Mathematical modeling and optimization of weld bead geometry in cladding by flux cored arc welding

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Abstract

In this paper, an attempt is made to determine input-output relationships of the cladding by flux cored arc welding process using regression analysis based on the a three factor, five level central composite experimental design with six centre points. After measuring bead width, depth of penetration and reinforcement; based on simple assumptions on the shape of bead geometry, other relevant bead geometry parameters are calculated. Several linear and curvilinear regression analyses are employed to establish the input-output relations and the best set of equations is then selected. Finally simulated annealing has been applied for parametric optimization of this welding technique.

Keywords: Flux cored arc welding (FCAW) – Regression - Optimization – Simulated Annealing (SA).

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In this paper, an attempt is made to determine input-output relationships of the cladding by flux cored arc welding process using regression analysis based on the a three factor, five level central composite experimental design with six centre points. After measuring bead width, depth of penetration and reinforcement; based on simple assumptions on the shape of bead geometry, other relevant bead geometry parameters are calculated. Several linear and curvilinear regression analyses are employed to establish the input-output relations and the best set of equations is then selected. Finally simulated annealing has been applied for parametric optimization of this welding technique.

Keywords: FCAW – Simplified weld bead geometry – Regression – Simulated Annealing

1. Introduction

Among fusion welding processes, flux cored arc welding (FCAW) has been widely used for cladding due to several advantages. Process parameters for FCAW should be well established and categorized to enable automation and robotization of arc welding. The selection of welding procedure must be more specific to ensure that adequate bead quality is obtained [1]. Further to obtain the desired quality welds, it is essential to have complete control over the relevant process parameters to obtain the required bead geometry and shape relationships on which the integrity of a weldment is based [1]. It has also been reported by some researchers that in FCAW, process quality can be represented by bead shape [2]. Thus, the weld bead geometry plays an important role in determining the mechanical properties of the weld. Therefore, it is very important to select and control the welding process parameters for obtaining optimal weld bead geometry.

Numerous research works exist on the modelling and optimization of process parameters in welding. Gunaraj and Murugan [3] used modelling and optimization of weld bead volume for the submerged arc process. Datta and Kumar [4] modeled and optimized features of bead geometry including percentage dilution in submerged arc welding. Comprehensive surveys in this field can be found in literature [5]. Nevertheless, most of the proposed models are complicated and highly non linear. In addition, most studies have attempted to model the directed measured BH, BW and

BP only, regardless of the important shape relations of the weld bead. Some important shape relations such as weld reinforcement form factor (WRFF) and weld penetration shape factor (WPSF), have significant impact on the quality of weld.

In the present work, an attempt has been made to carry out linear as well as curvilinear regression analyses on the FCAW data collected by Palani and Murugan [6] using a three factor, five level central composite experimental design with six centre points. The text is organized as follows: Shape relationships of simplified weld bead geometry are calculated. Input-output variables of the process have been identified and their feasible ranges have been set. Both linear as well as curvilinear regression analyses carried out in the present work and the results are stated and discussed. Finally SA algorithm is used to optimize the FCAW process.

2. Calculation of bead geometry (shape relationships)

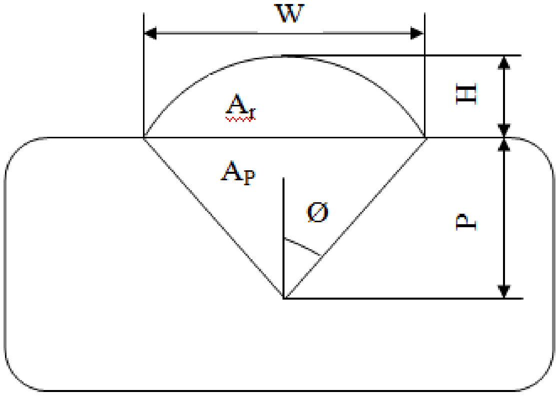

Figure 1. Simplified weld bead geometry.

Assuming the shape of bead cross-section to be a circular sector, from simple geometry, total bead cross sectional area can be easily approximately evaluated. Simplified bead geometry is shown in Figure 1.

