Optimization of Arc Welding Process Parameters Using a Genetic Algorithm

Genetic algorithms can determine near-optimal settings of welding process parameters within a large search space with relatively few experiments

BY D. KIM AND S. RHEE

ABSTRACT. The purpose of this study is to propose a method to decide near-optimal settings of the welding process parameters using a genetic algorithm. This method tries to find the near-optimal settings of the welding process parameters through experiments without a model between input and output variables. It has the advantage of being able to carry out searches without modifying the design space, which includes some irregular points. The method suggested in this study was used to determine the welding process parameters by which the desired weld bead geometry was formed in gas metal arc (GMA) welding. The output variables were the bead height and depth of penetration of the weld bead. These output variables were determined according to the input variables, which are the root opening, wire feed rate, welding voltage and welding speed. The number of levels for the input variables was 4, 16, 16 and 16, respectively, and the total search points were 16,384. This study describes how to obtain near-optimal welding conditions over a wide search space, conducting a relatively small number of experiments.

Introduction

Arc welding is one of the most widely used joining processes. The weld bead is formed by the melting and solidification of joined materials. The weld bead plays an important role in determining the mechanical properties of the weld. Its geometric parameters such as width, height and penetration are decided according to the welding process parameters, such as wire feed rate, welding voltage, welding speed, shielding gas and contact-tube-to-work distance (CTWD). Therefore, to produce good weld bead geometry, it is important to set up the proper welding process parameters. The welding process is a multi-input and multi-output joining process, and bead geometry is closely associated with the welding parameters. Therefore, identifying suitable combinations of welding parameters to produce the desired bead geometry can require many experiments, making this process time consuming and costly.

An efficient method for solving these problems is to use response surface methodology (RSM). Response surface methodology is a group of statistical and mathematical techniques useful in modeling, improving and optimizing processes. The general procedure of RSM for process optimization is as follows (Ref. 1):

1) Conduct screening experiments.

2) Move experimental region near the optimal point. (We called the best condition from this step the near-optimal condition.)

3) Develop a model within a relatively small region around the optimal point.

4) Determine the optimal settings for process parameters that maximize (or minimize) the objective function.

There have been many studies on screening experiments, modeling and optimization for welding processes. However, there have been few techniques to move the experimental region near the optimal welding conditions. In this paper, the focus is on searching for the near-optimal condition.

Some researchers (Refs. 2–4) developed linear models between the weld bead geometric parameters and welding process parameters by using regression analysis. Other researchers (Refs. 5, 6) used the Taguchi method to find robust welding conditions. These techniques provide good results over the regular experimental regions, including no irregular points. However, it is often impossible to establish an arc, and melt-through may occur under certain experimental points needed to satisfy the specific experimental design. The data obtained may be impossible to analyze or provide poor results. This forces the experimenter to modify the design space. Subramaniam, *et al.* (Ref. 7), used D-optimal experimental design to solve such problems by including and excluding operating points. A point of criticism of the optimal designs is they are frequently quite sensitive to the form of the model (Ref. 8).

Therefore, it is important to move the experimental region near the region of interest or optimal conditions, which show relatively good weld quality. This process is particularly important when the experimenter begins experimentation far from the region of optimal conditions. The full factorial design can result in optimal settings of the welding process parameters without deriving a model for the welding process. As the number of input parameters and level of input parameters increase, the number of experiments exponentially increases and the full factorial method for the problem becomes unrealistic.

To overcome these problems, this study introduced procedures to determine the near-optimal welding process parameters using a genetic algorithm. The genetic algorithm is a global optimization algorithm, and the objective function does not need to be differentiable. This allows the algorithm to be used in solving difficult problems such as

KEY WORDS

Arc Welding
Weld Quality
Optimization
Genetic Algorithm
Welding Parameters
Weld Bead Geometry

