An Integrated GA-Taguchi Model For Parametric Optimization Of Submerged Arc Welding Process

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Abstract

Genetic algorithm (GA), a biologically inspired method for optimization is based on certain parameters like population-size, cross-over fraction, mutation-rate etc. This paper has employed an integrated GA-Taguchi methodology for determination of optimized GA parameters for a submerged arc welding (SAW) process. Further process parameter optimization of SAW has been carried out using that optimized GA. The planned experiments are conducted in the semi automatic submerged arc welding machine. During experimentation, welding current, arc voltage, welding speed are considered as input parameters and weld bead width and weld bead hardness as output parameters. Weighted sum of regression models developed for weld bead width and weld bead hardness forms the objective function for GA optimization. On employing present integrated methodology, optimized value of GA parameters such as population-size, cross-over fraction and mutation-rate are determined as 100, 0.7 and 0.05 respectively. Optimization of SAW parameters using an optimized GA produces improved output compared to non optimized GA.

Keywords: Submerged Arc welding, weld bead width, weld bead hardness, Taguchi method, Genetic Algorithm.

Introduction

Submerged Arc Welding (SAW) is one of the major fabrication processes in manufacturing industry because of its inherent advantages, including deep penetration, complete fusion, and smooth weld bead. In this technique coalescence is produced by heating with an electric arc where the end of the electrode and molten pool are invisible being submerged under a blanket of granulated flux. Similar to other welding processes, the quality of SAW joint can be defined in terms weld bead geometry. The weld bead geometry itself is directly influenced by the welding input parameters. Therefore, appropriate selection of process control parameters is very crucial for achieving required weld bead quality. In recent years, various optimization methods have been applied to define the best output parameters through developing mathematical models to specify the relationship between the process parameters and the weld bead specifications. Design of Experiment (DOE) and numerical methods are employed to model welding processes. Most models are developed based on regression analysis for a given set of experimental welding data. Researchers have made many attempts to predict the process parameters of submerged arc welding to get smooth quality of weld. Kumaran et al [1] have employed Taguchi and regression analysis for optimal process parameter selection of SAW. Prediction and optimization of the weld bead volume for SAW was carried out by Gunaraj et al [2] using response surface methodology (RSM). In a similar study, prediction and control of weld bead geometry and shape relationship in SAW of pipes was studied by Gunaraj et al [3]. Dutta et al [4] have employed grey based Taguchi method for optimization of bead geometry for SAW. However, evolutionary algorithms such as genetic algorithms (GA), simulated annealing (SA) etc can be an effective means of optimization of process parameters. Kolahan et al [5] have employed genetic algorithm for optimisation of process parameters of SAW.

In present paper, an integrated GA-Taguchi methodology has been employed for optimization of a SAW process using an optimized GA. The important controlling parameters in SAW include welding voltage, wire feed rate, welding speed and welding current. The weld quality is specified by weld bead width and weld bead hardness Objective function for GA optimization has been developed through formation of weighted sum of the regression models connecting weld bead width and weld bead hardness with SAW input parameters and their weighted sum has formulated objective function for GA optimization. The work has been carried out in two steps: I) Initially, Taguchi method has been employed with a three level three factor design for optimization of GA parameters such as population-size, cross-over fraction, mutation-rate. II) Application of optimized GA for optimizing SAW process parameters: Regression models have been developed to connect weld bead width and weld bead hardness with SAW input parameters and their weighted sum has formulated objective function for GA optimization. Steps of proposed integrated GA-Taguchi methodology has been provided in Fig.1.
2.1 Experimentation
In the present work, experimental dataset for validation of the proposed GA-Taguchi model has been obtained from literature [6]. Eight sets of experiments on submerged arc welding of 100mmx50mmx12mm thick mild steel plates have been conducted based on design of experiments with semiautomatic saw-1000 setup. During experimental design, 2 levels of welding current, A (C), arc voltage, V (V), welding speed, mm/min (S), electrode stick out, mm (ESO) have been considered as independent operating variables. Corresponding output variables measured are as weld bead width, mm (BW) of top surface and weld bead hardness, HRC (H) by Rockwell hardness test machine. The experimental dataset and corresponding levels of the process parameter have been given in Table 2 and Table 3.

