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Comparison between genetic algorithms and response surface methodology in GMAW welding optimization

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Abstract

The response surface methodology (RSM) is a traditional technique for experimental process optimization. Recently, a new approach to this problem has been tried with the genetic algorithm (GA), which is most known in the numerical field. The present paper compares these two techniques in the optimization of a GMAW welding process application. The situation was to choose the best values of three control variables (reference 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. For the RSM, an experimental design was chosen and tests were performed in order to generate the proper models. In the GA case, the search for the 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. Results indicate that both methods are capable of locating optimum conditions, with a relatively small number of experiments.

Keywords: Optimization; GMAW; Genetic algorithm; Response surface methodology

1. 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 [1].

Recently, some papers have tried to establish a new approach for experimental optimization [2–4]. 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.

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The goal of this article is to compare the GA and RSM techniques in the determination of the optimal GMAW process parameters, reference voltage (T), wire feed speed (F) and welding speed (S). By optimum it is meant the adjusts that deliver the pre-defined values for the following responses: deposition efficiency (d_{exp}), penetration (p_{exp}), width (W_{exp}) and reinforcement (R_{exp}).

2. Response surface methodology

Response surface methodology is an empirical modeling approach using polynomials as local approximations to the true input/output relationship. This empirical approach is often adequate for process improvement in an industrial setting. By careful design of experiments, the objective is to optimize a response (output variable) that is influenced by several independent variables (input variables). An experiment is a series of tests, called runs, in which changes are made in the input variables in order to identify the reasons for changes in the output response.

The relationship between the response variable of interest (y), and the input variables (x_1, $x_2, \ldots, x_n$) is usually not known. In general, the experimenter approximates the system function with an empirical model of the form:

$$y = f(x_1, x_2, \ldots, x_n) \tag{1}$$

where "f" is a first- or second-order polynomial. This is the empirical or response surface model. The variables are known as *natural variables* since they are expressed in physical units of measurement. In the RSM, the natural variables are transformed into coded variables which are dimensionless. The successful application of RSM relies on the identification of a suitable approximation for "f".

The "f" function is a low order polynomial build with linear regression techniques. The necessary data for building the response models are generally collected by an experimental design. The most popular of the many classes of RSM designs is the central composite design (CCD). This is so due to the following three properties:

1. A CCD can be run sequentially. It can be naturally partitioned into two subsets of points; the first subset estimates linear and two-factor interaction effects while the second subset estimates curvature effects. The second subset need not be run when analysis of the data from the first subset points indicates the absence of significant curvature effects.
2. CCDs are very efficient, providing much information on experiment variable effects and overall experimental error in a minimum number of required runs.
3. CCDs are very flexible. The availability of several varieties of CCDs enables their use under different experimental regions of interest and operability.

3. 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 [5] made the first presentation of the GA techniques in the beginning of the 1960s and further development can be credited to Goldberg [6].

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.

There are basically six steps to be taken in a genetic algorithm optimization:

(1) *Decoding*: 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.

(2) *Creation of an initial population*: An initial set of individuals is created by a random generator.

(3) *Fitness evaluation*: This is a necessary procedure to decide the survivor 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.

(4) *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 [6]. 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:

$$p_k = \frac{f_k}{\sum_{j=1}^{n} f_j} \tag{2}$$

where n is population size. Then a biased roulette wheel is made according to these probabilities. The selection