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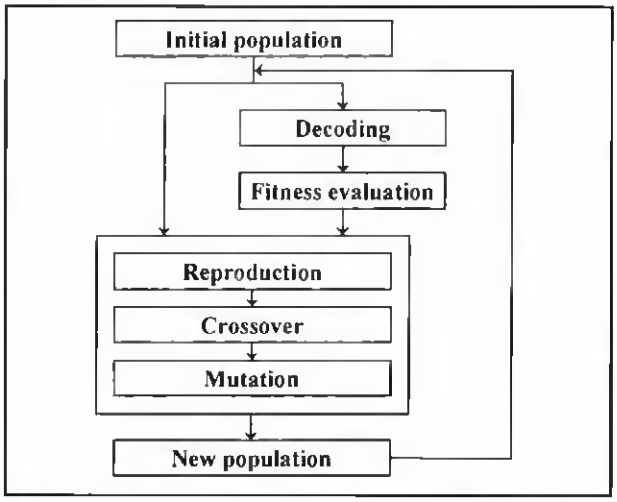

Fig. 1 — A general procedure of a genetic algorithm.

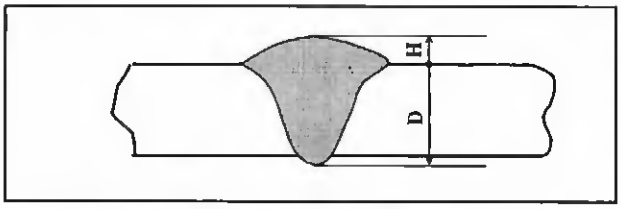

Fig. 2 — Weld bead geometry.

multimodal, discontinuous or noisy systems (Refs. 9–14). This is not possible with existing optimization algorithms.

Therefore, it is appropriate to apply a genetic algorithm to complex systems such as the welding process. Another advantage is that continuous search is possible without external influence by welding phenomena, such as melt-through. In order to determine the welding process parameters that produce the optimized weld bead geometry in GMA welding, this study used a genetic algorithm.

This optimization process does not derive the models to correlate input variables and output variables. Through experiments, the optimal settings of the welding process parameters can be found. The input variables that control weld bead geometry were the root opening, wire feed rate, welding voltage and welding speed. The output variables used were bead height and weld depth penetration.

Genetic Algorithms

Genetic algorithms are global optimization algorithms developed based on the mechanics of natural selection and genetics. In this study, a genetic algorithm was used to determine the optimal settings of welding process parameters that produced the desired weld bead geometry. The genetic algorithm, developed to solve many complex problems, has the following characteristics (Ref. 9):

First, the genetic algorithm uses a string of fixed length instead of a parameter value. Generally, the binary string comprised of 0 and 1 is used in the genetic algorithm. Secondly, when determining the solution within the search range, the genetic algorithm simultaneously considers a set of possible solutions. This parallel processing of the genetic algorithm may prevent the convergence of one particular local extreme point. Thirdly, as the genetic algorithm only uses the fitness value of each string, the fitness function does not need to be continuous or differentiable. Finally, while many optimization methods use the deterministic transition rule, the genetic algorithm instead uses the probability transition rule.

The general optimization procedure using a genetic algorithm is shown in Fig. 1. The initial population means the possible solutions of the optimization problem, and each possible solution is called an individual. Each individual is a binary string consisting of combinations of randomly generated zeroes and ones. This binary string is used to code the possible solution. In this paper, it expresses the welding process parameters that influence weld bead geometry. The values of the welding process parameters, shown as the binary string (strings of each parameter are concatenated to make one long string), are very effective in exchanging information between each individual. However, they need to be changed into real numbers when being applied to the optimization problem to evaluate the fitness.

Decoding is the process of changing the input variables that are coded by the binary string into a real number. For example, if an input variable (x_i) has a research range of $[x_{i,min}, x_{i,max}]$, and its binary string length is L_i, the real number ($x_{i,r}$) of the input variable can be shown in the following equation:

$$x_{i,r} = \frac{x_{i,max} - x_{i,min}}{2^{L_i} - 1} x_{i,b} + x_{i,min} \quad (1)$$

where, $x_{i,b}$ is the number in decimal form represented by the binary string. Each individual, represented by the binary string, is transformed to real numbers by Equation 1 and applied to the optimization problem. In other words, the welding experiment is performed with the welding process parameters that had been transformed to real numbers.

The fitness evaluation is a procedure necessary to decide the survival of each individual. Individuals with large fitness values represent better solutions and those values are what the user wants to maximize. Therefore, the objective function of the minimization problem must be transformed so that it becomes a maximization problem. This study used the bead height and weld bead depth of penetration to make the fitness function. According to results of the welding experiments, the weld bead geometry was measured and the fitness of each welding condition was calculated.

