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Modeling and optimization of MAG welding for gas pipelines using regression analysis and simulated annealing algorithm

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This study established input-output relationships for metal active gas (MAG) welding for gas pipelines. Regression analysis (RA) was performed on data collected as per Taguchi design of experiments. Adequacy of RA model was verified using ANOVA method. RA model was then embedded into a simulated annealing (SA) algorithm to determine optimal process parameters for weld bead geometry specification. Proposed method is found quite effective in predicting process parameters for weld bead geometry.

Keywords: MAG welding, Modeling, Process parameters optimization, SA algorithm, Weld bead geometry

Introduction

Quality of a weld joint is directly influenced by welding input parameters during welding. A common problem faced by manufacturer is control of process input parameters to obtain a good welded joint with required bead geometry and weld quality with minimal detrimental residual stresses and distortion. Roberts & Wells[1] estimated weld bead width by considering conduction heat transfer. Christensen *et al*[2] derived non dimensional factors to relate bead dimensions with operating parameters. Chandel *et al*[3] presented predictions of effect of current, electrode polarity, electrode diameter, and electrode extension on melting rate, bead height, bead width and weld penetration in submerged arc welding. Markelj & Tusek[4] mathematically modeled current and voltage in TIG welding. Kim *et al*[5] conducted a sensitivity analysis of a robotic GMAW (gas metal arc welding) process employing non-linear multiple regression analysis (RA) for modeling process and quantified respective effects of process parameters on weld bead geometry (WBG) parameters. Kim *et al*[6] compared experimental GMAW weld bead geometry results with those obtained from heat-transfer and regression models. Kim *et al*[7] applied modified Taguchi method to determine process parameters for optimum weld pool geometry in TIG welding of stainless steel. Tarng *et al*[8,9] determined optimum process parameters for submerged arc welding (SAW) in hard facing using grey-based Taguchi method. New trend in manufacturing processes parameters optimization is to use evolutionary algorithms such as genetic algorithm (GA)[10] and simulated annealing(SA)[11]. Other search methods have also been used for this purpose[12]. Along this line, SA Algorithm is a well known evolutionary method successfully adopted in different areas[13].

This study proposed a SA approach to establish relationships between process parameters (inputs) and responses (outputs) in metal active gas (MAG) welding using RA carried out on data collected as per Taguchi design of experiments (DOE).

Experimental

For modeling and optimization of MAG welding process (Fig. 1), a consumable electrode is used as filler with an active gas shielding to protect molten metal from oxidation. Important input parameters in MAG are welding speed (S), welding voltage (V), wire feed rate (F), nozzle-to-plate distance (D) and torch angle (A), whereas output parameters (responses) are bead height (BH), bead width (BW) and bead penetration (BP). Three levels were considered for input process parameters (Table 1) and 54 combinations of input process parameters were considered for Taguchi DOE

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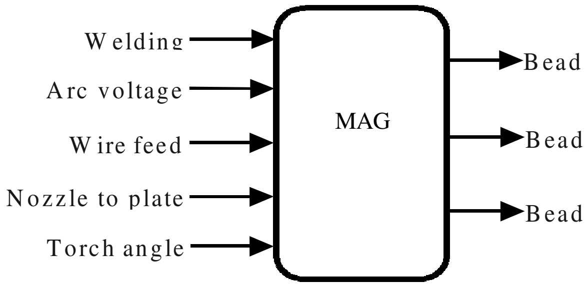

Fig. 1—Important input and output parameters for MAG welding process

Table 1— Input variables and their levels of GMAW welding process

Factor	Level -	Level 0	Level +
Welding speed (S), cm/m	10	17	24
Arc voltage (V), V	27	32	37
Wire feed rate (F), m/min	4	5.5	7
Torch angle (A), °	70	85	100
Nozzle-plate distance (D), cm	1	-	1.5

(Table 2). In combinatorial optimization, evolutionary algorithms (GA and SA) were used. Three sets of mathematical equations (linear, curvilinear and logarithmic) were developed to model relationships between process variables and WBG in gas metal arc welding. SA approach is proposed to determine optimal values for process parameters with respect to any given bead geometry. Proposed solution procedure is developed in such way that it can accurately determine best process variables through minimization of an error function with respect to any desired weld bead specifications.