Table 1. Experiment Welding Parameter Levels

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Welding Parameter</th>
<th>Level 1</th>
<th>Level 2</th>
</tr>
</thead>
<tbody>
<tr>
<td>C</td>
<td>Welding current, A</td>
<td>300</td>
<td>360</td>
</tr>
<tr>
<td>V</td>
<td>Arc voltage, V</td>
<td>25</td>
<td>27</td>
</tr>
<tr>
<td>S</td>
<td>Welding speed, mm/min</td>
<td>900</td>
<td>1000</td>
</tr>
<tr>
<td>ESO</td>
<td>Electrode stick out, mm</td>
<td>19</td>
<td>25</td>
</tr>
</tbody>
</table>

2.2 Model development
Experimental data in Table 2 is further used to develop the second order regression model as stated earlier to find the approximate relationship between four input variables and corresponding output variables and given as follows:

\[
BW = 271.562 - 0.791 \times C - 8.542 \times V - 0.065 \times S + 0.104 \times ESO + 0.026 \times C \times V + 0.125E - 0.03 \times C \times S + 0.833E - 0.03 \times V \times S \\
H = -548.479 + 0.208 \times C + 20.875 \times V + 0.526 \times S + 0.179 \times ESO - 0.009 \times C \times V - 0.417E - 0.04 \times C \times S - 0.018 \times V \times S + 0.0 \times C \times ESO 
\]

This model is developed by using SPSS software. Adequacy of model has been tested by Regression coefficient (R-square) value of the regression equation developed. As R-square value for the output parameters are 1 the model seems adequate.

Table 2. Input Design Matrix and Experimental Results

<table>
<thead>
<tr>
<th>Trial No.</th>
<th>C</th>
<th>V</th>
<th>S</th>
<th>ESO</th>
<th>BW</th>
<th>H</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>300</td>
<td>25</td>
<td>900</td>
<td>19</td>
<td>15.00</td>
<td>40.50</td>
</tr>
<tr>
<td>2</td>
<td>300</td>
<td>25</td>
<td>1000</td>
<td>25</td>
<td>15.00</td>
<td>51.00</td>
</tr>
<tr>
<td>3</td>
<td>300</td>
<td>28</td>
<td>900</td>
<td>25</td>
<td>16.00</td>
<td>50.00</td>
</tr>
<tr>
<td>4</td>
<td>300</td>
<td>28</td>
<td>1000</td>
<td>19</td>
<td>15.00</td>
<td>49.50</td>
</tr>
<tr>
<td>5</td>
<td>360</td>
<td>25</td>
<td>900</td>
<td>25</td>
<td>14.50</td>
<td>39.00</td>
</tr>
<tr>
<td>6</td>
<td>360</td>
<td>25</td>
<td>1000</td>
<td>19</td>
<td>14.00</td>
<td>43.50</td>
</tr>
<tr>
<td>7</td>
<td>360</td>
<td>28</td>
<td>900</td>
<td>19</td>
<td>19.00</td>
<td>41.00</td>
</tr>
<tr>
<td>8</td>
<td>360</td>
<td>28</td>
<td>1000</td>
<td>25</td>
<td>20.00</td>
<td>46.00</td>
</tr>
</tbody>
</table>

2.3 Formulation of objective function
Simultaneous optimization of bead width (BW) and bead hardness (H) indicate multi-objective nature of the problem and can be formulated as:

The objective functions:
Maximize BW (C, V, S, ESO)
H(C, V, S, ESO)

Subject to constraints:
\[
300 \leq C \leq 360 \\
25 \leq V \leq 27 \\
900 \leq S \leq 1000 \\
19 \leq ESO \leq 25 
\]