The next step is to use each individual's fitness and the genetic operators (reproduction, crossover and mutation) to produce the next generation of the population.

Reproduction is the process in which each individual may be duplicated according to its fitness. Through this operation process, individuals with higher fitness levels produce more offspring in the next generation than those with lower fitness levels. This explains Darwin's survival of the fittest theory. This study used the biased roulette wheel selection to imitate Darwin's survival of the fittest theory (Ref. 9). This selection approach is based on the concept of selection probability for each individual proportional to the fitness value. For individual k with fitness f_k, its selection probability p_k is calculated as follows:

$$p_k = f_k \Big/ \sum_{j=1}^{n} f_j \quad (2)$$

where n is population size. Then a biased roulette wheel is made according to these probabilities. The selection process is based on spinning the roulette wheel n times. The individuals selected from the selecting process are then stored in a mating pool.

Crossover is the process by which the strings are able to mix and match their attributes through random process. After reproduction, crossover proceeds in three steps. First, two strings (referred to as parents) are selected randomly from the mating pool. Second, an arbitrary location (called the crossover site) in both strings is selected randomly. Third, the portions of the strings following the

Table 1 — Search Range for Welding Parameters and the Corresponding Number of Bits and Number of Levels

Parameter	Range	Number of Bits	Number of Levels
Root opening	0–1.5 (mm)	2	4
Wire feed rate	1.35–14.40 (cm/s)	4	16
Welding voltage	15–30 (V)	4	16
Welding speed	3–10.5 (mm/s)	4	16

Table 2 — Results of Initial Generation

Individual Number	Root Opening (mm)	Feed Rate (cm/s)	Voltage (V)	Speed (mm/s)	Height (mm)	Depth (mm)	Objective Function	Fitness Function
1	0.0	5.70	26	10.5	1.7	2.0	12.29	0.075
2	1.0	1.35	22	7.0	1.4	3.4	4.42	0.185
3	0.5	3.09	15	4.0	3.9	0.9	26.92	0.036
4	0.5	4.83	25	4.5	2.7	4.3	2.88	0.258
5	1.0	12.66	24	9.0	—	—	40.38	0.024
6	1.0	13.53	25	10.0	—	—	40.38	0.024
7	1.5	7.44	24	6.0	—	—	40.38	0.024
8	1.0	9.18	21	5.5	3.5	4.0	6.25	0.138
9	1.5	12.66	20	9.0	—	—	40.38	0.024
10	0.0	3.96	30	9.5	1.1	1.6	15.37	0.061