Model Development

According to Taguchi L_{54} DOE matrix, out of a total of 54 combinations of input parameters (Table 2), last three columns were measured outputs for each test setting. These data can be used to develop mathematical models. Any of the above WBG is a function of process parameters, which are expressed by linear [Eq. (2)], curvilinear [Eq. (3)] or logarithmic functions [Eq. (4)] as

$$Y = f(S,V,F,D,A) \quad \ldots(1)$$

$$Y_1 = b_0 + b_1S + b_2V + b_3F + b_4D + b_5A \quad \ldots(2)$$

$$Y_2 = b_0 + b_1S + b_2V + b_3F + b_4D + b_5A + b_{11}S^2 + b_{22}V^2 + b_{33}F^2 + b_{44}D^2 + b_{55}A^2 + b_{12}SV + b_{13}SF + b_{14}SD + b_{15}SA + b_{23}VF + b_{24}VD + b_{25}VA + b_{34}FD + b_{35}FA + b_{45}DA \quad \ldots(3)$$

$$Y_3 = b_0\, S^{b1}\ V^{b2}\ F^{b3}\ D^{b4} A^{b5} \quad \ldots(4)$$

Choice of model depends on nature of initial data and required accuracy. Using RA in Minitab Software, linear, curvilinear and logarithmic functions were fitted to experimental data. Models representing relationship between process parameters and WBG can be stated as

Linear Model

$$BH = 5.12 + 0.707D - 0.00528\,A + 0.270\,F - 0.0754S - 0.0925\,V \quad \ldots(5)$$

$$BW = -6.20 - 1.48\,D + 0.0316\,A + 0.565F - 0.282S + 0.480V \quad \ldots(6)$$

$$BP = -1.53 - 0.726D - 0.00222A + 0.109\,F + 0.0313S + 0.0803\,V \quad \ldots(7)$$

Curvilinear Model

$$BH = 4.08 - 0.00184SV - 0.000707AV + 0.00271AF + 0.646\,DD - 0.0535\,DS + 0.00144\,SS \quad \ldots(8)$$

$$BW = 2.07 + 0.0169\,VV - 0.0211\,SV - 0.183\,DV + 0.0172\,SS + 0.710\,DF - 0.0309\,FS \quad \ldots(9)$$

$$BP = -1.55 + 0.0834\,V + 0.00596\,FS - 0.257\,DD \quad \ldots(10)$$

Logarithmic Model

$$BH = e^{2.39} D^{0.238} A^{-0.114} F^{0.528} S^{-0.434} V^{-1.08} \quad \ldots(11)$$

$$BW = e^{-1.55} D^{-0.197} A^{0.0894} F^{0.304} S^{-0.524} V^{1.80} \quad \ldots(12)$$

$$BP = e^{-4.08} D^{-0.721} A^{0.048} F^{0.372} S^{0.453} V^{2.20} \quad \ldots(13)$$

Above models were modified using stepwise elimination process. For instance, independent variable

Table 2—Design of experiments matrix for bead geometry parameters with respect to process parameters

No.	D cm	A°	F m/min	S cm/min	V v	BH mm	BW mm	BP mm
1	1	70	4	10	27	3.3	7.06	0.85
2	1	70	5.5	17	32	2.75	6.32	1.45
3	1	70	7	24	37	2.2	8.95	2.6
4	1	85	4	10	32	2.35	9.85	1.1
5	1	85	5.5	17	37	2.25	11.35	1.95
6	1	85	7	24	27	3.15	5.48	1.6
7	1	100	4	17	27	2.6	5.48	1.05
8	1	100	5.5	24	32	1.8	7.52	1.8
9	1	100	7	10	37	2.65	15.08	1.55
10	1.5	70	4	24	37	1.6	7.37	1.5
11	1.5	70	5.5	10	27	4.25	7.57	0.45
12	1.5	70	7	17	32	3.2	8.42	1.35
13	1.5	85	4	17	37	2.1	9.03	1.5
14	1.5	85	5.5	24	27	2.8	4.92	0.95
15	1.5	85	7	10	32	4.1	10.38	0.9
16	1.5	100	4	24	32	1.95	5.57	1.1
17	1.5	100	5.5	10	37	2.65	12.9	1.3
18	1.5	100	7	17	27	3.9	5.97	0.5
19	1	70	4	10	27	3.4	7.07	0.75
20	1	70	5.5	17	32	2.65	8.2	1.3
21	1	70	7	24	37	2.4	9.25	2.4
22	1	85	4	10	32	2.55	10.25	0.8
23	1	85	5.5	17	37	2.15	11.47	1.55
24	1	85	7	24	27	2.95	5.55	1.3
25	1	100	4	17	27	2.55	5.3	0.9
26	1	100	5.5	24	32	2.2	6.3	1.6
27	1	100	7	10	37	3.2	15.2	1.7
28	1.5	70	4	24	37	1.7	6.92	1.1
29	1.5	70	5.5	10	27	4	7.63	0.5
30	1.5	70	7	17	32	3.3	7.38	1.35
31	1.5	85	4	17	37	2.05	8.4	1.65
32	1.5	85	5.5	24	27	2.8	4.85	1.1
33	1.5	85	7	10	32	4.15	11.12	1
34	1.5	100	4	24	32	2	5.77	1.3
35	1.5	100	5.5	10	37	3.1	12.8	1.2
36	1.5	100	7	17	27	3.8	5.47	0.6
37	1	70	4	10	27	3.5	7.13	0.6
38	1	70	5.5	17	32	2.3	8.48	1.35
39	1	70	7	24	37	2	9.87	2.2
40	1	85	4	10	32	3	9.34	1.05
41	1	85	5.5	17	37	2.2	11.36	1.85
42	1	85	7	24	27	3.1	5.36	1.25
43	1	100	4	17	27	2.65	5.4	0.8
44	1	100	5.5	24	32	2.05	7.2	1.5
45	1	100	7	10	37	3.05	15.05	2
46	1.5	70	4	24	37	1.9	7.25	1.15
47	1.5	70	5.5	10	27	4.1	7.41	0.45
48	1.5	70	7	17	32	3.4	7.77	1.35
49	1.5	85	4	17	37	2.05	8.94	1.8
50	1.5	85	5.5	24	27	2.85	4.57	1
51	1.5	85	7	10	32	3.8	10.36	1.35
52	1.5	100	4	24	32	2.05	6.23	0.9
53	1.5	100	5.5	10	37	3.35	13.7	0.9
54	1.5	100	7	17	27	3.55	6.2	0.8

