} . Index of best particle among all particles in population is represented by g and location P_g by g_{best} . Velocity of i th particle is represented by $V_i = [v_{i1}, v_{i2}, \dots, v_{iD}]$ and is clamped to a maximum velocity, $V_{max} = [v_{max1}, v_{max2}, \dots, v_{maxD}]$, which is specified by user. PSO consists of, at each time step, regulating velocity and location of each particle toward its P_{best} and g_{best} locations, respectively, as¹²

$$v_{id}^{n+1} = wv_{id}^n + c_1r_1^n(p_{id}^n - x_{id}^n) + c_2r_2^n(p_{gd}^n - x_{id}^n) \quad \dots(3)$$

$$x_{id}^{n+1} = x_{id}^n + v_{id}^{n+1} \quad \dots(4)$$

PSO outputs have been termed as one output node representing state variable (HAZ). Experimental results are used for optimisation of tool life model using PSO (Fig. 1) Codes for PSO are written in Matlab 7.0 which follows logic of pseudo code (Fig. 2). PSO technique¹³ performs back propagation (BP) algorithms to predict diameter error in a boring machining. To overcome stagnation in searching a globally optimal solution, a PSO method with nonlinear time-varying evolution (PSO-NTVE) is proposed to approach optimal solution closely. When determining parameters in proposed method, matrix experiments with an orthogonal array are utilized,

in which a minimal number of experiments would have an effect that approximates full factorial experiments¹⁴. Changa & Ko¹⁵ proposed a method with nonlinear time-varying evolution based on neural network (PSO-NTVENN) to design large-scale passive harmonic filters (PHF) under abundant harmonic current sources. This method minimizes cost of filters, filters loss, and total

harmonic distortion of currents and voltages at each bus, simultaneously. An effective hybrid PSO approach¹⁶ (PSOHT) has been proposed to observe performance of PSO for function optimization in noisy environment.

Results and Discussion

After conducting first pass of 15 cutting experiments, HAZ readings are used to find parameters appearing in postulated first order model [Eq. (1)] and quadratic model. In order to calculate these parameters, least square method is used with the aid of Minitab. First-order linear equation used to predict surface roughness is expressed as

$$\text{HAZ}' = 0.88 + 0.150 \cdot \text{current} + 0.074 \text{Gap} - 0.000176 \text{Pressure} \quad \dots(5)$$

$$\text{HAZ}'' = -2.14 + 0.0420 \cdot \text{current} + 0.732 \text{Gap} +$$

$$0.0052 \text{ Pressure} + 0.006 \text{Gap} - 0.004 \text{Power} \times \text{Gap} \quad \dots(6)$$

Generally, increase of output current and stand-off gap cause larger HAZ. On the other hand, reduction in pressure causes slight increase in HAZ. A better HAZ is obtained with the combination of low output current, stand-off gap and high pressure. Relationship between output current and HAZ is statistically significant compared with other variables for linear form (Table 2) and quadratic form (Table 3). Predicted HAZ using second order RSM model closely match with experimental results (Fig. 3), exhibiting better agreement as compared to those from first-order RSM model. Analysis of variance (ANOVA) for first order and second order (Table 4)

```

For each particle
  Initialize particle
End

Do
  For each particle
    Calculate fitness value
    If fitness value is better
    than best fitness value (pBest) in history
      set current value as new
  pBeat
  End
  Choose particle with best
  fitness value of all particles as
  gBest
  For each particle
    Calculate particle velocity
    according Eq (3)
    Update particle position
    according Eq (4)
  End

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Fig. 2—A pseudo-code for PSO

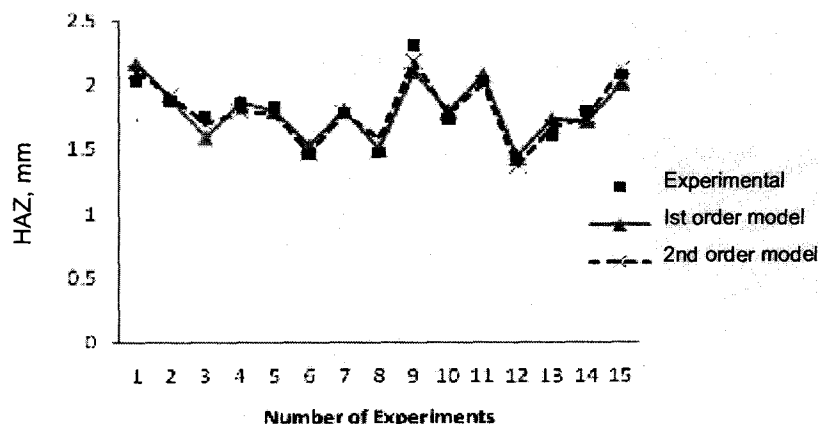


Fig. 3—Comparison between experimental and predicted results

Table 2—Estimated regression coefficients for HAZ (mm) for linear form

Term	Coefficient	Standard error of coefficient	T	Probability values
Constant	1.80551	0.02815	64.15	0
Output current, A	0.29125	0.03854	7.557	0
Stand-off gap, mm	0.07403	0.03854	1.921	0.081
Pressure, kPa	-0.01217	0.03854	-0.316	0.758

Table 3—Estimated regression coefficients for HAZ (mm) for quadratic form

Term	Coefficient	Standard error of coefficient	T	Probability values
Constant	1.79	0.06	28.16	0.00
Output current, A	0.29	0.04	7.50	0.00
Stand-off gap, mm	0.07	0.04	1.91	0.12
Pressure, kPa	-0.01	0.04	-0.31	0.77
Output current(A)*Output current(A)	0.04	0.06	0.62	0.56
Stand-off gap(mm)*Stand-off gap (mm)	0.01	0.06	0.11	0.92
Pressure(kPa)*Pressure(kPa)	0.00	0.06	-0.05	0.96
Output current(A)*Stand-off gap(mm)	-0.09	0.05	-1.65	0.16
Output current(A)*Pressure(kPa)	-0.07	0.05	-1.36	0.23
Stand-off gap(mm)*Pressure(kPa)	-0.05	0.05	-0.93	0.39

Table 4—ANOVA for first and second order models

Source	First order				Second Order			
	Degree of freedom	Sequential sum of squares	F	Probability	Degree of freedom	Sequential sum of squares	F	Probability
Regression	3	0.723636	20.3	0	9	0.794066	7.32	0.021
Linear	3	0.723636	20.3	0	3	0.723636	20.01	0.003
Square					3	0.004813	0.13	0.936
Interaction					3	0.065617	1.81	0.261
Residual error	11	0.130704			5	0.060274		
Lack-of-fit	9	0.12675	7.12	0.129	3	0.05632	9.5	0.097
Pure error	2	0.003954			2	0.003954		
Total	14	0.85434						

Table 5—Comparison of minimum optimised HAZ with experimental results

Output current	Stand-off gap	Pressure kPa	Experimental HAZ	Predicted HAZ	Deviation %
A	mm		mm	mm	
100	1	620.52	0.147	0.143	
100	1	620.52	0.145		
100	1	620.52	0.150		
			Avg:0.1473	0.143	2.72

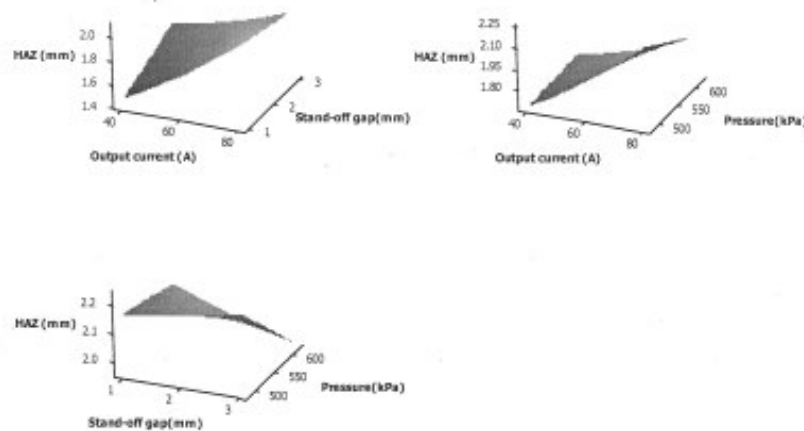


Fig. 4—Surface plot when all variables are fixed at highest values

indicates that model is adequate as P -value of lack-of-fit is not significant (>0.05). Surface plot (Fig. 4) indicates pattern of variables towards response. All variables are fixed at high values to observe changing of HAZ pattern toward output current, stand-off gap and air supply pressure.

Validation

Predicted HAZ using optimised HAZ model is compared with measured HAZ (Table 5). Validation experiment is performed in same machining environment as training experiment. Deviation of HAZ obtained by optimised HAZ model is 2.72%. Optimum cutting parameters for minimum HAZ are: output current, 100 A; stand-off gap, 1 mm; and pressure, 620.52 kPa.

Conclusions

Using PSO, an optimised minimum HAZ prediction model has been formulated for welding of AA6061-T6. Error analysis of prediction result with measured results is small (2.72% for minimum HAZ) and shows efficacy of prediction model. PSO combined with RSM can be very successively used for reduction of effort and time. It can solve problems having mathematical and time difficulties.

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