$\tan \varphi = W/2p$, (φ in degree) (1)

$A_t = (p+h)^2 \varphi$, (φ in radian) (2)

$A_p = 0.5\,WP$ (3)

$A_t = A_p + A_r$ (4)

$WPSF = W/P$ (5)

$WRFF = W/h$ (6)

$\%D = (A_p/A_t) \times 100$ (7)

In order to achieve optimum welding performance, it is important to properly set the welding parameters. The selected input process parameters in this study and their levels of the FCAW process are shown in Table 1.

Table 1. Input factors and their levels of the FCAW process

Parameter	Units	Notation	Factors levels				
			-1.68179	*-1*	*0*	*1*	*1.68179*
welding speed	cm/min	(S)	*26*	*29*	*34*	*39*	*42*
welding current	A	(I)	*176*	*190*	*210*	*230*	*244*
Nozzle-to-plate distance	mm	(N)	*15*	*17*	*20*	*23*	*25*

The calculated weld bead geometry is shown in Table 2.

Table 2: Calculated weld bead geometry

Sl. No.	*WPSF*	*WRFF*	*Ap*	*At*	*Ar*	*PD*
1	*11.78750*	*2.095556*	*3.772*	*39.40256*	*35.63056*	*9.572981*
2	*12.29091*	*2.846316*	*7.436*	*48.23621*	*40.80021*	*15.41580*
3	*11.10667*	*2.0825*	*3.124*	*31.42130*	*28.29755*	*9.941506*
4	*12.07000*	*2.84*	*6.035*	*38.76909*	*32.73409*	*15.56653*
5	*10.52222*	*2.036559*	*4.262*	*42.59872*	*38.33722*	*10.00382*
6	*10.90909*	*2.474227*	*6.600*	*49.19094*	*42.59094*	*13.41710*
7	*12.46667*	*2.280488*	*3.506*	*33.20728*	*29.70103*	*10.55868*
8	*15.52632*	*2.694064*	*4.484*	*38.11525*	*33.63125*	*11.76432*
9	*12.41429*	*2.109223*	*3.042*	*32.78241*	*29.74091*	*9.277843*
10	*13.58000*	*2.889362*	*6.790*	*46.28435*	*39.49435*	*14.67019*
11	*10.93636*	*2.358824*	*6.617*	*53.42848*	*46.81198*	*12.38384*
12	*10.20408*	*2.352941*	*4.900*	*37.67178*	*32.77178*	*13.00708*
13	*12.22222*	*2.444444*	*4.950*	*41.07470*	*36.12470*	*12.05121*
14	*14.11765*	*2.649007*	*5.100*	*41.39241*	*36.29241*	*12.32110*
15	*10.84694*	*2.415909*	*5.209*	*40.18815*	*34.97945*	*12.96078*
16	*10.00000*	*2.222222*	*5.000*	*41.54537*	*36.54537*	*12.03503*
17	*10.68421*	*2.393868*	*4.821*	*37.32659*	*32.50534*	*12.91640*
18	*10.91489*	*2.358621*	*4.822*	*38.88589*	*34.06369*	*12.40090*
19	*11.57895*	*2.449889*	*5.225*	*41.42384*	*36.19884*	*12.61351*
20	*9.41000*	*2.045652*	*4.705*	*42.69265*	*37.98765*	*11.02063*

Therefore, the responses considered are: Weld penetration shape factor (WPSF), Weld reinforcement form factor (WRFF), Area of penetration (Ap), Area of reinforcement (Ar), Bead cross sectional area (At) and %Dilution (%D).
Five levels are considered for each of the three input process parameters and thus, 20 combinations of input process parameters are to be considered for the central composite design of experiments. The aim of the present investigation is to establish relations between the process parameters (inputs) and responses (outputs) for FCAW process and finding the optimum input parameters using SA algorithm.