D [Eq. (8)] was eliminated because of its improper effect on penetration in curvilinear model. Adequacies of models were checked by analysis of variance (ANOVA) within confidence limit of 95% (Table 3). Given required confidence limit (Pr) and correlation factor (R^2) for these models, curvilinear model is found superior to other two, in terms of fitness to real data (Fig. 2). Therefore, curvilinear model is considered as best representative of actual MAG process in this paper[14].

Table 3— ANOVA results for weld bead geometry models

Model	Variable	R-square	F value	Pr>F
Linear	BH	94.1%	154.13	<0.0001
	BW	94.7%	171.87	<0.0001
	BP	83.9%	50.21	<0.0001
Curvilinear	BH	95.6%	45.67	<0.0001
	BW	98.3%	125.28	<0.0001
	BP	91.9%	24.04	<0.0001
Logarithmic	BH	94.0%	150.36	<0.0001
	BW	97.0%	310.96	<0.0001
	BP	81.5%	42.30	<0.0001

Simulated Annealing (SA) Algorithm

Mathematical models furnished above provide one to one relationships between process variables and WBG, and can be used in following two ways: 1) Predicting WBG based on given welding variables values; and 2) Determining process parameters for a desired weld bead specification. Later seems more practical, since welding variables are usually set in order to achieve desired WBG. In order to determine proper values of welding parameters, a set of non-linear equations are to be solved simultaneously.

SA algorithm[15] is a powerful optimization method inspired by metallurgical annealing process, where a solid is melted at high temperature until all molecules can move freely, and then is cooled gradually until thermal mobility is lost. In perfect crystal, all atoms are arranged in a low level lattice, so crystal reaches the minimum energy level. If metal is cooled too fast, it won't reach minimum energy state. At temperature T, solid is allowed to reach a certain thermal equilibrium status. Probability of being at energy level of E is determined by Boltzmann distribution as

$$pr(E) \quad \frac{1}{Z(T)} \quad \exp \quad \frac{E}{K_B.T} \qquad \ldots(14)$$

where Z(T) is a normalization factor depending on T, K_B is Boltzmann constant and exponential term is Boltzmann coefficient. With decrease in T, Boltzmann distribution focuses on a state with lowest energy and finally as T comes close to zero, this becomes the only possible state.

SA code employed in this paper operates based on a neighborhood structure, where at each step a small random change is made to current solution. Then, e objective function value of new solution is compared with that of current solution. A move is then made to new solution if it has a better value. A non-improving solution is also accepted with probability ($P_r = e^{-\Delta c/ck}$). Acceptance probability of non-improving solutions decreases as difference in costs *(Δc)* increases and as T decreases. Temperature (T_k), a positive number, is gradually decreased from a relatively high value to near zero as search progresses. Thus, at the start of SA, most worsening moves are accepted, but at the end, only improving moves are likely to be accepted. This helps to jump out of local optima. Cooling schedule is an important feature of this algorithm. Among different methods proposed, cooling with constant factor is a simple robust strategy as

$$T_{K \quad 1} \qquad * \, T_K \qquad K \quad 0,1,2,... \qquad \ldots(15)$$

In Eq. (15), α may vary with respect to size and complexity of problem and initial T. In most cases, it is taken 0.9-0.99. Details of SA technique and its various applications are reported[16,17].

A Numerical Example and Results

In order to adopt SA technique for predicting process parameters values, based on a given WBG, a suitable objective function should be defined. This function, in the form of error function, would determine "goodness" of any set of process variables with respect to resultant bead geometry. Objective function is defined as a squared error function given as

$$F \quad \frac{(BH_d \quad BH)^2}{BH_d} \quad \frac{(BW_d \quad BW)^2}{BW_d} \quad \frac{(BP_d \quad BP)^2}{BP_d} \qquad \ldots(16)$$

In Eq. (16), BH, BW and BP are WBGs obtained from curvilinear models [Eqs (8-10)]. Desired WBG

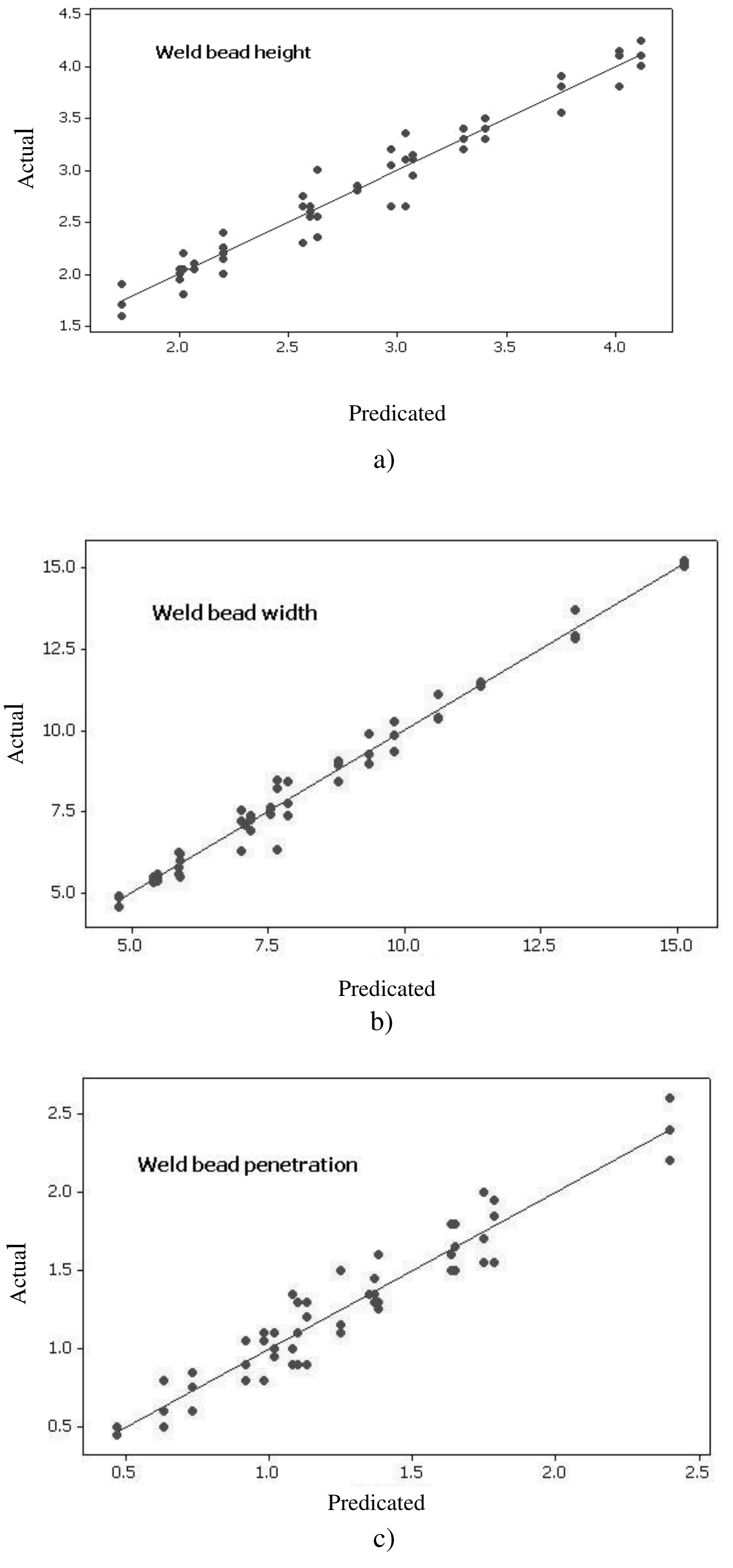

Fig. 2—Curvilinear model: actual values vs predicted values of: a) weld bead height; b) weld bead width; and c) weld bead penetration

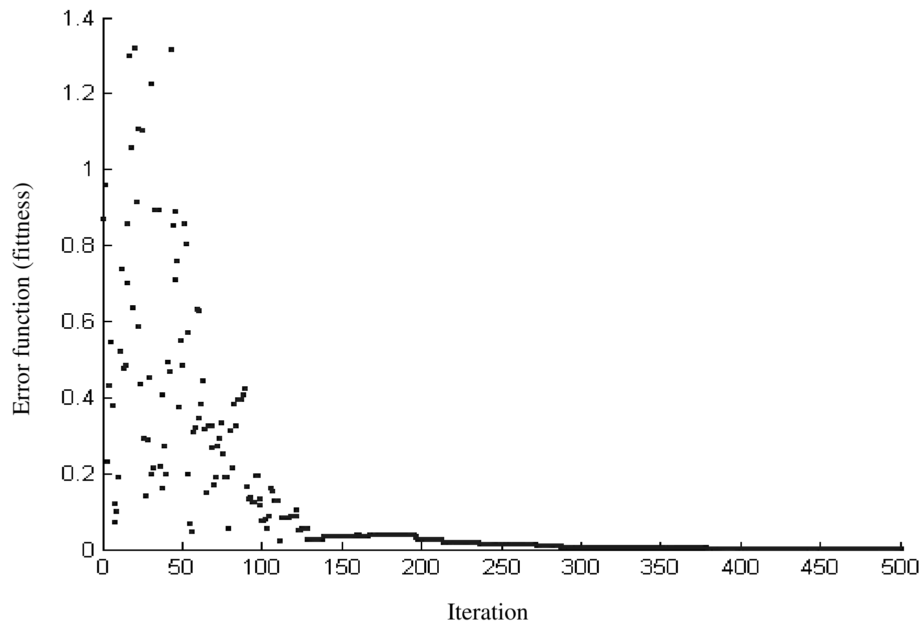

Fig. 3—Convergence rates for SA algorithm

Table 4 —Optimization results of proposed SA algorithm

No.	Process parameters by SA					Predicted value by SA mm			Target value mm			Average error %
	S	V	F	D	A	BH	BW	BP	BH_d	BW_d	BP_d	
1	10.0	37	7	1.0	70	3.15	15.15	15.15	3.20	15.20	1.70	0.67
2	18.5	32	7	1.5	70	3.19	7.44	7.44	3.30	7.38	1.35	2.20
3	16.5	37	6	1.0	97	2.20	11.33	11.33	2.20	11.36	1.85	0.12
4	17.0	29	4	1.3	92	2.65	5.42	5.42	2.65	5.40	0.80	0.35
5	10.0	27	6	1.5	83	4.09	7.38	7.38	4.10	7.40	0.45	1.55

values (BH_d, BW_d and BP_d) are target values. During search, process parameters are determined in such a way that error function is minimized. This would result in WBG parameters approaching to their desired values.

Proposed SA code was written in Matlab 7.0® and executed on a Pentium IV processor. Test runs were performed to find the best set of search parameters as follows: initial temperature (c_0), 20; cooling schedule function $c_{k+1}=\alpha c_k$ ($\alpha=0.95$); neighborhood generation pair wise interchange; and termination criterion, 500 iterations or 20s. Longer execution of algorithm, with more iterations and higher initial temperatures, showed no more improvement. Code was run for 5 example problems, with desired WBGs taken from some experiments performed. From final optimization results (Table 4), maximum error was about 2% while most WBGs specifications deviate < 1% from their desired values, indicating that proposed models are good estimations of MAG welding process. Convergence curve for one of the test runs (Fig. 3) illustrated that algorithm converges very quickly and most of the improvements were obtained within first 300 iterations (12 s of search time), indicating that the proposed SA procedure is quite efficient.

Conclusions

WBG is the most important quality measure in all types of welding techniques. Using DOE approach and RA, different mathematical models were developed to establish relationships between welding input parameters and WBG. ANOVA results denote that curvilinear models are best representative for actual MAG process, to calculate WBG for any given set of process parameters. Computational results indicated that proposed SA method can efficiently and accurately determine welding parameters for a desired bead geometry specification. One of extensions of this study may include use of heuristic techniques to predict optimal parameters for other kinds of welding processes or materials.

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