(3)

In the present study, the multi-objective process is reduced to single objective optimization problem using Z as a weighted sum of the output parameters and given as:
\[ Z = -W_1 \times BW - W_2 \times H \] (4)

Where \( Z \) is to be maximized and \( W_1, W_2 \) represent the weight of each output and is equal to 0.5 taken. –ve sign before an output indicates that the parameter is to be maximized. BW and H are computed using the Regression model developed (Eq.1-2) and finally the combined objective function is given as follows:

\[
Z = -W_1 \times (271.562 - 0.791 \times C - 0.542 \times V + 0.065 \times S + 0.104 \times ES0 + 0.026 \times C \times V + 0.125E \times 03 \times C \times S + 0.833E \times 03 \times V \times S) - W_2 \times (-549.479 + 0.200 \times C + 20.875 \times V + 0.526 \times S + 0.479 \times ES0 - 0.009 \times C \times V - 0.4178 - 0.018 \times C \times S + 0.018 \times V \times S + 0.0 \times C \times ES0) \] (5)

2.4 Genetic Algorithm

Genetic algorithm contains the principles of evolution and natural selection [7]. It belongs to a general category of stochastic search methods. This algorithm encodes a potential solution to a specific problem on simple chromosome string like data structure and applies specified operators to these structures so as to preserve critical information, and to produce a new set of population with the purpose of generating strings which map to high function values. The main characteristic of the GA and its several variations is that they operate simultaneously with a large set of search space points, instead of a single point (as the conventional optimization techniques). Genetic algorithm repeatedly modifies a population of individual solutions. At each step, it selects individuals at random from the current population to be parents and uses them to produce the children for the next generation. Over successive generations, the population "evolves" toward an optimal solution. Genetic algorithm uses three main types of rules at each step to create the next generation from the current population:

Selection rules select the individuals, called parents, which contribute to the population at the next generation.

Crossover rules combine two parents to form children for the next generation.

Mutation rules apply random changes to individual parents to form children.

Initial population size, crossover fraction and mutation rate are the key variables those directly influence optimization outputs. Therefore, if optimized set of these parameters are used to carry out GA optimization, best optimized output will be obtained. Therefore, optimisation of GA parameters have been carried out using Taguchi method.

2.5 Working of Taguchi method for optimization of GA parameters

Taguchi method employs a specially designed orthogonal array to study the entire factor space through only a small number of experiments. In the Taguchi method, the term ‘signal’ represents the desirable value for the output characteristic and the term ‘noise’ represents the undesirable value for the output characteristic. Therefore, the term ‘signal-to-noise ratio’ or S/N ratio in Taguchi method measures the deviation of quality characteristic from the desired value. In this work, three level of three process parameter ie Population-size, Cross-over fraction, Mutation rate are selected through some pilot experiments. The numeric value of variables at different level is furnished in Table 3.

Table 3. GA parameters with different levels

<table>
<thead>
<tr>
<th>Symbol</th>
<th>Welding parameters</th>
<th>Level 1</th>
<th>Level 2</th>
<th>Level 3</th>
</tr>
</thead>
<tbody>
<tr>
<td>P</td>
<td>Population-Size</td>
<td>50</td>
<td>75</td>
<td>100</td>
</tr>
<tr>
<td>C</td>
<td>Crossover Fraction</td>
<td>0.5</td>
<td>0.7</td>
<td>0.8</td>
</tr>
<tr>
<td>M</td>
<td>Mutation Rate</td>
<td>0.01</td>
<td>0.03</td>
<td>0.05</td>
</tr>
</tbody>
</table>

Taguchi method works according to the following steps:

(i) Computation of quality loss function: The control factors are P, C and M respectively. A specific combination of those control factors when employed in GA, upon optimization GA returns optimized combined objective function value \( Z \) that has been used for computing loss function. The combined objective function \( Z \) is weighted sum of weld bead width (BW) and weld bead hardness (H). As larger BW and H is desirable, \( Z \) belongs to higher the better quality characteristic. The loss function \( (\lambda) \) of the higher the better quality characteristic can be expressed as:

\[
\lambda_i = \frac{1}{n} \sum_{i=1}^{n} \frac{1}{y_{ij}^2} \] (6)

Where, \( y_i \) are the observed output (or quality characteristics) at the \( i^{th} \) trial, and \( n \) is the number of trials at the same level.