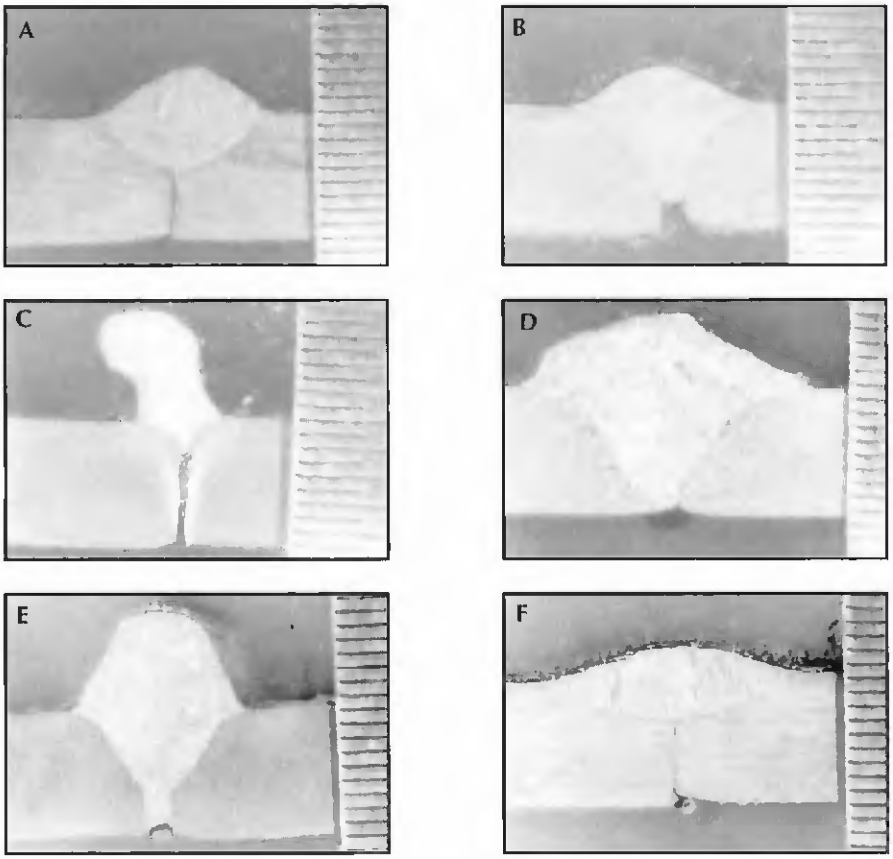

Fig. 3 — Cross sections of welds made using various combinations of process variables produced in initial generation. A — Root opening 0.0 mm, feed rate 5.70 cm/s, voltage 26 V, speed 10.5 mm/s; B — root opening 1.0 mm, feed rate 1.35 cm/s, voltage 22 V, speed 7.0 mm/s; C — root opening 0.5 mm, feed rate 3.09 cm/s, voltage 15 V, speed 4.0 mm/s; D — root opening 0.5 mm, feed rate 4.83 cm/s, voltage 25 V, speed 4.5 mm/s; E — root opening 1.0 mm, feed rate 9.18 cm/s, voltage 21 V, speed 5.5 mm/s; F — root opening 0.0 mm, feed rate 3.96 cm/s, voltage 30 V, speed 9.5 mm/s.

crossover site are exchanged between two parent strings to form two offspring strings. This process is applied to the other strings in the mating pool. This crossover does not occur with all strings, but is limited by the crossover rate. For example, if the crossover rate is 0.9, then 90% of the pairs are crossed, whereas the remaining 10% are added to the next generation without crossover.

After reproduction and crossover, mutation is performed by occasionally altering the value of a string position. In other words, a bit value of 0 is reversed to 1 and a bit value of 1 is reversed to 0. Every bit value in each string is a candidate for mutation, and its selection is determined by the mutation rate. The mutation rate is usually set at a low vale to avoid losing good strings. The mutation serves to recover information lost from reproduction and crossover. It also provides information that did not exist in the initial stage.

In the genetic algorithm, the population size, crossover rate and mutation rate are important factors in the performance of the algorithm (Refs. 10–15). A larger population size or higher crossover rate allows exploration of more of the solution space and reduces the chances of settling for poor solutions, but if they are too large or high, it results in wasted computation time exploring unpromising regions of the solution space. If the mutation rate is too low, many binary bits that may be useful are never tried, but if it is too high, there will be much random perturbation, and the offspring will lose the good information of the parents.

Gerfenstette (Ref. 11) and Alander (Ref. 14) suggested the optimal population size was 30 and a value between n and 2n (where n is the string length), respectively. The typical values for the crossover rate and the mutation rate range from 0.5 to 1.0 and 0.005 to 0.01, respectively (Ref. 13). Gerfenstette (Ref. 11) showed that the optimal crossover rate appeared to increase as the population size decreased, and the performance of mutation rates above 0.1 approached that of random search regardless of the other parameter settings. In addition, the optimal parameter settings were 30 of population size, 0.95 of crossover rate and 0.01 of mutation rate. These studies show that the control parameters of the genetic algorithm depend upon the specific problems studied.

When the process parameter settings have to be found through actual experiments as opposed to computer simulation, it is necessary to use the least number of individuals as possible. This is

because as the number of individuals increases, the number of experiments also increases, requiring more time and cost and decreasing the usefulness of optimization through the genetic algorithm. Fortunately, Reeves (Ref. 15) showed rather small populations sufficed for binary strings. However, it is noted that a small population size increases the chance of premature convergence to a poor solution. The control parameters of the genetic algorithm in this study were determined based on these studies.

Experimental Procedure

A genetic algorithm was used to determine the arc welding parameters that would produce an optimal weld bead geometry. Weld bead geometry plays an important role in determining the mechanical properties of a weld. This study, as shown in Fig. 2, used bead height and depth of penetration to describe weld bead geometry. These parameters for weld bead geometry were largely influenced by the root opening, wire feed rate, welding voltage and welding speed. In other words, the welding process parameters were the input variables while the bead parameters were the output variables of the arc welding process. After setting up the desired weld bead geometry, the genetic algorithm was used to determine the welding process parameters that produced the desired weld bead geometry.

The base metal was 4.5-mm-thick mild steel with a square-groove butt joint. A single-pass welding process was used. The filler metal was an AWS classification ER 705-6 with a 1.2-mm-diameter electrode. The shielding gas used was 100% CO_2 with a 20 L/mm flow rate. The four welding process parameters were determined according to the genetic algorithm. The search ranges were as follows: root opening, 0–1.5 mm; wire feed rate, 1.35–14.40 cm/s; welding voltage, 15–30 V; and welding speed, 3–10.5 mm/s. After performing the arc welding experiments under the conditions determined by the genetic algorithm, bead height and depth of penetration were measured.

Results and Discussion

In order to use the genetic algorithm to optimize welding process parameters, an index to evaluate the next generation's survival fitness was needed. This study made a fitness function using the weld bead geometry, which influenced weld quality. Excessive bead height and penetration do not produce good weld quality (Ref. 16). Therefore, this study used the following objective function, with bead height and depth of penetration:

$$J = (H_d - H)^2 + (D_d - D)^2 \qquad (3)$$

where H_d and D_d are the desired bead height and depth of penetration by the designer, and H and D are the bead height and depth of penetration obtained from the experiment. In this study, the desired values used were $H_d = 1.5$ mm, $D_d = 5.5$ mm. Thus, to obtain the desired bead geometry was to find the welding parameters that minimize J. Because the genetic algorithm is generally applied to maximization problems, the objective function J was transformed to $1/(J + 1)$, which was the fitness function. The search range for the welding parameters, and the corresponding number of bits and number of levels to find the welding process parameters that maximize $1/(J + 1)$ are shown in Table 1. Therefore, with all the number of cases shown in Table 1, the number of search points needed to find the optimal settings of input variables by using the full factorial experiments is 16,384. It can clearly be seen that applying this method is unrealistic. In this vast search space, the procedures for deciding the optimal welding parameters using the genetic algorithm are outlined below.

Control parameters of the genetic algorithm were initialized. A population size of 10, a crossover rate of 0.95 and mutation rate of 0.01 for the genetic algorithm based on Refs. 11 and 15 was used. The next step was to generate the welding process parameter sets formed by the binary strings as much as the population size, and then map the binary strings into the search range in Table 1 by using Equation 1. Then the arc welding experiments were performed with the mapped welding process parameter values.

After the experiments were performed, three samples were cut from each weldment and the transverse face of the weldments was surface ground and macroetched. Then, the weld bead geometry acquired from each welding condition was measured and its mean value applied to Equation 3, which calculated the objective function value. Using this value, the fitness function

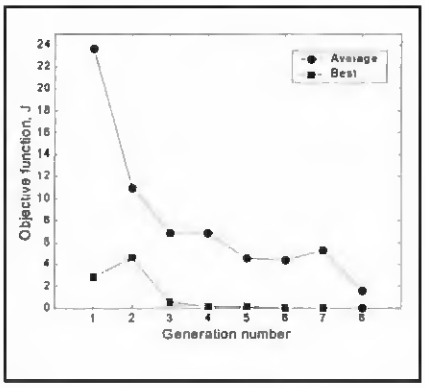

Fig. 4 — Results of the genetic algorithm.

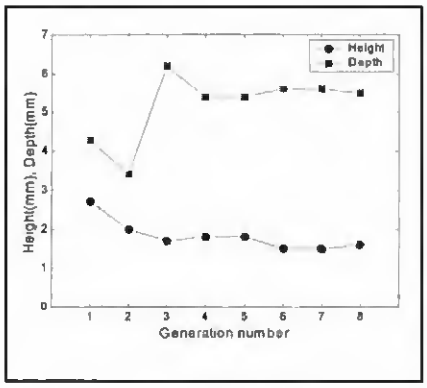

Fig. 5 — Results of the bead height and depth of penetration obtained from the genetic algorithm.

Table 3 — Results of the Fourth Generation

Individual Number	Root Opening (mm)	Feed Rate (cm/s)	Voltage (V)	Speed (mm/s)	Height (mm)	Depth (mm)	Objective Function	Fitness Function
1	1.5	7.44	26	8.5	–0.4	5.8	3.70	0.213
2	1.0	1.35	25	6.5	1.5	3.0	6.25	0.138
3	0.0	5.70	24	6.0	2.5	3.4	5.41	0.156
4	1.0	5.70	24	6.0	1.7	6.2	0.53	0.654
5	1.0	2.22	22	7.5	1.7	3.2	5.33	0.158
6	1.0	4.83	21	5.0	2.5	3.7	4.24	0.191
7	1.0	5.70	24	6.5	1.8	5.4	0.10	0.909
8	0.5	4.83	22	7.0	2.3	2.8	7.93	0.112
9	0.0	2.22	22	9.0	2.1	1.9	13.32	0.070
10	1.0	11.79	21	5.0	—	—	19.98	0.048

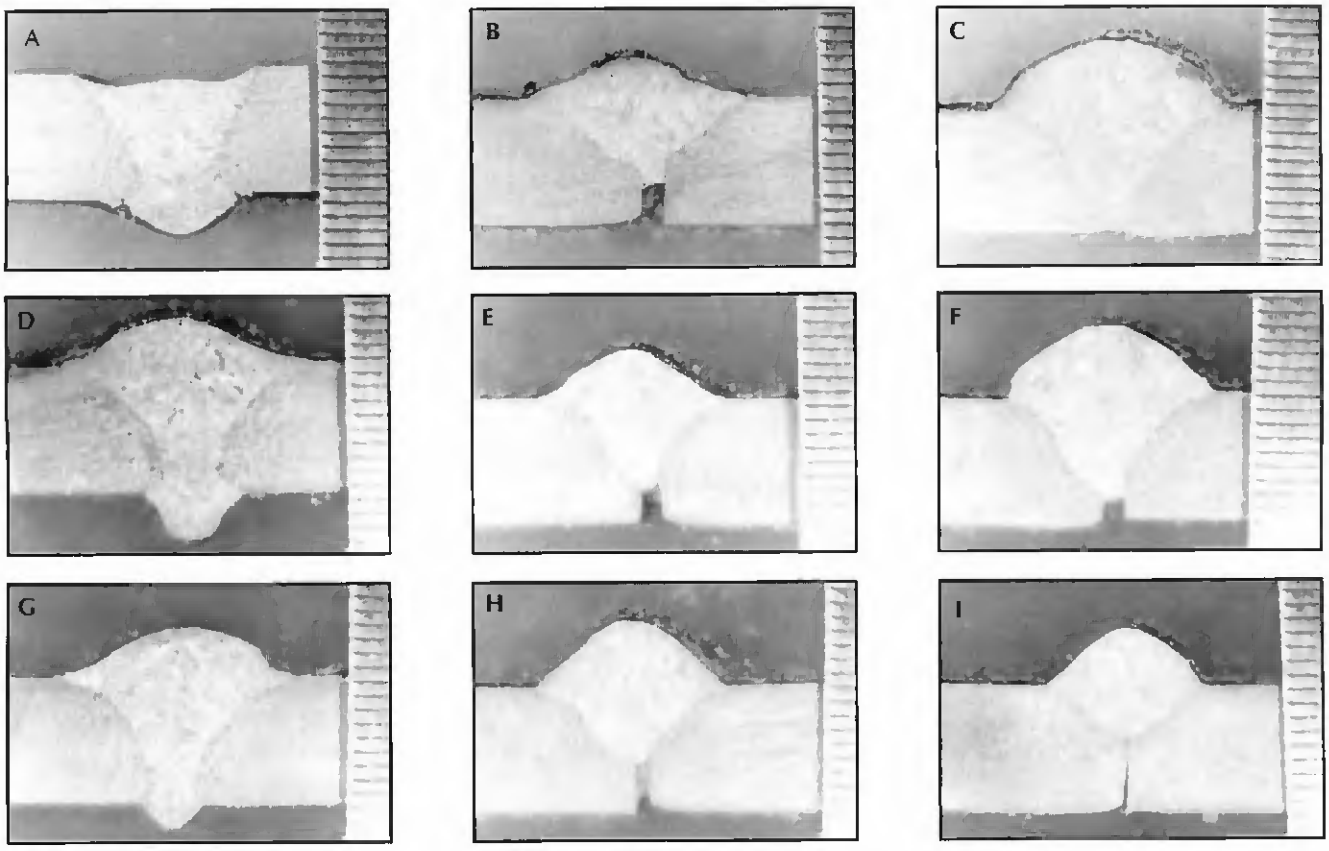

Fig. 6 — Cross sections of welds made using various combinations of process variables produced in the fourth generation. A — Root opening 1.5 mm, feed rate 7.44 cm/s, voltage 26 V, speed 8.5 mm/s; B — root opening 1.0 mm, feed rate 1.35 cm/s, voltage 25 V, speed 6.5 mm/s; C — root opening 0.0 mm, feed rate 5.70 cm/s, voltage 24 V, speed 6.0 mm/s; D — root opening 1.0 mm, feed rate 5.70 cm/s, voltage 24 V, speed 6.0 mm/s; E — root opening 1.0 mm, feed rate 2.22 cm/s, voltage 22 V, speed 7.5 mm/s; F — root opening 1.0 mm, feed rate 4.83 cm/s, voltage 21 V, speed 5.0 mm/s; G — root opening 1.0 mm, feed rate 5.70 cm/s, voltage 24 V, speed 6.5 mm/s; H — root opening 0.5 mm, feed rate 4.83 cm/s, voltage 22 V, speed 7.0 mm/s; I — root opening 0.0 mm, feed rate 2.22 cm/s, voltage 22 V, speed 9.0 mm/s.

value was also calculated. The welding process parameter values generated randomly from the first generation and the results from each experiment are shown in Table 2.

Irregular melt-through phenomena occurred in the welding conditions of experiments 5, 6, 7 and 9. The measured data from these conditions were regarded as "bad data." It was considered that the wire feed rate in experiments 5 and 6, the root opening in experiment 7, and both the root opening and wire feed rate in experiment 9 were relatively large. As reasonable measured data cannot be obtained from the above welding conditions, the largest objective function value among the "good data" multiplied by 1.5 was defined as the objective function values of the welding conditions that showed melt-through. As seen, the welding conditions that generated melt-through were not discarded but given low fitness values, as there was a possibility that there was important information in these conditions. For example, from the final experimental results based on the genetic algorithm, the root opening and the wire feed rate among welding conditions of experiment 7 do not provide good information, but the welding speed does. This information may be useful when deciding the welding conditions for the next generation. Cross sections of welds made using the welding conditions that produced good data in initial generation are shown in Fig. 3.

The population of the next generation was decided by using the three operators of the genetic algorithm, according to the calculated fitness function values of each individual. This process was repeated until satisfactory weld quality (J "0.1) was obtained, and several additional generations were created in order to verify the obtained optimal condition and prevent the sample with random error from being the actual best solution. As a result, this study repeated this experiment until the 8th generation was formed.

Figure 4 shows the results of the genetic algorithm until the 8th generation. The marker ● shows the average of the generation's objective function values, and the marker ■ shows the minimum value from each of the generations. From the figure, it is shown that as the generation increases, the objective function values decrease. The numbers the melt-through phenomena produced until the 8th generation were 4, 2, 1, 1, 0, 0, 1 and 0, respectively. The welding conditions of the 5th and 6th generation did not produce melt-through, but one of the welding conditions of the 7th did. As the objective function value of the welding condition with bad data was relatively high, it was seen that the average of each generation's objective function values continued to decrease and then increased slightly at 7th generation. Figure 5 shows convergence results of the bead height and depth of penetration obtained from the optimal settings of welding parameters of each generation. Notice that as the generation number increased, the bead geometric variables converged to the desired values.

From the above results, the optimal condition satisfying the termination condition (J "0.1) was found in the 4th generation. The experiments after the 4th generation verified the validity of the optimal condition obtained from the 4th

generation. The welding parameter values and the experiment results generated from the fourth generation are shown in Table 3. The optimal settings for welding parameters means the input variable values of the welding process with the maximum fitness function value were as follows: the root opening at 1.0 mm, the wire feed rate at 5.7 cm/s, the welding voltage at 24 V and the welding speed at 6.5 mm/s. Cross sections of welds made using the welding conditions that produced good data in the fourth generation are shown in Fig. 6. It is shown that the weld quality produced from the fourth generation (Fig. 6) is better than the weld quality produced from the initial generation — Fig. 3.

Fortunately, the optimal condition in this study was found in the 4th generation. As the specific rates of convergence vary by initial population or stochastic selection mechanism, however, another run may need more generations.

Conclusion

An effective method for deciding the optimal parameters in the arc welding process using a genetic algorithm was proposed.

In arc welding, the weld bead geometry is an important factor in deciding weld quality. This study used a genetic algorithm to determine the welding process parameter values that produced complete joint penetration. In the optimization of the welding process using the genetic algorithm, the objective function was made using weld bead height and depth of penetration. Weld bead geometry was determined depending on the root opening, wire feed rate, welding voltage and welding speed.

The proposed method can find the near-optimal settings of the welding process parameters with relatively few experiments. It can also be used to find the near-optimal welding conditions over the original full factorial candidate set, even if some irregular welding conditions, such as melt-through, are present.

Acknowledgments

This work was supported by the Brain Korea 21 Project and Critical Technology 21 Project of the Ministry of Science and Technology, Korea.

References

1. Myers, R. H., and Montgomery, D. H. 1995. *Response Surface Methodology*, John Wiley & Sons, Inc.

2. Konkol, P. J., and Koons, G. F. 1978. Optimization of parameters for two-wire AC-AC submerged arc welding. *Welding Journal* 57(12): 367-s to 374-s.

3. Yang, L. J., Chandel, R. S., and Bibby, M. J. 1993. The effects of process variables on the weld deposit area of submerged arc welding process. *Welding Journal* 72(1):11-s to 18-s.

4. Yang, L. J., Bibby, M. J., and Chandel, R. S. 1993. Linear regression equations for modeling the submerged arc welds. *Journal of Material Processing Technology* 39: 33–42.

5. McConnell, I. A., and McPherson, N. A. 1997. The application of statistical process design to a FCAW process. *Welding Journal* 76(10): 412-s to 416-s.

6. Tarng, Y. S., and Yang, W. H. 1998. Optimization of the weld bead geometry in gas tungsten arc welding by the Taguchi method. *International Journal of Advanced Manufacturing Technology* 14: 549–554.

7. Subramaniam, S., White, D. R., Jones, J. E., and Lyons, D. W. 1999. Experimental approach to selection of pulsing parameters in pulsed GMAW. *Welding Journal* 78(5): 166-s to 172-s.

8. Steinberg, D. M., and Hunter, W. G. 1984. Experimental design: review and comment. *Technometrics* 26(2): 71–97.

9. Goldberg, D. E. 1989. *Genetic Algorithms in Search, Optimization, and Machine Learning*, Addison-Wesley.

10. Gen, M., and Cheng, R. 1997. *Genetic Algorithms and Engineering Design*, John Wiley & Sons, Inc.

11. Grefenstette, J. J. 1986. Optimization of control parameters for genetic algorithms. *IEEE Trans. on Syst. Man Cybern* 16(1): 122–128.

12. Fogel, D. B. 1994. An introduction to simulated evolutionary optimization. *IEEE Trans. on Neural Networks* 5(1): 3–14.

13. Srinivas, M., and Patnaik, L. M. 1994. Adaptive probabilities of crossover and mutation in genetic algorithm. *IEEE Trans. on Syst. Man Cybern* 24(4): 656–667.

14. Alander, J. T. 1992. On optimal population size of genetic algorithms. *Proc. of CompEuro 92*, pp. 65–70. IEEE Computer Society Press.

15. Reeves, C. R.1993. Using genetic algorithms with small populations. *Proc. of the Fifth Intern. Conf. on Genetic Algorithms*, pp. 92–99.

16. ANSI/AWS D1.1-94, *Structural Welding Code — Steel*, 13th Ed. 1994. American Welding Society, Miami, Fla.