GMAW Welding Optimization Using Genetic Algorithms

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This article explores the possibility of using Genetic Algorithms (GAs) as a method to decide near-optimal settings of a GMAW welding process. The problem was to choose the near-best values of three control variables (welding voltage, wire feed rate and welding speed) based on four quality responses (deposition efficiency, bead width, depth of penetration and reinforcement), inside a previous delimited experimental region. The search for the near-optimal was carried out step by step, with the GA predicting the next experiment based on the previous, and without the knowledge of the modeling equations between the inputs and outputs of the GMAW process. The GAs were able to locate near-optimum conditions, with a relatively small number of experiments. However, the optimization by GA technique requires a good setting of its own parameters, such as population size, number of generations, etc. Otherwise, there is a risk of an insufficient sweeping of the search space.
***Keywords**: Optimization,GMAW, genetic algorithm, welding*

Introduction

The GMAW welding process is easily found in any industry whose products requires metal joining in a large scale. It establishes an electric arc between a continuous filler metal electrode and the weld pool, with shielding from an externally supplied gas, which may be an inert gas, an active gas or a mixture. The heat of the arc melts the surface of the base metal and the end of the electrode. The electrode molten metal is transferred through the arc to the work where it becomes the deposited weld metal (weld bead).

The quality of the welded material can be evaluated by many characteristics, such as bead geometric parameters (penetration, width and height) and deposition efficiency (ratio of weight of metal deposited to the weight of electrode consumed). These characteristics are controlled by a number of welding parameters, and, therefore, to attain good quality, is important to set up the proper welding process parameters. But the underlying mechanism connecting then (welding parameters and quality characteristics) is usually not known.

The experimental optimization of any welding process is often a very costly and time consuming task, due to many kinds of non-linear events involved. One of the most widely used methods to solve this problem is the Response Surface Methodology (RSM), in which the experimenter tries to approximate the unknown mechanism with an appropriate empirical model, being the function that represents it called a response surface model. Identifying and fitting from experimental data a good response surface model requires some knowledge of statistical experimental design fundamentals, regression modeling techniques and elementary optimization methods (Myers and Montgomery, 1995). This and other techniques (such as Taguchi) provide good results over regular experimental regions, i.e., with no irregular points. However, it is often very difficult 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, what often forces the experimenter to modify the design space (Kim and Rhee, 2001).

Therefore, it is important to move the experimental region closer to the region of interest, which show relatively good weld quality. This process is particularly of interest when experimentation begins 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. But as the number of the input parameters increases, the number of experiments exponentially increases and the full factorial method for the problem becomes unrealistic (Kim and Rhee, 2001).

Recently, some articles have tried to overcome these problems with a new approach for experimental optimization. They suggest using Genetic Algorithms (GAs) to sweep a region of interest and select the optimal (or near optimal) settings to a process. The GA 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 multimodal, discontinuous or noisy systems. After the GAs have found a regular region, further experimental optimization can be performed with conventional techniques, such as response surface methodology. Some examples of this kind of work are Sette et al (1996), Busacca et al (2001) and Kim and Rhee (2001).

The goal of this article is to explore the GAs technique in the determination of the near-optimal GMAW process parameters, welding voltage (T), wire feed speed (F) and welding speed (S). The search for the optimum was based on the minimization of an objective function, which takes into account the economic aspects (deposition efficiency, d_{exp}) and the geometric characteristics (penetration, p_{exp}, width, w_{exp}, and reinforcement, r_{exp}) of the bead.

Nomenclature

b = *number of bits*
d = *deposition efficiency, %*
f = fitness
F = *wire feed speed, m/min*
GA = *genetic algorithms*
GMAW = *gas metal arc welding*
i = *relative to a specific run (or experiment)*
Of = *objective function*
N = population size
p = *depth of penetration, mm*
pr = probability
r = *bead reinforcement, mm*
RSM = *response surface methodology*
S = *welding speed, cm/min*
T = *welding voltage, V*
V = *variable*
w = *bead width, mm*

Superscripts

max = relative to maximum values

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min = relative to maximum values
o = relative to initial population

Subscripts

exp = relative to experimental value
t = relative to target

Genetic Algorithms

Genetic algorithms are a set of computer procedures of search and optimization based on the concept of the mechanics of natural selection and genetics. Holland (1975) made the first presentation of the GA techniques in the beginning of the 60's and further development can be credited to Goldberg (1989).

The GAs operate over a set of individuals, usually represented by a binary string comprised between 0 and 1. This binary codification is randomly generated over the search space, where each individual represents a possible problem solution. When determining the solution within the search range, the genetic algorithm simultaneously considers a set of possible solutions. This parallel processing of the algorithm may prevent the convergence of one particular local extreme point. Another characteristic of these algorithms is as the GAs only use the fitness value of each string; the fitness function does not need to be continuous or differentiable.

The GMAW welding optimization procedure using genetic algorithm is shown in Figure 1. In this figure, **initial population** means the possible solutions of the optimization problem, and each possible solution is called an individual. In this work, a possible solution is formed by values of the welding voltage, T^o; the wire feed speed, F^o and the welding speed, S^o, which are shown as a binary string. However, they need to be changed into real numbers when being applied to the optimization problem, since the experimenter sets the welding equipment with real values, instead of binary codes.

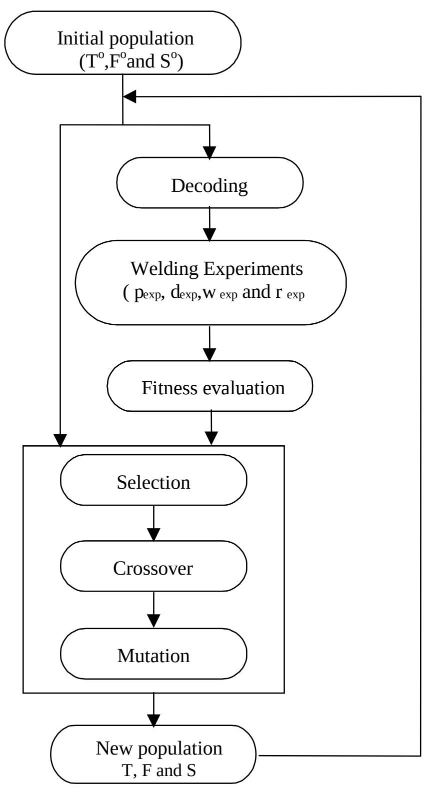

Figure 1. The GWAW welding optimization procedure using genetic algorithm.

Decoding is the process of changing the input variables that are coded as a binary string into a real number. The binary codification is used to represent each variable V_i as a b-bit binary number, which approximates 2^b discrete numbers in the range of the variables, according to:

$$V_i = V_i^{max} + \frac{bin}{2^b - 1}\left(V_i^{max} - V_i^{min} \right) \tag{1}$$

where: V_i^{min} and V_i^{max} are the lower and upper bounds of the i-th continuous variable and *bin* is an integer number between zero and 2^b-1. Each individual, represented by the binary string, is transformed into a real number by Equation (1) and applied to the optimization problem.

After decoding, the values of each individual obtained (T, F and S), are used to set up the **welding experiment**. While the experiment is being conducted, the algorithm stands by until the weld bead is completed and the desired responses (p_{exp}, d_{exp}, w_{exp} and r_{exp}) are measured. According to the results of the welding experiments, the fitness value of the previous welding condition is calculated.

The **fitness evaluation** is a necessary procedure to decide the survival of each individual. Individuals with large fitness values are what the user wants to maximize. Considering the minimization of an objective function, during the evaluation operation, a proper fitness index is assigned to each candidate set in such a way that the lower the value of the objective function associated to an individual candidate, the higher the fitness index given to it. The responses used in this study were used to make the fitness function, Equation (2), as shown below:

$$Of(i) = cp\frac{\left(p_t - p_{exp(i)}\right)^2}{p_t} + cd\frac{\left(d_t - d_{exp(i)}\right)^2}{d_t} + cw\frac{\left(w_t - w_{exp(i)}\right)^2}{w_t} + cr\frac{\left(r_t - r_{exp(i)}\right)^2}{r_t} \tag{2}$$

where:

Of(i) - Value of the objective function at the "i" experiment;
p_t - Target (desirable) value for the depth of penetration;
$p_{exp(i)}$ - Experimental value for the depth of penetration at the "i" experiment;
d_t - Target value for the deposition efficiency;
$d_{exp(i)}$ - Experimental value for the deposition efficiency at the "i" experiment;
w_t - Target value for the bead width;
$w_{exp(i)}$ - Experimental value for the bead width at the "i" experiment;
r_t - Target value for the bead reinforcement;
$r_{exp(i)}$ - Experimental value for the bead reinforcement at the "i" experiment;
cp,cd,cw and cr -Weights that give different status (importance) to each response.

The responses evaluated in this work do not have equal importance. The most important response is the depth of penetration, followed by the deposition efficiency, bead width and reinforcement. In order to transpose these statuses to the objective function, weights were included. These weights are the values put in front of each response term (0.5, 0.3, 0.1 and 0.1) respectively.

The next step is to use each individual fitness and the genetic operator (reproduction, crossover and mutation) to produce the next generation of the **new population (T, F and S)**. The individual evolution (that is, the problem solution) is done by three operators (Goldberg,1989):

Selection – this process is responsible for the choice of which individual, and how many copies of it, will be passed to the next generations. An individual is selected if it has a high fitness value, and the choice is biased towards the fittest members. This study used the biased roulette wheel selection to imitate Darwin's survival of the fittest theory (Goldberg, 1989). 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:

$$p_k = f_k \Big/ \sum_{j=1}^{n} f_j \tag{3}$$

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 - this step takes two strings (parents) from the mating pool and performs a randomly exchange in some portions between them to form a new string (children). After selection, 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 crossover site are exchanged between two parent strings to form two offspring strings. This crossover does not occur with all strings, but is limited by the crossover rate.

Mutation - in a binary coding scheme, it involves switching individual bits along the string, changing a zero to one or vice-versa. This operator keeps the diversity of the population and reduces the possibility that the GAs find a local minimum or maximum instead of the global optimal solution, although this is not ever guaranteed. The mutation rate is usually set at a low value to avoid losing good strings. It also provides information that did not exist in the initial stage.

The main characteristic of the GAs is that they operate simultaneously with a huge set of search space points, instead of a single point (as the conventional optimization techniques). Besides, the applicability of the GAs is not limited by the need of computing gradients and by the existence of discontinuities in the objective function (performance indexes). This is so because the GAs work only with function values, evaluated for each population individual. The major drawback in the GAs is the large use of computational effort when compared with the traditional optimization methods.

Experimental Procedure

The aim of this article is to find the optimum adjusts for the welding voltage, wire feed speed and welding speed in a GMA welding process. The optimum adjusts are the ones that deliver the pre-selected values of four responses: deposition efficiency (100%), bead width (8.5 mm), depth of penetration (5.3 mm) and reinforcement (1.5 mm). These values were developed in Correia & Ferraresi (2001). In other words, the optimum parameters are those who deliver responses the closest possible of the cited values. And it is assumed that the near optimum point is within the following experimental region, defined by the GA search ranges for T, V and S (see in the Table 1).

Table 1. GA search ranges.

Parameters	Range
Welding voltage (T), V	29.0 - 34.2
Wire feed speed (F), m/min	3.9 - 9.7
Welding speed (S), cm/min	50 - 70

The application involved in this work is the welding of 9.5 mm thick mild steel with a square-groove butt joint (1.2 mm root opening). A single pass welding process was used. The filler metal was an AWS classification ER 70S-6 with a 1.2 mm diameter electrode. The shielding gas used was 100% CO_2 with a 13 l/min flow rate.

Inside the experimental space, the GAs chose, randomly, the initial welding setup, i.e., the parameters values of the first experiment. After it (the first exp.) was done, its response characteristics were measured and fed into the GAs. Then, based in the previous information, the algorithm chose another setup, which was done and its data again fed into the algorithm. The process continued until the optimum was found, i.e., until the objective function (Eq. 2) reached its minimum. The parameters of GA computations are shown on Table 2.

Table 2. Parameters of GA computations.

Accuracy (number of bits)	30
Population size	7
Number of generation allowed	4
Mutation rate	1 %
Crossover rate	90 %
Type of crossover	Single

In the GA, the population size, crossover rate and mutation rate are important factors in the performance of the algorithm. A large population size or a higher crossover rate allows exploration of the solution space and reduces the chances of settling for poor solution. However, if they are too large or high, it results in wasted computation time exploring unpromising regions of the solution space. In this work, the population size and number of generation are small in order to maintain the total number of experiments in an acceptable level.

About the mutation rate, if it is too low, many binary bits that may be useful are never tried. However, if it's too high, there will be much random perturbation, and the offspring will loose the good information of the parents. The 1% value is within the typical range for the mutation rate. The crossover rate is 90 %, i.e., 90% of the pairs are crossed, whereas the remaining 10% are added to the next generation without crossover. The chosen type of crossover was single, which means that a new individual is formed when the parent genes are swapped over at some random single point along their chromosome. Accuracy is the bit quantity for each variable.

Results and Discussion

Table 3 presents the settings and the resultant values of the evaluated responses for all the experiments performed, as well as the values of the correspondent objective function.

Table 3. Results of all generations.

Run	T (V)	F (m/min)	S (cm/min)	p_{exp} (mm)	d_{exp} (%)	w_{exp} (mm)	r_{exp} (mm)	Objective Function
1	30.3	6.9	54.5	5.0	55.6	6.5	0.7	4.749
2	28.1	8.3	54.0	5.5	87.7	8.5	1.7	0.169
3	28.0	9.0	57.5	6.5	89.5	7.7	2.0	0.229
4	31.5	6.9	60.0	4.5	57.2	6.2	1.0	4.404
5	27.9	9.7	56.5	6.0	91.4	7.2	2.5	0.164
6	28.5	9.7	70.0	6.0	91.6	6.5	2.0	0.138
7	31.4	6.9	52.5	4.5	60.0	7.2	1.5	3.748
8	28.5	9.7	70.0	6.0	91.6	6.5	2.0	0.138
9	28.5	8.3	59.0	5.5	88.2	8.0	1.7	0.147
10	28.7	9.7	64.5	5.5	92.2	6.5	2.2	0.112
11	28.5	9.7	70.0	6.0	91.5	6.5	2.0	0.138
12	27.7	9.7	69.5	6.0	93.0	6.5	2.5	0.163
13	31.3	5.4	51.5	3.5	79.3	6.0	1.5	1.074
14	28.5	9.7	70.0	6.0	91.8	6.5	2.0	0.138
15	27.7	9.7	69.5	6.0	93.3	6.5	2.5	0.163
16	28.7	9.7	69.5	6.0	92.0	6.5	2.0	0.138
17	28.7	9.7	64.5	5.5	92.0	6.5	2.2	0.112
18	28.7	9.7	64.5	5.5	92.2	6.5	2.2	0.112
19	27.7	9.7	69.5	6.0	93.4	6.5	2.5	0.163
20	28.5	9.7	69.5	6.0	91.7	6.5	2.0	0.138
21	28.6	9.7	64.5	5.5	92.3	6.5	2.2	0.112
22	28.4	9.7	70.0	6.0	91.6	6.5	2.0	0.138
23	28.7	9.7	64.5	5.5	91.9	6.5	2.2	0.112
24	28.8	9.7	69.5	6.0	91.7	6.5	2.0	0.138
25	28.7	9.7	64.5	5.5	92.3	6.5	2.2	0.112
26	28.7	9.7	64.5	5.5	92.1	6.5	2.2	0.112
27	28.9	9.7	64.5	5.5	92.2	6.5	2.2	0.112
28	28.8	9.7	64.5	5.5	92.2	6.5	2.2	0.112

All the experiments performed according to the genetic algorithm had a relatively good quality (in the sense of lack of bead defects) with no problems of melt-through, porosity or cracks. Considering quality as closeness to defined targets, the genetic algorithm did not manage to achieve all the established targets. The final value of the objective function was 0.11, which is a relatively low value (compared to its initial value) and can be considered satisfactory weld quality, according to Kim and Rhee (2001). And this final value for the objective function repeats itself in the last four experiments of the Table 3 with the same settings, suggesting that this is not some random error (this stabilization can be better seen in the Figure 2). But Table 4 shows that the discrepancy between targets and obtained values was quite big for some responses, mainly the bead width and the bead reinforcement.

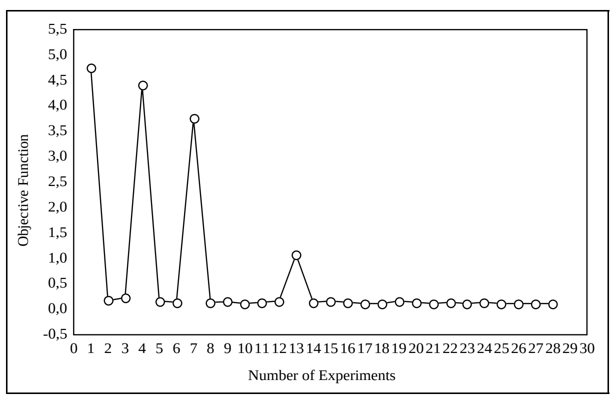

Figure 2. Convergence of the genetic algorithm.

Table 4. Comparison between target and obtained values.

	Target Values	Final Values	Difference (%)
Depth of penetration (mm)	5.3	5.5	3.8
Deposition efficiency (%)	100.0	92.2	7.8
Bead width (mm)	8.5	6.5	23.5
Bead reinforcement (mm)	1.5	2.2	46.7

The discrepancy between target and final values can not be credited to insufficient generations, since the Figure 2 shows a good pattern of stabilization for the objective function. In addition, Figures 3, 4 and 5 show that the stabilization also exists when considering the individual values of the setting parameters. The welding voltage had a minor variation in its last values, but nothing significant in terms of practical purposes. The wire feed speed and the welding speed presented good stabilization in their final values. It should be said that maybe a higher population size would allow a better sweeping of the search space. An evaluation on the influence of new values for the GA parameters (other than presented in Table 2) should be considered in future works.

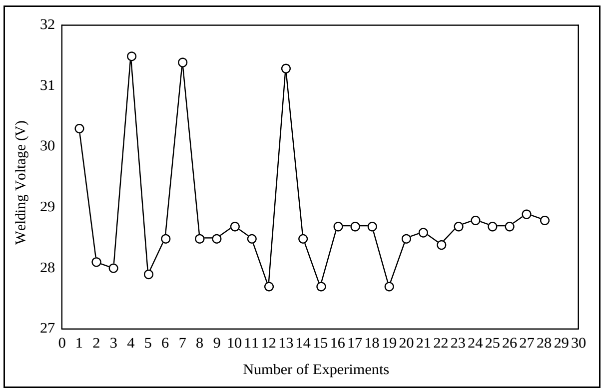

Figure 3. Convergence of the welding voltage.

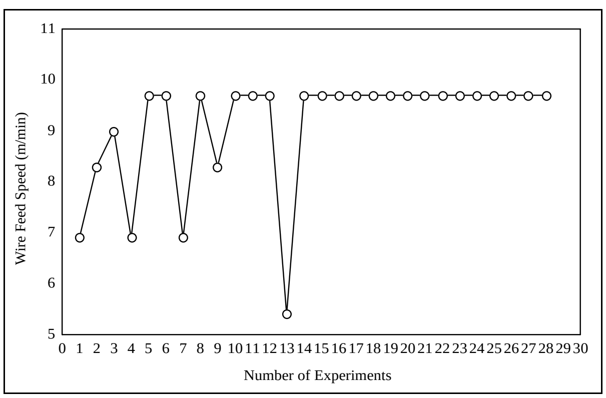

Figure 4. Convergence of the wire feed speed.