3. The solution procedure – SA algorithm

For real and large size optimization problems, the traditional optimization methods are often inefficient and time consuming. With the advent of computer technology and computational capabilities in the last few decades, the applications of heuristic algorithms are widespread. These techniques are usually based on the physical or natural phenomena. In 1953, Metropolis proposed a procedure used to simulate the cooling of a solid for reaching a new energy state. The annealing process, used in metal working, involves heating the metal to a high temperature and then letting it gradually cools down to reach a minimum stable energy state. If the metal is cooled too fast, it won't reach the minimum energy state. Later Kirkpatrick and his colleagues [7] used this concept to develop a search algorithm called Simulated Annealing (SA). Among different heuristic algorithms, SA is one of the most powerful optimization methods that simulates the cooling process of a molten metal. The general stages of the SA algorithm are as follows:

1. BEGIN: Initialize the temperature parameter T_0 and the cooling schedule; r ($0 < r < 1$) and the termination criterion (e.g. number of iterations $k = 1 \dots K$). Generate and evaluate an initial candidate solution (perhaps at random); call this the current solution, c.

2. Generate a new neighbouring solution, m, and evaluate this new solution.

3. Accept this new solution as the current solution if:

   3-a) The objective value of new solution, f (m), is better than of the current solution, f (c).

   3-b) The value of acceptance probability function given by ($\exp(f(m) - f(c)) / T_k$) is greater than a uniformly generated random number “rand”; where $0 < rand < 1$.

4. Check the termination criterion and update the temperature parameter (i.e., $T_k = r * T_{k-1}$) and return to Step 2.

The main advantages of SA are its flexibility, its fewer tuning parameters, and its ability to escape local optima and to approach global optimality.

4. Modeling

To develop the mathematical models, various linear and curvilinear regression functions have been fitted to the experimental data. The best set of models is then chosen based on two criteria, namely; correlation coefficient and Analysis of Variance (ANOVA) results, with 95% confidence level. The calculated coefficient of determination R^2, P-value and F-value for regression functions are shown in Tables 3, 4 and 5, respectively.

Table 3. The calculated R^2 for regression functions

objective function	WPSF	WRFF	Ar	Ap	At	%D
First order	21.5	73.5	81.0	85.2	83.3	78.2
Second order	81.6	**86.8**	**87.2**	95.3	**89.7**	91.8
Third order	**93.0**	91.2	88.5	**96.3**	90.5	**95.4**

Table 4. The calculated P-value for regression functions

objective function	WPSF	WRFF	Ar	Ap	At	%D
First order	0.262	0.000	0.000	0.000	0.000	0.000
Second order	0.010	**0.002**	**0.002**	0.000	**0.001**	0.000
Third order	**0.017**	0.033	0.065	**0.003**	0.040	**0.006**

Table 5. The calculated F-value for regression functions

objective function	WPSF	WRFF	Ar	Ap	At	%D
First order	1.46	14.77	22.74	30.69	26.70	19.10
Second order	4.93	**7.28**	**7.58**	22.68	**9.68**	12.37
Third order	**6.16**	4.77	3.55	**12.01**	4.38	**9.49**

Based on Tables 3 to 5, for WPSF, Ap and %D third order and for WRFF, Ar and At second order polynomial equations are selected. To improve the models, insignificant factors should be removed from equations using step backward elimination with 95 percent confidence level. Therefore, the modified regression models are as follows:

$$\begin{aligned} WPSF = {} & 243 - 16.8\,S + 0.000947\,I^2 + 0.545\,S^2 - 0.0135\,I{*}S - 0.0207\,I{*}N - 0.0872 \\ & S{*}N + 0.00181\,N^3 - 0.00532\,S^3 + 0.000735\,N{*}I{*}S \end{aligned} \tag{8}$$

$$WRFF = 0.929 + 0.000102\,I^2 + 0.00774\,N^2 - 0.00148\,I{*}N \tag{9}$$

$$Ar = 110 - 4.40\,S + 0.000297\,I^2 + 0.0531\,S^2 \tag{10}$$

$$Ap = -15.2 + 0.168\,I - 0.761\,S + 0.00991\,S^2 + 0.0306\,S{*}N - 0.000151\,N{*}I{*}S \tag{11}$$

$$At = 106 + 0.184\ I - 5.26\ S + 0.0643\ S^2 \qquad (12)$$

$$\%D = -129 + 15.1\ N - 0.0662\ S^2 - 0.854\ N^2 + 0.0114\ I{*}S + 0.0108\ I{*}N + 0.143\ S{*}N + 0.0141N^3 + 0.000673\ S^3 - 0.000743\ N{*}I{*}S \qquad (13)$$

5. Optimization

SA Algorithm is used to optimally determine input parameters levels in order to obtain any desired set of outputs. Usually, for high quality joint in FCAW the Ar, WRFF and WPSF should be as low as possible while Ap and %D should be at their highest possible values. To achieve this, a multi-objective fitness function, based on mean square error, is defined as follows:

$$Fitness = \frac{(WPSF_d - WPSF)^2}{WPSF^2} + \frac{(WFRR_d - WFRR)^2}{WFRR^{\,2}} + \frac{(Ar_d - Ar)^2}{Ar^{\,2}} + \frac{(Ap_d - Ap)^2}{Ap^{\,2}} + \frac{(\%D_d - \%D)^2}{\%D^{\,2}} \qquad (14)$$

Where, $WPSF_d$, $WFRR_d$, Ar_d, Ap_d and $\%D_d$ are the desired values of the process output characteristics set by the operator. The algorithm along with its objective function has been coded in Matlab software. In our computations, the relative importance (weights) of the output parameters are set to unity. In practices, these weights may be set at any relative values as required. SA parameters settings are as follows: initial temperature: 1000, cooling rate: 0.99, termination criterion: 1000 iterations. The convergence curve of the SA is shown in Figure 2.

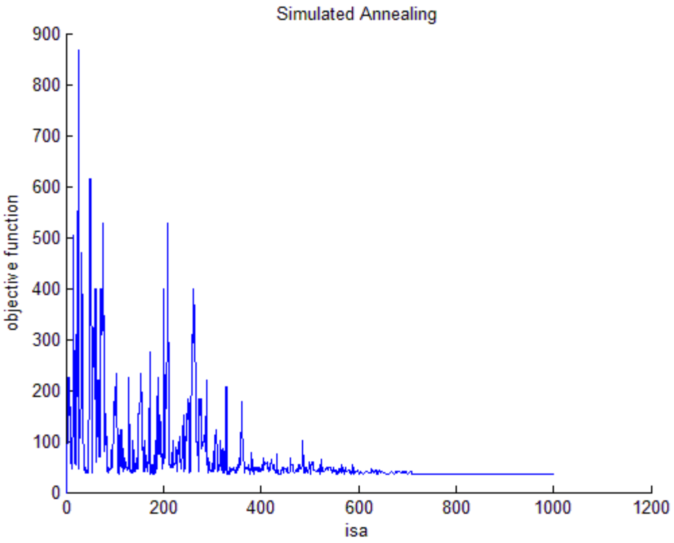

Figure 2: The convergence curve of the SA algorithm

The best input parameters to gain optimum results are as follows: S: 29, I: 244, N: 20. Since in all runs, which were started from random point, lead to one specific above mentioned answer, the answer is the global answer of the process.

6. Conclusion

Weld bead geometry is the most important quality measure in all types of welding techniques. To achieve a high quality weld, welding parameters should be set in such way that the desired bead geometry is obtained. The relationships between bead geometry and welding parameters are quite complicated involving many interactions. The main trust of this research was to establish the mathematical relationships between input and output parameters and to explore the possibility of using SA algorithm in predicting input parameters values in Flux Cored Arc Welding. Along this line, using DOE approach and regression analysis, different mathematical models were developed to establish the relationships between welding input parameters and weld bead geometry. The ANOVA results denote that the curvilinear models are the best representative for the actual FCAW process. The direct use of these models is to calculate weld bead geometry for any given set of process parameters. In this research, these models were put to use as a part of prediction procedure for determining process parameters for any desired weld bead geometry. To achieve this, a SA technique was developed to minimize an error function consisting of desired and calculated weld bead geometry. By minimizing such a function, the process parameters can be determined so as the resultant bead geometry has the least deviation from its desired value. Computational results indicate that the proposed SA method can efficiently and accurately determine welding parameters for a desired bead geometry specification.

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