International Journal of Engineering Research and Applications (IJERA) ISSN: 2248-9622
NATIONAL CONFERENCE on Developments, Advances & Trends in Engineering Sciences
(NCDATES- 09th & 10th January 2015)

RESEARCH ARTICLE OPEN ACCESS

An Evolutionary Modeling Approach for Submerged Arc welding process

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ABSTRACT
Submerged arc welding is a widely used fabrication processes in industry because of its high deposition, deep penetration, and improved working environment. Also it is preferred process for automation. The principal requisite to automate a process is to develop the governing relationships between process parameters and weld bead geometry. The present work proposes a novel application of an evolutionary algorithm called genetic programming, for modeling of submerged arc welding. Open circuit voltage, wire feed rate, welding speed, and nozzle-to-plate distance are considered for predicting the certain bead geometrical parameters.
Keywords: *Submerged arc welding; Weld bead geometry; Evolutionary approach, Genetic programming;*

I. INTRODUCTION

Submerged arc welding is a widely accepted fabrication process in industry where the joining of large metal parts is taken up in large scale. The basic principle of the process involves the generation of an electric arc between electrode and weld pool. The heat of the arc melts surface of the base metal and end of the electrode. The metal melted off the electrode is transferred through the arc to the work-piece, where it becomes the deposited weld metal. A blanket of granular flux on work pieces shields the arc and the molten metal.

In any arc welding process, bead geometrical parameters plays an important role in determining the mechanical properties of the weld and hence quality of the weld [1]. In submerged arc welding, bead geometrical variables are greatly influenced by the process parameters such as open circuit voltage, wire feed rate, welding speed, and nozzle-to-plate distance [2, 3]. Therefore to accomplish good quality it is imperative to setup the right welding process parameters. Quality can be assured with embracing automated techniques for welding process. Welding automation not only results in high quality but also results in reduced wastage, high production rates with reduce cost to make the product.

To automate an arc welding, it is essential to develop the governing relationships between the process parameters and the bead geometrical variables. These relationships are important to optimize weld quality and total process cost. The traditional practice of selecting the process parameters is based on a trial-and-error methods and/or experience and judgment of the particular welder. Although it is a costlier and time-intensive process, yet it does optimize neither the quality nor the cost.

Data found in literature confirm that there are many scientific researchers who have studied the performance characteristics of submerged arc welding. The effect of welding parameters on weld bead geometry and heat effected zone was studied in ref [4]. Multiple linear regression analysis was applied to establish mathematical models for the bead geometry [5, 6]. However, the linear regression techniques are inadequate to describe the submerged arc welding, as it is a highly non-linear process. Ping Li et al. [7] applied self-adaptive offset neural networks to modeling. However, neural networks do not establish the quantitative relationships between the input variables and the output variables. Gunaraj et al. [8] have determined the main and the interaction effects of process parameters on the bead geometry using response surface methodology (RSM). In the RSM, a model of certain degree has to be determined in advance. Because of this pre-specified degree of the model, RSM may often not handle a highly non-linear responsive data.

In the present work, an evolutionary algorithm is proposed for modeling of submerged arc welding process. Genetic programming (GP) is proposed for developing the relationships between the weld bead geometry and the input variables. GP is such a generalized method that it can handle any much of complexity between input variables and output parameters.

II. EXPERIMENTAL WORK

Based on the literature survey [2,3] and the trail experiments, it was found that the parameters such as open circuit voltage (x_1), wire feed rate (x_2), welding speed (x_3), and nozzle-to-plate distance (x_4) have significant affect on weld bead geometrical features such as penetration (P), reinforcement (R), bead width (W), and bead volume (V).

In the present work, they were considered as the decision variables and other parameters were set to be constant over the experimental domain. The base metal welded was Medium carbon steel with the dimensions of 8mm×110mm×65mm, the first one being the thickness of the plate followed by length and width respectively. The welding was performed with a submerged arc welding machine, model MAESTRO 800, made by ADOR welding limited, India. The semi-automatic welding system has a control unit by which the welding variables (Open circuit voltage, wire feed rate and welding speed) can be pre-set. The electrode wire used in coil form was Automelt EL8 (AWS A5.17/5.23) of 3.15mm diameter and baked auto melt flux (A55/ (F7AZ/PZ-EL8)) was used for welding. The wire was kept at 90^0 to the work piece.

100 bead-on-joint welds were made by varying the input variables within the feasible range. For measuring the bead geometry feature each welded joint was sectioned perpendicular to the weld direction. The specimens were then prepared by the usual metallurgical polishing methods and etched with 3% Nital. The profiles were then traced using a precision optical profile projector and the bead dimensions were measured accurately.

III. GENETIC PROGRAMMING METHODOLOGY

Evolutionary approaches attempt to find the best solution to a problem by mimicking the process of evolution in nature using Darwin's theory of *survival of the fittest*. Individual potential solutions are selected based on their fitness from the initially generated random population. The potential solutions are then recombined to produce better solutions. The extreme popularity of these techniques is due to their success at searching highly complex non-linear spaces and their robustness in practical applications. Genetic programming is a relatively new approach when compared to other variations of evolutionary algorithms such as evolutionary strategies, genetic algorithms and evolutionary programs. The genetic programming approach finds a polynomial function consisting of the constants and variables and optimally fitting to measured process parameters. The polynomial function may take the form defined by:

$$y = f\left(x_1, x_2, x_3, x_4\right) \quad (1)$$

Where *y* may be desired output variable (penetration, reinforcement, width or volume) which is expressed mathematically as a function of the input process parameters (voltage, wire feed rate, carriage speed and nozzle to plate distance)

The main principles of Genetic programming (GP) and its related terminology were developed by Koza [9]. Since then this technique has found applications in diversified fields such as machine learning, artificial intelligence, symbolic regression, surface roughness prediction, etc., but its application to a welding modeling is believed by the authors to be entirely new.

In GP, a solution to a problem is represented as a computer program, which has a hierarchical composition (tree like structure) of primitive *functions* and *terminals* appropriate to particular problem domain. In GP terminology, inputs are usually called *terminals* and user specifies a number of *functions* that manipulate terminals. The set of primitive *functions* typically include: arithmetic operations (+, –, *, /), boolean operations (AND, OR, NOT), logical operations - (IF-THEN-ELSE), and non-linear functions (sin, cos, tan, exp, log). Compatibility between the functions and terminals must be ensured in order to impeccably pass information between each other. Typical representation of an individual in GP is as a tree structure.

IV. 4. IMPLEMENTATION OF THE METHODOLOGY

For modeling the bead geometry in submerged arc welding through genetic programming, the experimental data obtained were grouped into two sets: training dataset and validation dataset. The training data set is used to predict the expression that best suits to the problem and the validation data is used to test the predicted model. The training and testing data should have similar statistical properties (i.e., mean, standard deviation, range or any other suitable measures).

To decide the elements of functional sets, initially some trial runs were conducted with different combinations. It was found that the probability of successful solution was the greatest, when only the basic arithmetic functions were used. The arithmetic elements that were considered are addition, subtraction, multiplication, and division. The terminal set consists of all input variables of the welding process that have been taken into consideration in the present study.

4.1 Fitness measure

An average percentage deviation of all experimental data for an individual was introduced as the fitness measure and is defined below:

$$\delta = \sum_{i=1}^{n} \frac{\delta_i}{n} \tag{2}$$

where, δ is the fitness, n is the total number of observations and δ_i is the percentage deviation of single sample data. The percentage deviation of single sample data produced by an individual is

$$\delta_i = \frac{|M_i - P_i|}{M_i} \times 100\% \tag{3}$$

where, M_i is the experimentally measured value and P_i is the value predicted by the model.

4.2 Initial settings for GP run

Preliminary experiments were performed to determine the best parameter settings for the GP. These preliminary test runs in the GP system were executed for the output parameters independently. This limit is necessary since GP has the tendency to evolve uncontrollably large trees, if the tree size is not limited. Thus, a maximum tree size of 6 evolves simple expressions that are easy to interpret.

The software was developed in VC^{++} on a Pentium system with 2.8GHz processor. Tests with populations of different sizes of 2000, 3000 and 5000 were also performed. In all cases, the best results were achieved with the large populations. However, the computation times were also increased from an average of 3 minutes for the population size of 100 to more than 10 minutes for the population size of 5000. Thus, a reasonable size of 3000 was considered.

4.3 GP modeling results

GP being probabilistic by nature, so for non-trivial symbolic regression problems every time the algorithm is used it is possible that it will land at differing approximate solutions. In order to exploit this intrinsic variation, it is helpful to perform multiple runs and to employ a statistical analysis of the results. In this study, several independent runs of the genetic programming for each of the bead geometry feature were tested. In each run, 70 data for training which were randomly sampled from 100 data were used. The rest 30 data was used to validate the generated model. It may be noted that for the bead penetration the best model was evolved in the 22nd run, and for bead reinforcement in the 28th run, for bead width, in the 13th run.

After the implementation of the algorithm, the following best models were evolved for bead geometry in terms of open circuit voltage (x_1), wire feed rate (x_2), welding speed (x_3), and nozzle-to-plate distance (x_4).

$$P = 0.958 - x_3 + x_2 + \left(0.0067\,(x_1 + 0.1205\,(x_4 + 29)) + \frac{x_4}{854.4}\right) \tag{4}$$

$$R = \frac{132.75}{(x_4 - x_3 + 0.0098 + 2.288(x_1 + x_3))} + \frac{0.437\left(\frac{x_3}{x_4} - x_3 + x_2\right)}{x_3\left(\frac{x_4}{29} + x_3 + 0.792\right)} \tag{5}$$

$$W = \frac{5x_1x_2}{x_4} + \frac{0.535x_2x_4}{x_1(4 + x_3x_4)} + \frac{0.008x_1}{(x_2x_3)^2} \tag{6}$$

V. CONCLUSIONS

Weld quality in an arc welding process is strongly characterized by bead geometry. This is because bead geometry plays a vital role in determining the mechanical properties of the weld. The present work proposes a new and efficient approach for empirical modeling of weld bead parameters of submerged arc welding using Genetic programming for the first time in the literature. The results revealed that in each case the GP algorithm could produce an accurate input-output model based exclusively on experimental data. The proposed approach neither requires any strict mathematical rule nor any prior knowledge of how to get the solution of the problem. GP uses evolutionary principles to evolve automatically mathematical models that best suit to the given experimental data. No assumptions about the shape, size, and complexity of the problem are required. GP is such a generalized approach that this can be applied any welding process under any number of variables.

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