(ii) Computation of S/N ratios: S/N ratio (SNR) is computed to determine the quality index of each design point using total normalized quality loss values. The MSNR corresponding to \( ij^{th} \) trial condition (SNR\(_{ij}\)) is calculated as:

\[
SNR_{ij} = -10 \log_{10}(\lambda_i) \] (7)

(iii) Optimization of process parameters: Mean of all MSNR values at a specific level of a process parameter is used to describe the effect of a process parameter or factor on quality characteristics at that level. A parameter level corresponding to the maximum average MSNR is called the optimum level for that parameter.
The predicted value of MSNR \( \text{MSNR}_{opt} \) at optimum parameter levels is calculated by using following formula:

\[
\text{MSNR}_{opt} = \frac{\text{MSNR}}{k} + \sum_{i=1}^{k} (\text{MSNR}_i - \text{MSNR})
\]

(8)

Where \( \text{MSNR} \) is the mean MSNR of all experimental runs, \( k \) is the number of significant control factors, and \( \text{MSNR}_i \) is the average MSNR for \( i^{th} \) control factor corresponding to optimum parameter level. Further an experiment is conducted with optimum parameter levels determined by Taguchi method for validation of the predicted response.

3. Results and Discussion

Problem formulation and methodology for optimization with GA-Taguchi hybrid modeling are already discussed in section 2. In present study, \( L_9 \) orthogonal array design matrix of control factors i.e. GA parameters has been considered for analysis. For each set of GA parameters provided by design matrix, program code for GA is run to return the output i.e. combined objective function value \( Z \) (Eq.5). Quality loss function and subsequent signal-to-noise ratio has been computed using Eq. (6) and Eq. (7).

Table 5. Effect of factors on S/N ratio

<table>
<thead>
<tr>
<th>Factor</th>
<th>Mean of S/N ration (dB)</th>
<th>Maximum -Minimum Rank</th>
</tr>
</thead>
<tbody>
<tr>
<td>Population size</td>
<td>0.0281</td>
<td>0.0402</td>
</tr>
<tr>
<td>Crossover Fraction</td>
<td>0.0358</td>
<td>0.0497*</td>
</tr>
<tr>
<td>Mutation Rate</td>
<td>0.0289</td>
<td>0.0500</td>
</tr>
</tbody>
</table>

*Optimum level

Finally a validation experiment has been conducted to find whether optimum condition suggested by Taguchi optimization technique produce necessary improvement. Predicted value of MSNR with optimized parameter levels is computed using Eq.8 and given in Table 6. The validation experiment has been conducted with above mentioned optimum levels of operating parameters and optimized output with corresponding MSNR is given in Table 6. The significant improvement in MSNR (i.e. 0.0725) is observed to be during comparison with initial parameter setting. \( Z \) values at optimum levels of process parameters to be 33.61275 compared to initial parameter setting output \( Z \) of 33.32756. Therefore, considerable improvement in \( Z \) has been obtained.
4. Conclusion

In present work aims at developing a GA-Taguchi hybrid model as a tool of optimization of any experimental data set with reasonable accuracy. The model initially employed Taguchi for successfully optimizing GA and further employed optimized GA for optimization of SAW parameters. Results indicate a combination of population size: 100, crossover fraction: 0.7 and mutation rate: 0.05 can produce best optimization result. A validation run with that parameter setting certainly shows an improvement in optimization performance in GA. The objective function used for GA optimization has converted a multi-objective problem into single objective one. But the same model can be used for true multi-objective one also.

References:


