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PREDICTION OF WELD BEAD WIDTH IN SUBMERGED ARC WELD OF MILD STEEL USING FUZZY LOGIC MODELING

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ABSTRACT

Artificial Intelligent tools such as expert systems, artificial neural network, and fuzzy logic support decision-making in intelligent manufacturing systems. Success of intelligent manufacturing systems depends on effective and efficient utilization of intelligent tools. This paper discusses the development of a fuzzy logic model to predict weld quality for Submerged Arc Welding process (SAW) under given set of input weld parameters such as welding current, arc voltage, welding speed, and electrode stickout. The model is developed using Matlab toolbox functions and is validated.

Keywords: *Fuzzy Logic, Weld Quality, Submerged Arc Welding.*

1. Introduction

Weld bead width is a major parameter in evaluating the quality of weldments. Quality of weld plays an important role in the performance of a welded product as it improves fatigue strength, corrosion resistance, creep life and reduces rework and scrap. Researchers are attempting many techniques to establish the SAW process. Apps et al [1] studied the effects of weld variables on bead shape and size in submerged-arc welding.

Fractional factorial techniques [2] were used to predict dimensions of the weld bead in automatic SAW. Revaandra and Parmar [3] used mathematical model to predict weld bead geometry for the flux cored welding process. Kim et al [4] studied the effects of welding process parameters on weld bead width in gas metal arc welding process.

Multiple regression analysis [5-7] has been applied to predict the process parameters for gas metal arc welding. Due to the inadequacy and inefficiency of the mathematical models to explain the nonlinear properties existing between the input and output parameters, intelligent systems such as Artificial Neural Network (ANN), fuzzy logic and expert system have emerged. ANN technique is used to handle problems of nonlinearity. ANN technique [8– 16] has been used to predict the weld bead geometry and penetration in shielded metal-arc welding. For the submerged arc welding machine, it is not easy to measure with on-line the controlled output, the bead width size. Simultaneously, it is very difficult to control the system in real time because the controlled system is nonlinear, time-varying, uncertain and fast-response controlled system. Fuzzy control [17, 18] systems are effective to handle uncertain, nonlinear as well as dynamic time-varying processes control systems. Fuzzy logic model for predicting weld pool size in GMA welding processes was developed by Boo and Cho [19]. Fuzzy logic is applied to control the gap parameters for Electro Discharge Machining Rajurkar and Wang [20]. Tarng et al [21] used fuzzy logic in the Taguchi method for the optimization of the submerged arc welding process. Xue et al [22] used fuzzy model to predict and control the bead width in the robotic arc-welding process. This paper addresses the development of fuzzy logic model to predict the process parameters of SAW process for consistent weld quality.

2. Proposed Methodology

Proposed scheme to predict weld bead width is shown in Fig. 1. Experiments are designed according to Taguchi’s principles and its results are used to develop a multiple regression model**.** Multiple sets of data from multiple regression analysis are utilized to train the fuzzy model. The trained fuzzy model is used to predict the quality of weld. Results are validated by running confirmatory experiments.

2.1 Data collection

Experimentation is designed using Taguchi method, a systematic application of design of experiments technique to improve weld quality. It uses a special design of orthogonal arrays to study the entire process parameter space with a small number of experiments. An L_8 orthogonal array is selected with number of factors involved is four and number of levels as two to conduct experiments in the semiautomatic SAW (SURARC of type XRCP 1200) machine.

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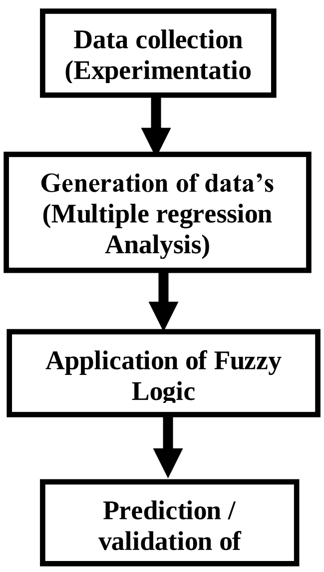

Fig. 1 Developed Fuzzy Model to Predict Weld Bead Width

Table 1: Weld Bead Width Observed for Different Trials of Experiment

Welding current (Ampere)	Arc voltage (Volt)	Welding speed (mm/min)	Electrode stickout (mm)	Weld bead width (mm)
360	25	400	19	13.0
360	25	400	25	11.0
360	30	420	19	12.5
360	30	420	25	13.5
390	25	420	19	14.5
390	25	420	25	14.0
390	30	400	19	14.5
390	30	400	25	15.0

Single pass butt-welding is performed on commercially available steel of IS 2062 grade (0.25%C, 0.20%Si, 0.75%Mn and balance Fe) (500 mm x 50 mm x 6mm) keeping the electrode positive and perpendicular to the plate. Electrode (diameter, of 3.15 mm) utilized is AWS ER70S-6. Sizes of 10mm (width) samples are cut from the test piece. Then the specimens are cleaned, polished and etched. Profile projector is used to measure the weld bead width. Experimental observations for different combinations of weld parameters are shown in Table 1.

Table 2: Crisp Values for Inputs

Input	Crisp Values
Welding current (ampere)	360 – 390
Arc voltage (volts)	25 – 30
Welding speed (mm/min)	400 – 420
Electrode stickout (mm)	19 - 25

2.2 Data generation

Multiple Regression analysis is done in Statistical Package for Social Science software to generate 31 sets of additional data for training and testing the proposed fuzzy model. The equation obtained is given as

Weld bead width in mm = -34.833 + (6.667×10^{-2} × welding current in Amperes) + ($0.750\times$arc voltage in Volt) + (1.25×10^{-2} × welding speed in mm/min) - (4.17×10^{-2} × electrode stick-out in mm).

2.3 Development of fuzzy logic system

The first step in the development of fuzzy logic model is to take the inputs and determine the degree to which they belong to each of the appropriate fuzzy sets via membership functions. In the fuzzy logic system, the input is always a crisp numerical value limited to the universe of discourse of the input variable. The input variables are welding current, arc voltage, welding speed and electrode stick out. The crisp values for respective inputs are listed in Table 2. The output is a fuzzy degree of membership in the qualifying linguistic set. The fuzzy logic system is based on rules and each of the rules depends on resolving.

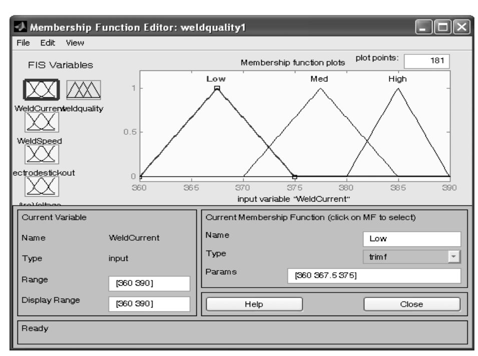

Fig. 2 Membership Function for Weld Current

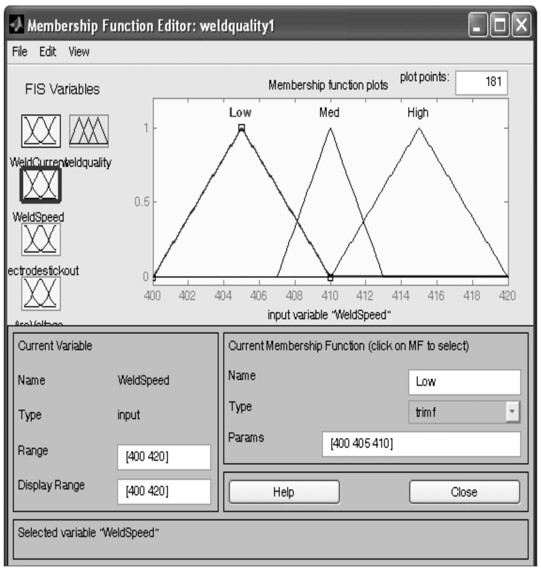

Fig. 3 Membership Function for Weld Speed

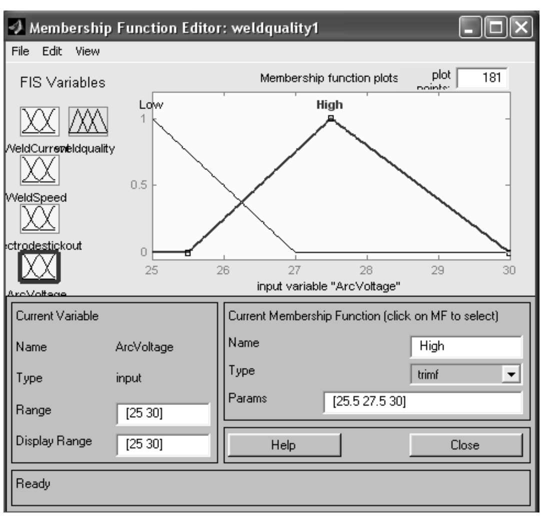

Fig. 4 Membership Function for Electrode Stick Out

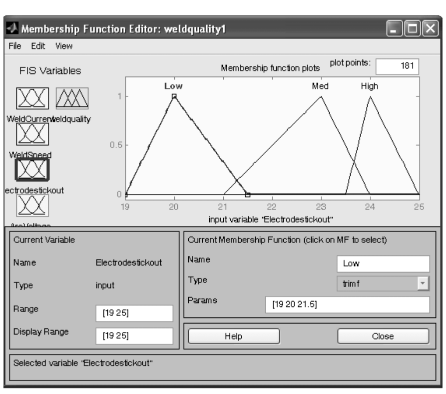

Fig. 5 Membership Function for Arc Voltage

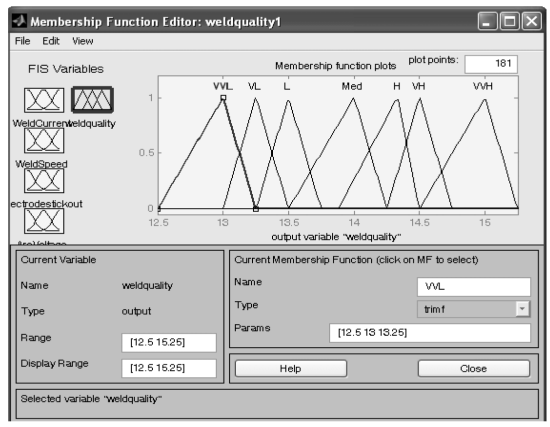

Fig. 6 Membership Function for Weld Bead Width

inputs into a number of different fuzzy linguistic sets. Before the rules are evaluated, the inputs are fuzzified according to each of these linguistic sets. The inputs are fuzzified and the degree to which each part of the antecedent is accommodated for each rule. The input to the fuzzy operator is two or more membership values from fuzzified input variables. The membership functions for input and output variable is shown from Fig. 2 to 6 .The output is a single truth-value.

The decisions are based on the testing of all the rules in fuzzy inference system. The input of the aggregation process is the list of truncated output functions returned by the implication process for each rule. The input for the defuzzification process is a fuzzy set and the output is a single number. Fuzziness helps the rule evaluation during the intermediate steps, the final desired output for each variable is a single number. However, the aggregate of a fuzzy set encompasses a range of output values and so must be defuzzified in order to resolve a single output value from the set. Centroid method of defuzzification is used in developing the model.

3. Results and Discussions

After developing the fuzzy logic system for the prediction of the weld bead width, it is tested by giving various input values using fuzzy rule viewer or simulink. Fig. 7 shows the rule viewer of aggregation for getting the single fuzzy set membership function as output. If the input values are changed, the corresponding output is automatically obtained from the developed fuzzy system. In simulink, welding current, arc voltage, welding speed and electrode stick out are entered as the input to the multiplexer and the output obtained from the fuzzy logic controller is shown in Fig. 8. Comparison between measured and predicted values of weld bead width from the developed model is shown in Fig. 9. Confirmatory experiments are done to validate the developed fuzzy model and results are given in Table 4. Input parameters for the confirmatory experiments are given in Table 3. Percentage of error is calculated by [(Actual value – Predicted value)/Predicted value] X 100. The errors in bead width prediction very rarely exceed by 20%, and thus the developed fuzzy model was able to predict with significant accuracy.

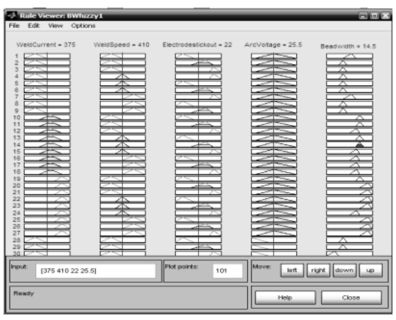

Fig. 7 An Example Output of Fuzzy Inference System for Prediction of Bead Width

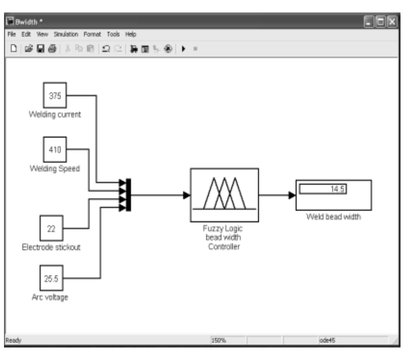

Fig. 8 Simulink Window of Fuzzy Model to Predict Weld Bead Width

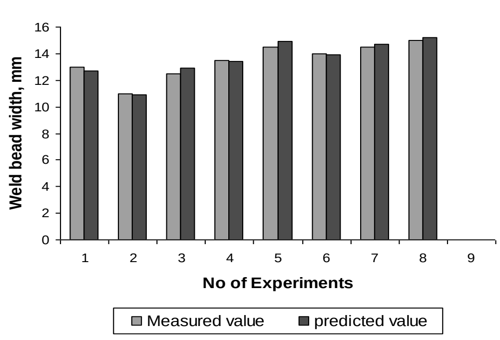

Fig. 9 Comparison of Weld Bead Width between Measured and Predicted Values

Table 3: Input Parameters for Confirmatory Experiments

Welding current (Ampere)	Arc voltage (Volt)	Welding speed (mm/min)	Electrode stickout (mm)
390	30	410	19
370	25	420	21
380	30	400	25
360	30	400	19
390	30	410	19

Table 4: Results from Confirmatory Experiments

Observed weld bead width, mm	weld bead width predicted, mm	Percentage error calculated for weld bead width, mm
14.7	15.700	-6.36
12.5	12.608	-0.856
14.0	13.809	1.383
13.0	13.522	-3.86

The developed model is forwarded to predict weld quality under different weld conditions.

4. Conclusion

SAW experiments are designed, conducted and analyzed to develop fuzzy logic model to predict the quality of weld. Results from the developed model are compared with experimental results. Results indicate that the developed model shows a good agreement with experimental results. Further confirmatory experiments are done to validate this approach. With these encouraging results the developed model can be further improved by including other welding input parameters such as type of flux, width and depth of flux layer, polarity and type of current which also affect weld bead width. Hardware controls are to be setup for online weld bead width monitoring.

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