Evolutionary Algorithm On Cold Metal Transfer Process For Feature Extraction

G.Dhivyasri, M.Manikandan, Dhamodhar Reddy and Koushik P
1, 2, 3, 6 Department of Electronics and communication
1, 2, 3, 6 KPR Institute of Engineering and Technology, India
dhivyasrigopal@gmail.com, m.manikandan@kpriet.ac.in, dhamodharreddy@gmail.com, koushikprabakaran@gmail.com

Chella Babu
Department of Electrical and Electronics
Siddartha Institute of Science and Technology, India
babu2342@gmail.com

K. Vinoth Kumar
EMC Calibration Engineer
OSRAM Continental Pvt.Ltd., India
vinothkumarkarmegam@gmail.com

Abstract - In order to achieve the desired bead geometry in a welding operation it is of prime importance to select suitable process parameters. In this research, pulsed MIG welding of 316L austenitic stainless steel is performed and its bead geometry is studied, such as penetration depth bead width and height of reinforcement. The optimization approach based on the Genetic Algorithm (GA) is implemented to ensure the optimal combination of process variables and bead geometry. Regression model are initially generated by using experimental data. GA is then generated to optimize the parameters of the method and bead geometry parameters by minimizing the objective function based on the least square error. Pulsed MIG welded parameters was experimentally tested by microscopic analysis and EDAX analysis for three sample sets. The finding suggest that expected and experimental values are close in agreement. Finally, the effect of the welding current on the elemental composition is seen. The research shows that in the GA based method, the rate of convergence is faster.

Keywords - Pulsed MIG, DOP, BW, RH, GA

1. Introduction

The 316L grade of austenitic stainless steel is durable, long lasting, resistant to corrosion, heat resistant and has excellent welding capability. The carbide formation is lower in 316L stainless steel due to low carbon content, and the presence of molybdenum makes it highly corrosion resistant, enabling them to find their extensive application in the chemical, construction, oil and marine environment. In the last 20 years, stainless steel use has increases at a rate of 5%.

316L stainless steel is often related by the system of arc welding. Welding defects such as lack of penetration, solidification cracking in austenitic stainless steel is caused by the welding parameters.

Many experiments are needed to identify a suitable pulsed MIG process parameter to achieve the desired weld bead geometry. This involves the implementation of a welding parameter optimization technique as experimental trial runs result in material wastage. Pulsed MIG Welding is performed on 316L stainless steel. Pulse welding is a process in which high peak electric current and low base electric current are applied at regular time intervals to break away the droplet formation at the electrode wire tip using electromagnetic pinch force generated by the current pulse is shown in Figure 1.

Fig.1: Pulsed MIG Welding
Some of the research reports addressing the optimization of welding parameters using soft computing techniques in MIG and TIG welding are presented as follows. In order to relate the weld parameters to the quality of weld finish, [1] presented a neural network model to predict the weld bead geometry. [2] developed a GA based computational model to determine the optimal weld parameters in TIG welding, using 304LN and 316LN stainless steels to achieve the target weld bead geometry. The regression model resulted in good correlation between the measured and calculated process parameters. [3] presented the soft computing techniques in modelling and predicting the microstructures of stainless steel welding. A neural network model is developed to predict the solidification modes in stainless steels and fuzzy logic systems are used to monitor and control the weld processes. Thus, author combined the different soft computing techniques to analyze the welding of stainless steels. [4] presented a genetic algorithm approach to optimize the process parameter and predict the weld bead geometry of 1100 aluminium using TIG welding process. This proposed method is found to be effective in determining the weld bead geometry for TIG welding. [5] addressed the modelling and optimization of deposition efficiency in pulsed Metal Inert Gas (MIG) welding. GA and differential evolution were deployed in maximizing the deposition efficiency and the latter was found to yield optimal solution. [6] applied decision trees to identify weld central line in austenitic stainless-steel joints to find flaws during ultrasonic testing. Their model was found to be very swift and quantitative. [7] investigated the influence of welding parameters on AISI 316 weld joining. The ANOVA techniques is used to investigate the strength of the stainless-steel materials. The results state that tensile strength and bend strength of the material is influenced by the current and weld speed. [8] performed tensile and hardness tests to determine the susceptibility of friction stir welded aluminium alloys. [9] analysed the mechanical properties of Inconel using pulsed current gas welding. In order to obtain the target weld bead geometry, this study seeks to apply the GA model to optimise weld parameters, namely welding current, voltage and weld speed during pulse d MIG welding of 316L stainless steel. For welding 316L sheets, experiment design is performed by regression models are generated from the experimental data and then GA is applied. Using microscopic analysis, the optimised findings from the GA model are then experimentally checked [10].

2. Experimentation
The 316L Stainless steel sheets (2mm thickness) of dimension 150mm x 150mm were joined by MIG welding process using DAIHEN’s FD-B6 MIG welding robot and PLC based FD11 manipulator controller. The filler wire is SS308 of 1.2mm diameter. The shielding gas used is Argon 98%/CO₂ 2% at 18 litres/minute flow rate. The FD11 manipulator controller consists of a PLC programmer in which the user can program the robotic movements to perform welding [11],[12]. The experimental setup is shown in the Figure 2.

Fig.2: Experimental setup with FD-B6 MIG welding robot

The welding parameters are shown in following Table 1.

Table 1: Experimental Data of 316L welded in FD-B6 MIG welding robot

| Trial No. | Welding Speed (cm/min) | Welding Current (A) | Welding Voltage (V) | DOP (mm) | BW (mm) | RH (mm) |
|-----------|------------------------|---------------------|---------------------|----------|---------|---------|
| 1         | 55                     | 70                  | 15                  | 1.0108   | 3.2233  | 1.547   |
| 2         | 55                     | 73                  | 14.9                | 1.0106   | 3.2456  | 1.658   |
| 3         | 55                     | 75                  | 14.2                | 1.0103   | 3.2606  | 1.7058  |
| 4         | 55                     | 77                  | 14.3                | 1.005    | 3.265   | 1.7222  |
| 5         | 55                     | 80                  | 14.4                | 0.9761   | 3.2664  | 1.7786  |
| 6         | 55                     | 83                  | 14.5                | 1.1321   | 3.267   | 1.7456  |
| 7         | 55                     | 85                  | 14.6                | 1.1677   | 3.672   | 1.6149  |
| 8         | 55                     | 87                  | 14.6                | 1.1752   | 3.7145  | 1.71    |
| 9         | 55                     | 90                  | 14.7                | 1.1872   | 3.7445  | 1.7181  |
| 10        | 55                     | 93                  | 14.8                | 1.1645   | 3.7298  | 1.9856  |
| 11        | 55                     | 95                  | 14.9                | 1.1511   | 3.6798  | 2.0574  |
| 12        | 55                     | 97                  | 14.9                | 1.1401   | 3.7546  | 2.0114  |
| 13        | 55                     | 100                 | 14.9                | 1.3367   | 3.8895  | 1.8565  |
| 14        | 55                     | 105                 | 15.1                | 1.2369   | 3.9871  | 1.8457  |
| 15        | 55                     | 110                 | 15.2                | 1.2245   | 3.9962  | 1.8341  |

3. Results and Discussions
The optimization of Pulsed-MIG welding parameters using Genetic Algorithm is done in two steps. First, regression models are developed by correlating the three MIG process parameters; welding current (I), voltage (V) and weld speed (WS) with the three-weld bead geometry; depth of penetration (DOP), bead width (BW) and reinforcement height (RH) using the experimental data. Then GA is implemented in MATLAB tool in which the objective function is evaluated using the developed regression models.
Regression Model development for Pulsed MIG Welded SS316L

Regression models are developed using multiple regression method. The standard regression model notation is given by Equation (1).

\[
\text{Parameter} = a_0 + a_1 \cdot I + a_2 \cdot V + a_3 \cdot WS + a_4 \cdot I^2 + a_5 \cdot V^2 + a_6 \cdot WS^2 + a_7 \cdot V \cdot I + a_8 \cdot I \cdot WS + a_9 \cdot V \cdot WS \tag{1}
\]

The relationship between three weld-bead geometry parameters and the process variables are estimated as in Equation (2), Equation (3) and Equation (4).

\[
DOP = 0.311 + 0.0512 \cdot I + 0.1312 \cdot V + 0.2017 \cdot WS + 0.4932 \cdot I^2 - 0.5110 \cdot V^2 + 0.0021 \cdot WS^2 + 0.0017 \cdot V \cdot I + 0.0098 \cdot I \cdot WS + 0.0021 \cdot V \cdot WS \tag{2}
\]

\[
BW = 0.3617 + 0.0745 \cdot I + 0.2698 \cdot V + 0.1693 \cdot WS - 0.0002 \cdot I^2 - 0.0063 \cdot V^2 + 0.0013 \cdot WS^2 - 0.0002 \cdot V \cdot I + 0.0123 \cdot I \cdot WS + 0.0076 \cdot V \cdot WS \tag{3}
\]

\[
RH = -0.3063 + 0.0042 \cdot I + 0.1012 \cdot V + 0.0102 \cdot WS + 0.0003 \cdot I^2 - 0.013 \cdot V^2 + 0.0012 \cdot WS^2 - 0.0102 \cdot V \cdot I + 0.0006 \cdot I \cdot WS + 0.0213 \cdot V \cdot WS \tag{4}
\]

From the Figure 3, Figure 4 and Figure 5 it may be clearly noted that a closed agreement is observed between the predicted value and experimental values of DOP, BW and RH obtained from the regression equations. Thus, all the three regression models.

Development for Genetic Algorithm

Genetic Algorithm is developed in MATLAB tool to optimize the pulsed MIG welded process parameters during the welding of SS316L. The flow chart in Figure 6 depicts the procedure involved during the execution of GA. The search space defines the input parameter ranges for welding current (I), welding voltage (V) and weld speed (WS) as shown in Table 2 within which optimal solution is identified by the GA [13-14].
Search space

(Range of parameters)
- 
- \[ I_{min}, I_{max} \]
- 
- \[ V_{min}, V_{max} \]
- 
- Constant weldspeed - \( WS \)

Population Initialization

\[ I_0, V_0, WS_0 \]

Evaluation of fitness function

Reproduction

Crossover

Mutation

New population

\[ I_1, V_1, WS_1 \]

Meet termination condition

Yes

Obtaining the target & predicted DOP, BW, RH

End

Experimental Validation

In the investigation, hardly any objective weld dabb calculations are picked haphazardly from the trial information, and GA is applied to streamline Pulsed MIG welding measure boundaries. At whatever point the GA is executed, it brought about various arrangements of cycle factors that all delivered a similar arrangement of target weld dabb calculation. It was recognized that weld dabb math target can be achieved by various blends of welding measure factors; i.e., various mixes of welding current, voltage, and weld speed, with every mix equipped for bringing about a similar objective weld dabb calculation.

For experimental validation, on 316L sheets with process variables (welding current, welding voltage and welding speed) referred to in case 1, case 2 and case 3, bead tests were conducted. The samples were then cross-sectioned and etched for microscopic analysis in order to measure the DOP, BW and RH experimental values. GA is used to predict their corresponding welding current, voltage and weld velocity combinations and their subsequent DOP, BW and RH. The obtained results are presented in Table 3.

It should be noted that a strong agreement of far less error or percent is observed between expected and experimental values. This GA ability makes it superior to Artificial Neural Networks (ANN) and high precision regression models. Table 4 shows the microscopic images of the experimentally validated samples in case 1, case 2 and case 3.
Table 3: Comparison between actual and predicted pulsed MIG process parameters for 316L stainless steel welds.

| Parameters          | Case 1                  | Case 2                  | Case 3                  |
|---------------------|-------------------------|-------------------------|-------------------------|
|                     | Actual Value | Predicted Value | Error %  | Actual Value | Predicted Value | Error %  | Actual Value | Predicted Value | Error %  |
| Welding current (A) | 100         | 100            | 0        | 95          | 95             | 0        | 80          | 80             | 0        |
| Welding Voltage (V) | 14.9        | 14.9           | 0        | 14.9        | 14.9           | 0        | 14.4        | 14.4           | 0        |
| Weld Speed (cm/min) | 55          | 55             | 0        | 55          | 55             | 0        | 55          | 55             | 0        |
| DOP (mm)            | 1.3367      | 1.3365         | 0.0149   | 1.1511      | 1.1506         | 0.0434   | 0.9761      | 0.9758         | 0.0307   |
| BW (mm)             | 3.8895      | 3.8880         | 0.0385   | 3.6798      | 3.6760         | 0.1032   | 3.2664      | 3.2643         | 0.0642   |
| RH (mm)             | 1.8565      | 1.8558         | 0.0377   | 2.0574      | 2.0560         | 0.0680   | 1.7786      | 1.7743         | 0.2417   |

Table 4: Experimental results

| Tag    | Welding Current (A) | Microscopic image | DOP (mm) | BW (mm) | RH (mm) |
|--------|---------------------|-------------------|----------|---------|---------|
| Sample 1 | 80                  | ![Microscopic image](image1) | 0.9761   | 3.2664  | 1.7786  |
| Sample 2 | 95                  | ![Microscopic image](image2) | 1.1511   | 3.6798  | 2.0574  |
| Sample 3 | 100                 | ![Microscopic image](image3) | 1.3367   | 3.8895  | 1.8565  |

It is observed that with the increase in welding current, the DOP and bead width also increases. For the current of 100A, the value of DOP and bead width are 1.8565 mm and 3.8895mm respectively. While reinforcement...
height is (2.0574mm) for a welding current of 95A. It may be noted that with increase in welding current the elemental composition of carbon and iron reduces while the elemental composition of chromium and nickel increases. Increase in chromium content improves the hardness of steel and increases the corrosion resistance. While, Nickel improves the toughness and ductility of the steel. Whereas, low amount of carbon is preferable since increased amounts of carbon reduces weldability of stainless steel.

4. Conclusion

In this study, optimization of welding process parameters in Pulsed-MIG butt welding on 316L stainless steel is performed. Regression models are built from the experimental data and regression plots show a strong agreement between the expected value and the experimental DOP, BW and RH values obtained from the regression equations. Then the developed Genetic Algorithm based optimization gave best solution for size of population – 100; No. of generation – 200; crossover rate – 0.75; mutation rate – 0.006 and mutation type – single point cross over.

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