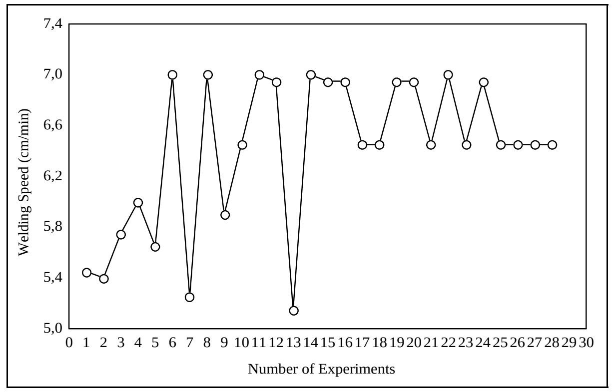

Figure 5. Convergence of the welding speed.

The explanation for the GA inability in accomplishing all targets can be credited to the weights used in the objective function (Equation 2). As seen, the most important responses are the depth of penetration (0.5 weight) and the deposition efficiency (0.3 weight) and the minimization process was led by these ones. But a look in Table 3 reveals that there are other compromises available, such as experiment 2, where lower deposition efficiency gives room to better adjusted bead width and bead reinforcement.

A final note on the GA optimization is about its inner mechanism of random search. Figure 6 shows the experimental region that should be investigated and the points suggested by the GA. These points are not equally distributed in the search space, as in a conventional statistical project would be. And many of the points are coincident, which reduces even more the swept region. So, there is a chance of existing non-tested points with even a better compromise between the responses.

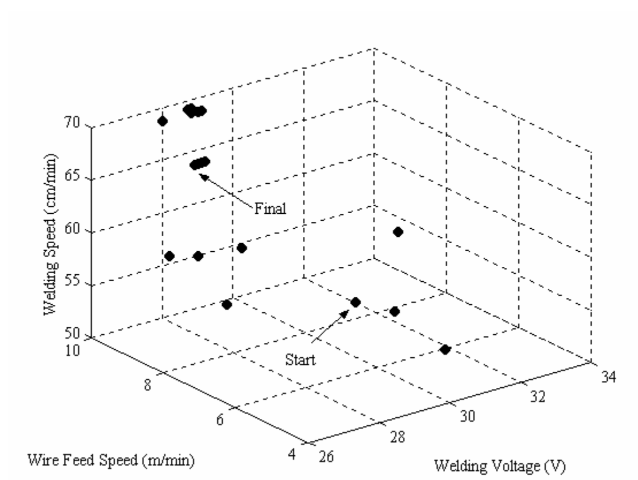

Figure 6. Search space and the points analyzed by the GA.

Conclusion

The possibility of a GMAW welding optimization procedure using genetic algorithm is investigated in this work; more specifically, the determination of the near-optimal GMAW process parameters, welding voltage (T), wire feed speed (F) and welding speed (S). The search for the optimum was based on the minimization of an objective function, which takes into account the economic aspects (deposition efficiency) and the geometric characteristics (penetration, width and reinforcement) of the bead.

It was found that the GA can be a powerful tool in experimental welding optimization, even when the experimenter does not have a model for the process. The most important response (depth of penetration) had a difference from its target lower than 4%.

However, the optimization by GA technique requires a good setting of its own parameters, such as population size, number of generations, etc. Otherwise, there is a risk of an insufficient sweeping of the search space. In addition, it is suggested the use of conventional statistical projects to investigate the space around the conditions found by the GA, in order to obtain models and/or perform a fine-tuning of the optimal parameters.

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