Determination of Optimal Conditions for a Gas Metal Arc Welding Process Using the Genetic Algorithm

D. Kim and S. Rhee

Abstract

A genetic algorithm was applied to the arc welding process as to determine the near-optimal settings of welding process parameters that produce the good weld quality. This method searches for optimal settings of welding parameters through the systematic experiments without the need for a model between the input and output variables. It has an advantage of being capable to find the optimal conditions with a fewer number of experiments rather than conventional full factorial designs.

A genetic algorithm was applied to the optimization of the weld bead geometry. In the optimization problem, the input variables were wire feed rate, welding voltage, and welding speed. The output variables were the bead height, bead width, and penetration. The number of levels for each input variable is 16, 16, and 8, respectively. Therefore, according to the conventional full factorial design, in order to find the optimal welding conditions, 2048 experiments must be performed. The genetic algorithm, however, found the near optimal welding conditions in less than 40 experiments.

Key Words : Arc welding, Genetic algorithm, Optimization, Welding process parameter, Welding Speed, Welding Voltage, Weld bead geometry, Wire feed rate

1. Introduction

The arc welding process is a multi-input/output process, and because the welding output parameters are coupled, many experiments and efforts are needed to adjust the welding process parameters, in order to obtain the good welding results. To solve such problems, a model between the input and output parameters is formulated, and a method of using this model to determine the welding process parameters is suggested. One of the modeling methods is based on the analytical or numerical methods[1-3].

Nonetheless, because the welding process is basically complicated and non-linear, it is difficult to induce a model for the welding process through the physical law or numerical method, the welding process cannot be accurately expressed, as the induced model itself is based on many hypotheses.

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Another modeling method is based on experimental data. Some studies induced the linear model between the weld bead geometry parameters and the welding process parameters[4,5], while others used the artificial neural network to induce a nonlinear model[6-8]. However, because the welding process model induced through the regression analysis or artificial neural network is highly accurate in small experimental regions, the accuracy is decreased as the experimental region expands. Another problem is that a phenomenon such as the burn-through occurs in the search region of the welding process parameters, or the bead geometry obtained in the welding conditions cannot provide accurate data needed in inducing a model. Therefore, a model for the welding process should be induced within the region in which relatively good welding quality can be acquired, and experimental data has mainly been used in finding the region of interest. However, a great deal of experiments and experiences are needed in order to find the region of interest through an empirical method, and it is difficult to apply in new welding processes.

In this study, the welding process parameters that show good weld quality were determined through a genetic algorithm which is systematic and can be done in only a small number of experiments. In the genetic algorithm, the objective function that is to be optimized does not have to be differentiable. Also, because the genetic algorithm is a global optimization algorithm, it is possible to solve discontinuous or multi-modal objective functions, to which it is difficult to apply the conventional gradient-based optimization methods[9,10]. Therefore, the genetic algorithm is advantageous in that it is easily applicable to complicated systems as the welding process, and can carry out searches without being affected by welding phenomena such as burn-through. In this study the genetic algorithm was used to determine the welding process parameters by which the desired weld bead geometry are formed in gas metal arc (GMA) welding. Through this method, the welding process parameters can be found through a series of experiments, without inducing the model between input and output parameters. The input parameters which control the weld bead geometry were the wire feed rate, welding voltage, and welding speed, while the output parameters were the bead height, bead width, and penetration depth.

2. A genetic algorithm for optimizing welding processes

The genetic algorithm is a global optimization algorithm developed on the basis of natural selection and genetics. In this study, the genetic algorithm was used to determine the welding process parameters that produce the desired weld bead geometry. The characteristics of the genetic algorithm are as follows[9].

First, a binary string consisting of 0 and 1 is generally used instead of the input parameter values in the genetic algorithm. Second, search is carried out in the genetic algorithm in consideration of a set of possible solutions in the search region. Therefore, convergence to one local extremum can be prevented, while the global extremum can be found effectively. Thirdly, because the genetic algorithm uses only the fitness function value of each string, the fitness function does not need to be continuous or differentiable. Finally, whereas many optimization methods use the deterministic transition rule, the genetic algorithm uses the probability transition rule.

A general optimization procedure using the genetic algorithm is shown in Fig. 1. The initial population

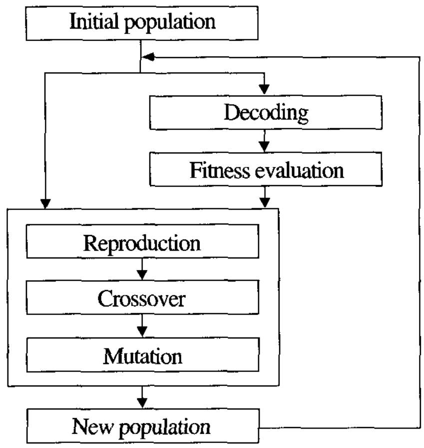

Fig. 1 A general procedure of a genetic algorithm

means the possible solution group of the optimization problem, and each possible solution is called an individual. The individual is generally a binary string encoded with randomly generated combinations of 0 and 1. This binary string, in this paper, means the welding process parameters of which effect the weld bead geometry. Although the welding process parameters, which are expressed through a binary string, are effective in exchanging genetic information between individuals, they must be converted into real values in order to be applied to optimization problems that evaluate fitness. Unlike the general optimization algorithms that perform the search from one starting point, the genetic algorithm begins the search after generating a population of a certain size. The size of the solution group is an important factor that effects the optimization performance of the genetic algorithm. In this study, the number of individuals was kept as low as possible, as more individuals mean more experiments must be performed.

Decoding is the process by which an input parameter encoded into a binary string is transformed into a real value. For example, if welding process parameter χ_i that has a search region of $[\chi_{i,\min}, \chi_{i,\max}]$ and a string length of L_i is expressed in a binary string, the real value $\chi_{i,r}$ of the welding process parameter χ_i can be calculated through the following equation.

$$\chi_{i,r} = \frac{\chi_{i,\max} - \chi_{i,\min}}{2^{L_i} - 1} \chi_{i,b} + \chi_{i,\min} \tag{1}$$

Where, $\chi_{i,b}$ is the value of the binary string transformed into a decimal number, the each individual which is expressed in a binary string through equation (1) is transformed into a real value and applied to the optimization problem. In other words, the welding experiment is carried out according to each welding process parameter that has been converted into a real value.

The fitness evaluation is used to determine the survival of each individual in the genetic algorithm. An individual of the larger fitness of each problem means a better solution, and therefore, the fitness function means the objective function that the user desires to optimize. In this study, the bead height, bead width and penetration depth were used to form the fitness function, and after the welding experiment was performed, the acquired bead geometry was measured to calculate the fitness of each welding condition.

The next stage is to form the individual group of the next generation, by using the fitness of each individual and the exchange of information between the individuals comprised of binary strings. This individual group is determined through reproduction, crossover and mutation, which are genetic operators.

Reproduction is the process in which each individual is duplicated according to its fitness. Through this process, the individual with a higher level of fitness can produce more artificial offspring than those with a lower level of fitness. The roulette wheel selection method was used in this study to enact this process. If the fitness value of the individual i is f, the sum of the fitness values of all individuals is $\sum_{i=1}^{n} f_i$, and the average fitness value is $\bar{f}$, in an individual group comprised of n number of individuals, the probability of individual i being selected is $f_i / \sum_{i=1}^{n} f_i$ and individual i produces an average of $f_i / \bar{f}$ offspring. Therefore, an individual with a fitness level higher than the average can produce more than one offspring, while the individual with a fitness level lower than the average will probably not be able to produce offspring. However, no matter how low the fitness level is, there is a $f_i / \sum_{i=1}^{n} f_i$ possibility of that individual to be selected. This prevents the individual group from losing its diversity, avoiding premature convergence before a good selection is found. The individual selected through this method is saved in the mating pool.

Crossover is a process imitating the natural phenomenon of organisms exchanging genes, and follows three stages. First, two strings are randomly selected from the mating pool. Second, the crossover position is randomly selected. Thirdly, a part of the strings are exchanged according to the crossover position. Through this process, the information between the individuals is combined, creating new individuals. Such crossover does not occur in all of the strings, as the process is restricted by the crossover rate.

Whereas reproduction and crossover uses only the information that is present in the individuals, mutation provides information that does not exist in the individual group. Reversing a random bit value carries out this calculation process. In other words, a bit value of 0 is reversed to 1, and a bit value of 1 is reversed to 0. This process can restore information that was lost during the reproduction and crossover processes, and can provide information that was not available in the initial individual group. This process is also restricted by the mutation rate.

The number of individuals, crossover rate, and mutation rate are important factors in the performance of the genetic algorithm[10, 11]. Particularly, when the optimal conditions for the genetic algorithm are 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 utility of the optimization through the genetic algorithm. In order to obtain good results with the least number of individuals, control parameters were established in the genetic algorithm, based on the study conducted by Reeves[11].

3. Experimental method

Optimization through the genetic algorithm was applied to the arc welding process. The formation of the weld bead is important in determining the mechanical property of the weld. In this study, the bead height, bead width and penetration depth were used to express the weld bead geometry, as shown in Fig. 2. These bead geometry parameters are greatly affected by the setting of the welding process parameters, which were wire feed rate, welding voltage and welding speed. Therefore, the welding process parameters and bead geometry parameters can be seen as the input and output

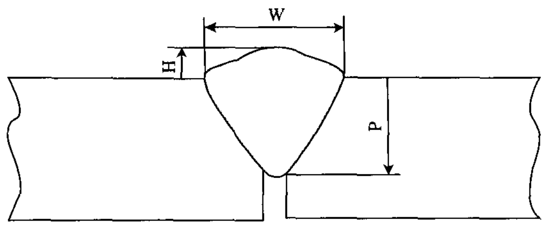

Fig. 2 Weld bead geometry

parameters of the arc welding process, respectively. After setting the desired weld bead geometry, the genetic algorithm was used to determine a set of welding process parameters that produce the desired weld bead geometry.

The base metal to which welding was to be performed was mild steel of 5.8mm thickness, with square groove joint types and root openings set at 1.0mm. The welding power source was a welding machine with characteristics of inverter type constant voltage. The AWS classification ER 70S-6 filler wire with a diameter of 1.2mm was used. Also, the contact tube-to-work piece distance was set at 15mm. The shielding gas used in the experiment was 100% CO_2 gas, with flow rate of 20 l/min. The three welding process parameters were set through the genetic algorithm. The range of each welding process parameter must be determined in consideration of the influence on the output variable, and the resolution. In this study, the range of the welding process parameters were established as following, based on references on arc welding conditions[14] and several preliminary experiments. The search region of the wire feed rate was 45 ~ 120 mm/s, the welding voltage 15 ~ 30 V, and the welding speed 5 ~ 12 mm/s. After performing welding on each set of welding parameters determined through the genetic algorithm, the bead height, bead width and penetration depth were measured.

4. Experiment results and discussion

In order to optimize the welding process parameters using the genetic algorithm, an index to evaluate the survival of the following generation is necessary. In this study, the objective was to obtain the partial penetration weld[12]. The bead height, bead width and penetration depths, which are the weld bead geometry parameters which affect weld quality, were used to form the following objective function.

$$J=(H_d - H)^2+(W_d - W)^2+(P_d - P)^2 \qquad (2)$$

Where, H_d, W_d, and P_d are the bead height, bead width and penetration depth desired by the designer, and H, W, and P are the bead height, bead width, and penetration depth obtained through the experiment. In this optimization problem, H_d= 1.5mm, W_d= 7mm, and P_d= 4mm were established as the desired bead geometry. Therefore, obtaining the desired bead geometry means finding the welding parameters in which J is minimized. Because the genetic algorithm is generally applied to maximization problems, objective function J was transformed to $1/(J+1)$ to form the fitness function. Also, the search range, number of bits, and number of levels of the process parameters were set as shown in Table 1. Therefore, 2,046 search points are needed to find the optimal process parameters through the full factorial experiment using the number of levels shown in Table 1. This method requires too many experiments, and was thus deemed unrealistic. The procedure in which the optimal welding process parameters are obtained using the genetic algorithm in such a large search region is as follows.

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
Wire feed rate	45 - 120 (mm/s)	4	16
Welding voltage	15 - 30 (V)	4	16
Welding speed	5 - 12 (mm/s)	3	8

First, the control parameters of the genetic algorithm are initialized. In this study, the number of individuals was set at 12, the crossover rate at 0.95, and the mutation rate at 0.01. Next, the same number of binary strings was generated as the number of individuals. Although the binary strings are generally randomly selected, the initial binary strings were determined using the orthogonal array based on Reeves' study[12], in order to obtain good results with a small number of individuals. Because the number of bits of the three welding process parameters is 11, an orthogonal array comprised of 11-row (L_{12}) was used to form the binary string shown in Table 2. Each row of this orthogonal array represents each individual comprised of the three welding process parameters, and rows 1~4 represent the binary string corresponding to the wire feed rate, rows 5~8 the welding voltage, and rows 9~11 the welding speed. The binary strings of the welding parameters set through the orthogonal array were transformed to values within the region shown in Table 1, using equation (1). Also, the transformed welding process parameter values were used to perform the arc welding experiment. After the experiment, the weld bead geometry obtained in each condition was measured, and the objective function value was calculated, with which the fitness function value was calculated. The first generation of welding process parameters generated through the orthogonal array and the experimental results under each condition are shown in Table 3.

Table 2 L_{12} Orthogonal array for initial generation

Individual numbera	Bit number										
	1	2	3	4	5	6	7	8	9	10	11
1	0	0	0	0	0	0	0	0	0	0	0
2	0	0	0	0	0	1	1	1	1	1	1
3	0	0	1	1	1	0	0	0	1	1	1
4	0	1	0	1	1	0	1	1	0	0	1
5	0	1	1	0	1	1	0	1	0	1	0
6	0	1	1	1	0	1	1	0	1	0	0
7	1	0	1	1	0	0	1	1	0	1	0
8	1	0	1	0	1	1	1	0	0	0	1
9	1	0	0	1	1	1	0	1	1	0	0
10	1	1	1	0	0	0	0	1	1	0	1
11	1	1	0	1	0	1	0	0	0	1	1
12	1	1	0	0	1	0	1	0	1	1	0

Table 3 Results of initial generation

Individual numbera	Feed rate (mm/s)1	Voltage (V)	Speed (mm/s)	Height (mm)	Width (mm)	Penetration(mm)	Objective function	Fitness function
1	45	15	5	-	-	-	41.00	0.024
2	45	22	12	1.0	4.2	2.1	11.70	0.079
3	60	23	12	1.3	4.9	2.5	6.70	0.130
4	70	26	6	1.6	8.2	3.3	1.94	0.340
5	75	28	7	1.3	8.7	2.8	4.37	0.186
6	80	21	9	2.5	5.4	2.8	5.00	0.167
7	100	18	7	-	-	-	41.00	0.024
8	95	29	6	2.0	12.2	4.2	27.33	0.035
9	90	28	9	1.2	8.1	3.2	1.94	0.340
10	115	16	10	-	-	-	41.00	0.024
11	110	19	8	-	-	-	41.00	0.024
12	105	25	11	2.2	5.9	3.8	1.74	0.365

Because penetration was hardly formed in the welding under the conditions of experiments 1, 7, 10 and 11, the welded parts were separated during the cutting operation, and the data measured under these conditions were labeled as "bad data." The penetration was hardly formed in experiments 1, 7, 10 and 11 because the welding voltages were relatively low compared to the given wire feed rate. Because it was impossible to obtain suitable measurement data under the 4 conditions, the search was performed in this study by multiplying 1.5 to the largest objective function obtained among the other welding conditions, to establish the objective function value of these four welding conditions. The reason that a fitness value was given to these conditions instead of eliminating them from the experiment was that they might retain important data.

Using the fitness values calculated from each individual, the roulette wheel selection method was used to select 10 individuals. Crossover was performed on the selected individuals as much as the crossover rate permitted, and mutation was performed, to determine a 2nd generation individual group. This was repeated until welding conditions that produces the satisfactory weld bead geometry has had been obtained. In this study, this process was repeated until the 3rd generation. This was because a near-optimal condition in which relatively satisfactory bead geometry was obtained was found in the 3rd generation. Also, the near-optimal condition was found in the 3rd generation through only 36 experiments. The welding process parameters generated in the 3rd generation and the experiment results are shown in Table 4. In experiment 7, the welding speed was low compared to the wire feed rate, causing a burn through, and thus being classified as "bad data." The data obtained in experiment 8 was also classified as "bad data", as the welding voltage was small compared to the given wire feed rate.

Table 4 Results of the third generation

Individual number	Feed rate (mm/s)	Voltage (V)	Speed (mm/s)	Height (mm)	Width (mm)	Penetration(mm)	Objective function	Fitness function
1	75	24	9	1.7	6.3	3.4	0.89	0.529
2	70	28	11	0.8	6.7	3.1	1.39	0.418
3	95	29	12	1.0	7.2	3.3	0.78	0.562
4	105	26	8	2.4	8.2	4.6	2.61	0.277
5	70	26	9	1.2	5.9	3.1	2.11	0.322
6	80	21	7	2.5	5.8	3.1	3.25	0.235
7	105	25	5	-	-	-	4.88	0.170
8	110	19	11	-	-	-	4.88	0.170
9	75	24	8	1.7	6.9	3.7	0.14	0.877
10	95	30	9	0.6	8.4	4.4	2.93	0.254
11	75	23	11	1.6	5.4	3.3	3.06	0.246
12	105	26	9	2.4	7.2	4.4	1.01	0.498

Fig. 3 shows the results of the genetic algorithm until the 3rd generation. The symbol '●' represents the average value of the objective functions of individuals that comprises each generation, and symbol '■' represents the minimal objective function value among the individuals that comprise each generation. It can be seen through the figure that as the generation increases, the objective function value converges to a smaller value. The number of "bad data" generated until the 3rd generation was 4, 2 and 2, respectively. Fig. 4 shows the generation history of the weld bead geometry values obtained in the welding process parameter values in which the objective function of each generation was minimized.

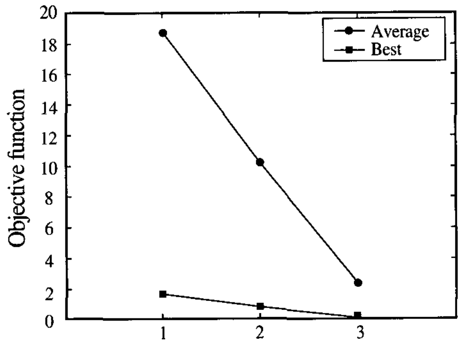

Fig. 3 Results of the genetic algorithm

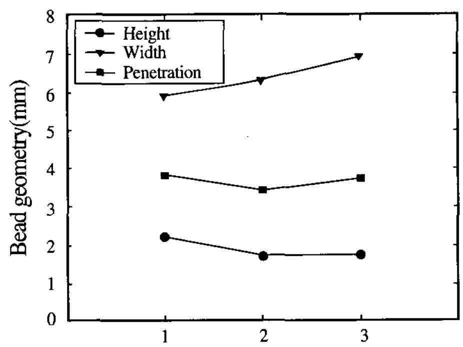

Fig. 4 Results of bead height, bead width, and penetration obtained from the genetic algorithm

As the optimal welding condition means the set of the welding process parameter values in which the fitness function value is maximized, the optimal welding conditions were defined as a wire feed rate of 75mm/s, welding voltage of 24V, and welding speed of 8mm/s, as shown in Fig. 4. The bead height obtained under this condition was 1.7mm, the bead width 6.9mm, and penetration depth 3.7mm. Although this value deviated somewhat from the desired value, it can be seen that relatively satisfactory results were obtained. Also, although the experiment can be continued in order to obtain more satisfactory results, it was decided that it was more effective to use the response surface methodology based on the near optimal point obtained through the genetic algorithm.

5. Conclusion

Because the arc welding process is complicated, professional knowledge on the welding process and many experiments are needed to determine the welding condition in which good weld quality is obtained. Also, in order to obtain a model of the welding process through experiments, preliminary tests are necessary to find the region in which relatively good weld quality is obtained. In this study, an experiment plan was suggested in which the near-optimal condition was found, based on a fixed quantity numerical index and genetic algorithm which shows satisfactory weld quality without the need for professional knowledge.

The method suggested in this study was used to determine the welding condition in which the partial penetration desired by the designer is produced. Because the weld bead geometry is an important factor in determining the weld quality in the arc welding process, the bead height, bead width, and penetration depth of the bead geometry parameters has had been used to form an objective function as to evaluate the weld quality. Meanwhile, the welding process parameters that affects the weld bead geometry were the wire feed rate, welding voltage, and welding speed therein. It was possible to find the welding process parameters that formed the desired partial penetration while excluding the areas in which burn-through occurred or the penetration was hardly formed in the large search range of the three welding process parameters, through the genetic algorithm. This method made it possible to obtain the near-optimal condition with a significantly smaller number of experiments than the factorial experimental method.

Therefore, this method is heavily effective not only in determining the near-optimal condition, but also as the preliminary experiments needed to induce the welding process models as well.

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