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# MULTI OBJECTIVE OPTIMIZATION OF FLUX CORED ARC WELD PARAMETERS USING FUZZY BASED DESIRABILITY FUNCTION*

M. SATHEESH[1**] AND J. EDWIN RAJA DHAS[2]

[1]Dept. of Mechanical Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, Tamil nadu, India
Email: satheeshudaya@gmail.com
[2]Dept. of Automobile Engineering, Noorul Islam Centre for Higher Education, Kumaracoil, Tamil nadu, India

**Abstract–** In recent years much research has been conducted to study the variations in welding parameters and consumables on the mechanical properties of steels to optimize weld integrity. The quality of weld is a very important working aspect for the manufacturing and construction industries. In the present work, an attempt has been made to apply an efficient technique, fuzzy based desirability method to solve correlated multiple response optimization problems, in the field of flux cored arc welding. This approach converts the complex multiple objectives into a single fuzzy reasoning grade. Based on fuzzy reasoning grade, optimum levels of parameters (Welding current, arc voltage and electrode stickout) were identified. Experiments were performed based on Taguchi method. Weld bead hardness and material deposition rate are selected as quality targets. Significant contributions of parameters are estimated using Analysis of Variance (ANOVA). Confirmation test is conducted and reported. It is found that the electrode stickout is the most significant controlled factor for the process according to the weighted fuzzy reasoning grade of the maximum weld bead hardness and material deposition rate. The proposed technique allows manufacturers to develop intelligent manufacturing system to achieve the highest level of automation.

**Keywords–** ANOVA, Deposition rate, Desirability, Flux cored arc welding, fuzzy, orthogonal array

## 1. INTRODUCTION

Flux Cored Arc Welding (FCAW) process is a fully automated process, in which the welding electrode is a tubular wire that is continuously fed to the weld area. The flux materials are in the core of the tube. The outer shell of the tube conducts the electricity that forms the arc and then becomes the filler metal as it is consumed [1]. Recent studies indicate that FCAW has a number of advantages over the common welding techniques such as manual metal arc welding and gas metal arc welding [2]. Ghazvinloo *et al.* [3] studied the effect of arc voltage, welding current and welding speed on fatigue life, and impact energy and bead penetration of AA6061 joints by robotic metal inert gas welding. Effect of FCAW parameters on weld width and tensile properties of weld metal in low carbon steel were investigated [4]. FCAW in repair weld technique provides better control over current and heat input to carry out the temper bead repair. As a fully automatic process, FCAW has cost advantages over other commonly used processes [5].

Quality of a weld joint is greatly influenced by welding parameters [6, 7]. Important parameters of flux cored arc welding are: welding current, intensity, voltage, speed of welding, wire diameter, length of wire stickout, thickness and gas flow rate. These parameters have to be selected and precisely controlled in a judicious manner to achieve weld of desired quality. Weld quality depends on features of bead geometry, mechanical–metallurgical characteristics of the weld metal and HAZ, and on weld chemistry [8]. The

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**Corresponding author

problem faced by the weld operator is how to control the process input parameters to obtain a good welded joint with the required bead geometry and weld quality with minimal detrimental residual stresses and distortion. Hence these parameters should be selected to reach the desired target by the area of application of the weldment. To do so, weld input parameters should be chosen by the skill of the engineer or machine operator which is a time-consuming trial and error development effort. In order to overcome this problem, various optimization methods have emerged to define the desired output variables through developing mathematical models to establish the relationship between the input parameters and output variables. Toyofumi *et al*. [9] and Tsai *et al*. [10] observed the optimization values of welding conditions in spiral pipes and process parameters in hardfacing. Tarng and Yang [11] applied Taguchi method to the optimization of the submerged arc welding process. Gunaraj and Murugan [12] applied Response Surface Methodology for prediction and optimization of weld bead quality in submerged arc welding of pipes by establishing mathematical models. Curvilinear equations [13], linear regression equations [14], multiple regression analysis [15] and Taguchi method [11] have been used to model SAW process. Sabbaghian *et al.* [16] successfully applied Taguchi method to optimize the process conditions in the production of Lipase.

However, traditional Taguchi technique cannot solve multi-objective optimization problem efficiently and effectively. The most commonly used approach for multi objective problem is to assign weights for every response. To overcome these limitations Taguchi based grey relational analysis approach [17] was developed to handle uncertain systematic problem with only partial known information. Tarng *et al*. [18] applied grey based Taguchi method for optimization submerged arc welding process parameters in hardfacing. In Grey Taguchi approach, all quality features are assumed to be independent. But in actual case, the assumption may deviate. To overcome this, instead of Grey-Taguchi, Pearson and Hotelling developed Principal Component Analysis (PCA). Biswas *et al*. [19] applied PCA in Taguchi method to optimize the bead geometry of Submerged Arc Weld parameters.

The individual priority weights are required to be assigned to different responses. In practice, these responses may not be of equal importance. Degree of significance of various responses depends on application area and functional requirements of the product. For good joint strength, the weldment should have higher hardness and maximum deposition rate [20]. In general, weld hardness is of vital importance. Therefore, priority weight of hardness is to be set more compared to deposition rate. Assignment of response priority weights basically depends on the judgment of the decision maker. Change in value of the priority weights yields change in the value of aggregated quality index. Moreover, the above-mentioned approaches are based on the assumption that responses are uncorrelated. Interdependence of the responses has been assumed negligible while in practice any change in one response remarkably affects another response. Thus, judgment of priority weights in conjunction with assumption of negligible response correlation may lead to vagueness in the solution. To overcome these limitations, hybrid methods have been introduced by researchers. Taguchi based Utility theory optimization concept [21] has been applied to predict process parameters of Submerged Arc Welding. Naveen Sait *et al*. [22] used Taguchi method in combination with desirability function to optimize machining parameters of glass-fibre-reinforced plastic. Genetic algorithm with Taguchi method was used to optimize parameters of submerged arc welding in hardfacing process [23] and weld bead geometry in plasma transferred arc hard faced austenitic stainless steel plates [24]. Recently, optimization of machining parameters for the milling operation was carried using particle swarm optimization algorithm [25]. Katherasan *et al*. [26] optimized the parameters of FCAW process for better bead geometries using particle swam optimization algorithm. Ankita Singh *et al*. [27] investigated optimization of bead geometry of submerged arc weld using fuzzy based desirability function approach. Lin *et al*. [28] applied the hybrid Taguchi- Fuzzy logic method for optimization of electrical discharge machining process parameters. Mostafa Jafarian *et al*. [29] used Fuzzy - Topsis method to select the welding process at high pressure vessel manufacturing. Esme *et al.* [30] applied design of experiments and neural networks for prediction of surface roughness in wire electrical discharge Machining. In this article, application of desirability approach combined with fuzzy logic analysis is applied to optimize the multiple quality characteristics of flux cored arc welding parameters.

## 2. FUZZY BASED DESIRABILITY FUNCTION METHODOLOGY

### *a) Desirability function*

Desirability function approach is a powerful tool for solving the multiple performance characteristics optimization problems, where all objectives attain a definite goal simultaneously. Desirability between 0 and 1 represents the closeness of a response to its ideal value. If a response falls within the unacceptable intervals, the desirability is 0, and if a response falls within the ideal intervals or the response reaches its ideal value, the desirability is 1. The aim of this approach is to convert a multiple performance characteristics optimization problem into a single response optimization problem with the objective function of overall desirability. Then the overall desirability function is optimized. The desirability function method was introduced by Harrington [31], who used the exponential type transformation of response value to its desirability. Kim and Lin [32] presented a more general desirability transformation, which is flexible to the analysts. According to Derringer and Suich [33] approach, one- and two-sided desirability functions are used depending on whether the response is to be maximized or minimized or has an assigned target value. Let $L_i$ and $H_i$ be the lower and upper specification limits and $T_i$ be the target value of the $i$ th response respectively (such that $L_i \le T_i \le H_i$). For a response $y_i$ with a target value (nominal is best), the individual desirability is defined as Eq. (1).

$$d_i = \begin{cases} 0, \ y_i < L_i \\ [(y_i - L_i)/(T_i - L_i)]^{s_i}, L_i \le y_i \le T_i \\ [(H_i - y_i)/(H_i - T_i)]^{t_i}, T_i \le y_i \le H_i \\ 0, \ y_i > H_i \end{cases} \tag{1}$$

where the weights $s_i$ and $t_i$ determine how strictly the target value is desired. If the response $y_i$ is at its goal or target, then $d_i$ = 1, and if the response is outside the acceptable region, $d_i$ = 0. The value of $d_i$ increases as the "desirability" of the corresponding response increases.

Similarly, one-sided desirability functions for minimizing or maximizing case may be performed. For larger the- better problem, the individual desirability is given by Eq. (2).

$$d_i = \begin{cases} 0, \ y_i < L_i \\ [(y_i - L_i)/(T_i - L_i)]^{s_i}, L_i \le y_i \le T_i \\ 1, \ y_i > T_i \end{cases} \tag{2}$$

and for smaller-the-better problem, the individual desirability is calculated using Eq. (3)

$$d_i = \begin{cases} 1, \ y_i < T_i \\ [(H_i - y_i)/(H_i - T_i)]^{t_i}, T_i \le y_i \le H_i \\ 0, \ y_i > H_i \end{cases} \tag{3}$$

The individual desirability values have been accumulated to calculate the overall desirability using Eq. (4).

$$D_o = (d_1^{w_1} d_2^{w_2} \ldots . d_n^{W_n})^{1/\sum Wi} \tag{4}$$

Here $D_o$ is the overall desirability value, $d_i$ is the individual desirability value of $i$ th quality characteristic and $n$ is the total number of responses. $W_i$ is the weight for $i$ th attribute. Sum of all attribute weights should be equal to 1. However, overall desirability $D_o$ can be treated as equivalent aggregated quality index but the problem arises in assigning priority weights of various responses. Literature shows that previous investigators determined optimal setting of process parameters [34] by maximizing $D_o$ in the experimental domain. The results obtained thereof may be inaccurate because the exact value of priority weight to be assigned to each individual response is difficult to predict. Therefore to sort-out these limitations, fuzzy logic approach combined with desirability function has been introduced. The flow chart of the fuzzy logic controller coupled with desirability function method used in the study is depicted in Fig. 1.

### *b) Fuzzy logic analysis*

The theory of fuzzy logic was initiated by Zadeh [35]. It is a way of representing information that mimics human reasoning about information [36]. The most interesting fact about fuzzy logic is that fuzzy inferences make it possible to deduce a proposition similar to the consequence from some propositions that are similar to the antecedent [37].

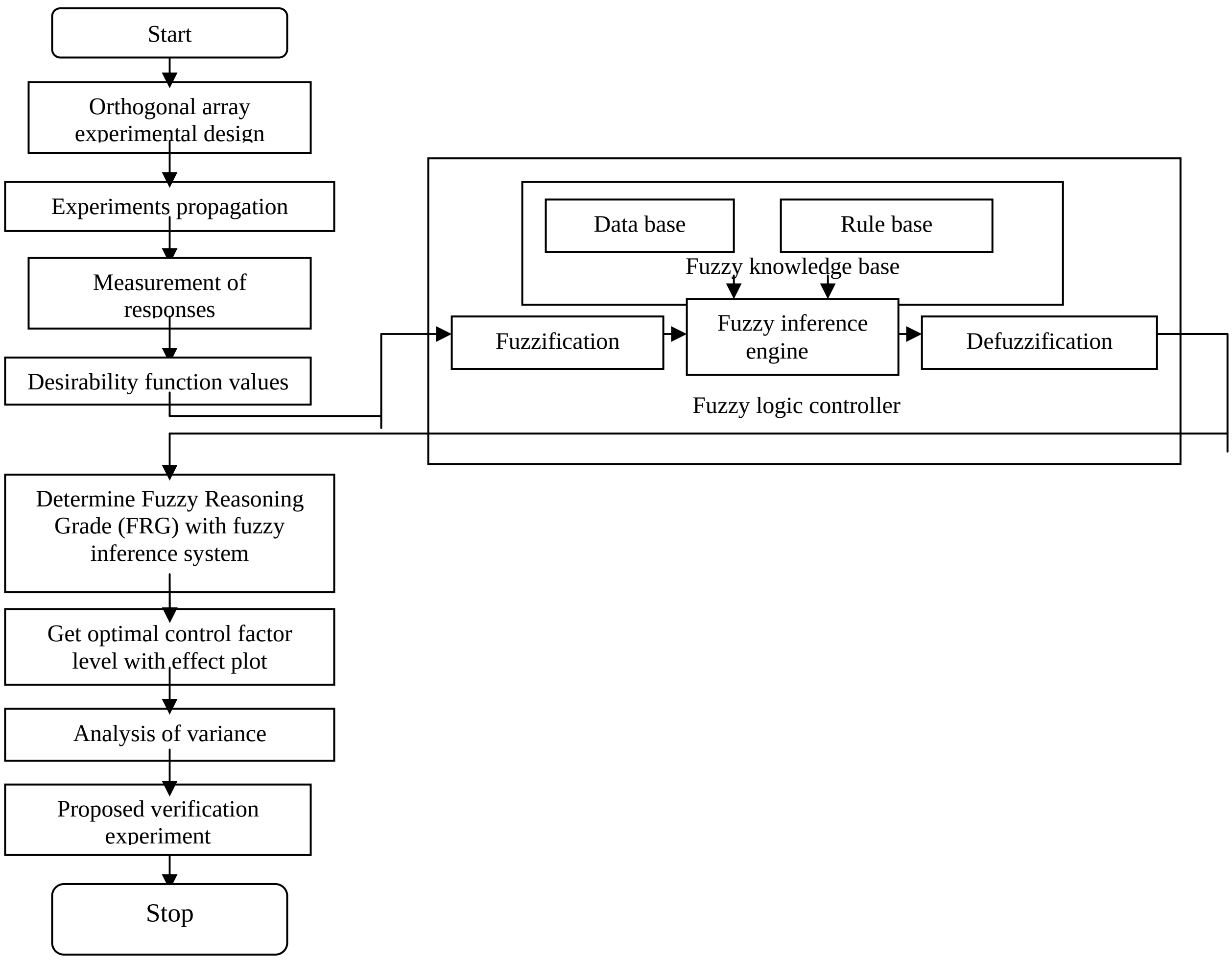


Fig. 1. Flowchart of fuzzy logic controller coupled with Taguchi method

Fuzzy controllers and fuzzy reasoning [38] have found particular applications in very complex industrial systems that cannot be modeled precisely even under various assumptions and approximations.

The fuzzy logic approach combined with Taguchi techniques has been applied to optimize multiple objectives in machining process [39]. Fuzzy system is composed of a fuzzifier, an inference engine, a data base, a rule base, and defuzzifier. In the study, the fuzzifier initially uses membership functions to convert crisp inputs into fuzzy sets. Once all crisp input values have been fuzzified into their respective linguistic values, the inference engine will access the fuzzy rule base of the fuzzy expert system to derive linguistic values for the intermediate as well as the output linguistic variables. The fuzzy rule base consists of a group of if-then control rules with the two desirability function values, $x_1$ and $x_2$ one multi response output $y$, that is:

Rule 1: if $x_1$ is $A_1$ and $x_2$ is $B_1$ then $y$ is $C_1$ else

Rule 2: if $x_1$ is $A_2$ and $x_2$ is $B_2$ then $y$ is $C_2$ else

. . . . . . . . . . . . . . . . . . . . . . . . . . . . . .

Rule $n$: if $x_1$ is $A_n$ and $x_2$ is $B_n$ then $y$ is $C_n$.

$A_i$, and $B_i$, are fuzzy subsets defined by the corresponding membership functions, i.e. $\mu_{A_i}$ and $\mu_{B_i}$.

Suppose $x_1$ and $x_2$ are the two desirability values, the membership function of the multi-response output $y$ is expressed in Eq. (5).

$$\mu_{E_o}(y) = (\mu_{A_1}(x_1) \wedge \mu_{B_1}(x_2) \wedge \mu_{C_1}(y)).....\vee \\ (\mu_{A_n}(x_1) \wedge \mu_{B_n}(x_2) \wedge \mu_{C_1}(y)) \tag{5}$$

Where $\wedge$ and $\vee$ are the minimum and maximum operation respectively. Equation (5) is illustrated in Fig. 2.

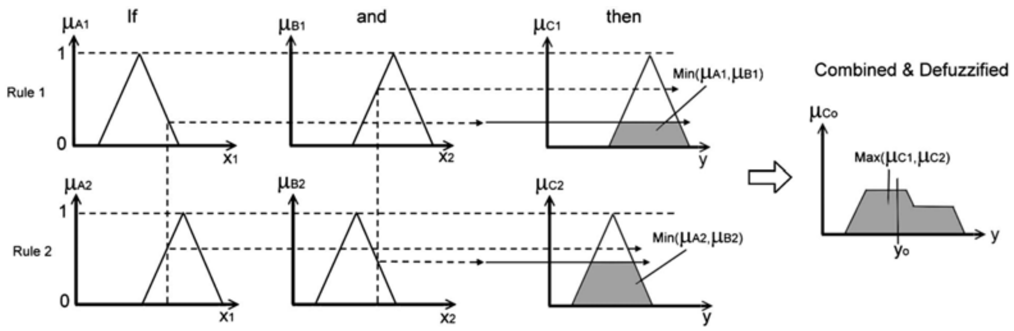


Fig. 2. Mamdani implication methods with fuzzy controller operations

Finally, a centroid defuzzification method is adopted to transform the fuzzy multi-response output $\mu_{c_o}(y)$ into a non- fuzzy value $y_o$, Eq. (6).

$$y_o = \frac{\sum y\mu_{C_o}(y)}{\sum \mu_{C_o}(y)} \tag{6}$$

## 3. EXPERIMENTAL METHODS

Experiments were conducted using SUPRA INVMIG 500 welding machine by DC electrode positive power supply. Test pieces of size 200mm×150mm×6 mm were cut from low carbon structural steel (IS: 2062) plate and its surfaces were ground to remove oxide scale and dirt before welding. Flux cored mild steel electrode (E71T-1) of 1.2 mm diameter was used for welding. $CO_2$ gas at a constant flow rate of 15 L/min was used for shielding. The experimental setup used consists of a traveling carriage with a table for supporting the specimens. The welding torch is held stationary in a frame mounted above the work table, and it was provided with an attachment for both up and down movement and angular movement for setting the required nozzle-to-plate distance and welding torch angle, respectively. Single pass welding bead on joint weld with square butt weld is performed on the weld plates by varying the initial parameters as shown in Table 1. The working ranges for the process parameters were selected from the American Welding Society handbook [40]. Based on the designed $L_{27}$ orthogonal array combination a series of joining processes is performed in welding machine. Each trial of experiment was done twice and the average value taken. The photograph of the experimental set up is shown in Fig. 3. Deposition rate and hardness are considered as objectives. The metal deposition rate was calculated with the help of stop watch and length of the electrode melt during the welding process. Hardness test was performed using Brinnel Hardness testing machine. The experimental design and observed values from the specimens are given in Table 2.

Table 1. Process parameters and their levels

| No | Process parameters | Level-1 | Level-2 | Level-3 |
|---|---|---|---|---|
| 1 | Welding current (I), ampere | 180 | 220 | 260 |
| 2 | Arc voltage (V), volts | 20 | 24 | 28 |
| 3 | Electrode stickout (S), mm | 19 | 21 | 24 |

Fig. 3. Photographic view of experimental setup

## 4. RESULTS AND DISCUSSION

### *a) Orthogonal array experiment*

In the present study, the interaction between the welding parameters is neglected. Therefore, degrees of freedom due to the three sets and three level welding process parameters are analyzed. The degrees of freedom for the orthogonal array should be greater than or at least equal to those for the process parameters. In this study, an orthogonal array with two columns and 27 rows is used. This array has 6 degrees of freedom and it can handle three-level process parameters. Experimental layout for the welding process parameters using the orthogonal array is shown in Table 2.

### *b) Multi objective optimization*

Since the traditional Taguchi method deals with single response, it is necessary to convert two objectives into single performance index. Therefore, desirability values have been computed for the selected response parameters. In this calculation, linear desirability function has been chosen (desirability function index unity). While calculating various desirability values, a Higher-the-better (HB) criterion has been selected for hardness and deposition rate. (Eq. (2)). These selections are based on functional requirements of the weldment when subjected to application field. The calculated individual desirability values corresponding to each parameter are shown in Table 3. In order to calculate overall desirability, a fuzzy inference system has been proposed to obtain individual response desirability values. These values have been treated as two inputs and Fuzzy Reasoning Grade (FRG) as output. The optimal process setting may be evaluated by maximizing this FRG.

In this study, the most popular defuzzification method is the centroid calculation, which returns the centre of area under the curve. The defuzzifier converts the fuzzy value into non-fuzzy value which is called fuzzy reasoning grade. The MF adopted in this is trapezoidal MF, which has a flat top and is really just a truncated triangle curve. There are five fuzzy subsets assigned in the desirability values for bead hardness and deposition rate: very small, small, middle, large and very large as shown in Fig. 4. Nine fuzzy subsets are assigned in the multi-response output: tiny, very small, small, small-medium, medium, medium-large, large, very large, and huge (Fig. 5).

Table 2. Experimental results of Hardness and Deposition rate

| Ex.No. | I | V | S | Hardness (HB) | Deposition rate (Kg/hr) |
|---|---|---|---|---|---|
| 1 | 1 | 1 | 1 | 320.96 | 2.12 |
| 2 | 1 | 1 | 2 | 496.41 | 2.15 |
| 3 | 1 | 1 | 3 | 469.83 | 2.21 |
| 4 | 1 | 2 | 1 | 465.45 | 1.48 |
| 5 | 1 | 2 | 2 | 589.83 | 1.92 |
| 6 | 1 | 2 | 3 | 519.96 | 2.21 |
| 7 | 1 | 3 | 1 | 433.83 | 1.44 |
| 8 | 1 | 3 | 2 | 580.99 | 1.48 |
| 9 | 1 | 3 | 3 | 519.83 | 2.16 |
| 10 | 2 | 1 | 1 | 329.96 | 2.58 |
| 11 | 2 | 1 | 2 | 259.83 | 5.26 |
| 12 | 2 | 1 | 3 | 445.07 | 2.86 |
| 13 | 2 | 2 | 1 | 449.96 | 2.45 |
| 14 | 2 | 2 | 2 | 595.07 | 2.01 |
| 15 | 2 | 2 | 3 | 265.07 | 5.61 |
| 16 | 2 | 3 | 1 | 389.96 | 2.37 |
| 17 | 2 | 3 | 2 | 549.96 | 2.31 |
| 18 | 2 | 3 | 3 | 459.83 | 2.26 |
| 19 | 3 | 1 | 1 | 269.96 | 4.08 |
| 20 | 3 | 1 | 2 | 485.09 | 3.39 |
| 21 | 3 | 1 | 3 | 345.09 | 4.32 |
| 22 | 3 | 2 | 1 | 424.15 | 3.01 |
| 23 | 3 | 2 | 2 | 515.09 | 3.75 |
| 24 | 3 | 2 | 3 | 488.41 | 3.83 |
| 25 | 3 | 3 | 1 | 319.96 | 3.97 |
| 26 | 3 | 3 | 2 | 464.15 | 4.18 |
| 27 | 3 | 3 | 3 | 449.83 | 3.71 |

Various degrees of membership of the fuzzy sets are calculated based on the values of $x_1, x_2$ and *y*. Thus, straightaway 25 fuzzy rules are derived based on the larger S/N ratio being the better process response. A fuzzy multi-response output is produced from these rules by taking the max–min inference operation.

Table 3. Individual desirability values and fuzzy reasoning grade

| Ex. No | Individual desirability values | | Fuzzy reasoning Grade (FRG) |
|---|---|---|---|
| | Hardness | Deposition rate | |
| 1 | 0.182 | 0.163 | 0.200 |
| 2 | 0.706 | 0.170 | 0.442 |
| 3 | 0.626 | 0.185 | 0.405 |
| 4 | 0.613 | 0.010 | 0.306 |
| 5 | 0.984 | 0.115 | 0.557 |
| 6 | 0.776 | 0.185 | 0.471 |
| 7 | 0.519 | 0.000 | 0.250 |
| 8 | 0.958 | 0.010 | 0.486 |
| 9 | 0.776 | 0.173 | 0.464 |
| 10 | 0.209 | 0.273 | 0.237 |
| 11 | 0.000 | 0.916 | 0.459 |
| 12 | 0.553 | 0.341 | 0.445 |
| 13 | 0.567 | 0.242 | 0.406 |
| 14 | 1.000 | 0.137 | 0.569 |
| 15 | 0.016 | 1.000 | 0.500 |
| 16 | 0.388 | 0.223 | 0.317 |
| 17 | 0.865 | 0.209 | 0.543 |
| 18 | 0.597 | 0.197 | 0.399 |
| 19 | 0.030 | 0.633 | 0.322 |
| 20 | 0.672 | 0.468 | 0.580 |
| 21 | 0.254 | 0.691 | 0.474 |
| 22 | 0.490 | 0.376 | 0.438 |
| 23 | 0.761 | 0.554 | 0.647 |
| 24 | 0.682 | 0.573 | 0.628 |
| 25 | 0.179 | 0.607 | 0.393 |
| 26 | 0.609 | 0.657 | 0.632 |
| **27** | 0.567 | 0.544 | 0.551 |

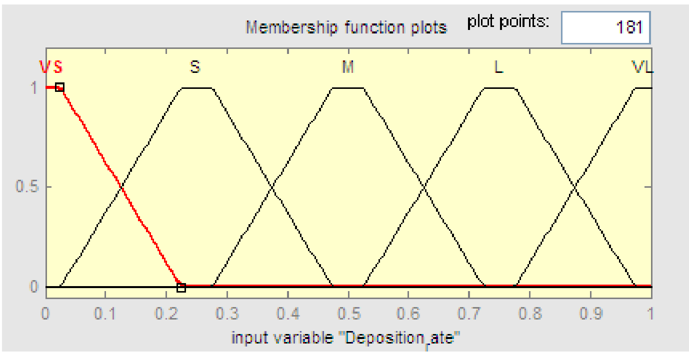


Fig. 4. Membership functions for desirability function

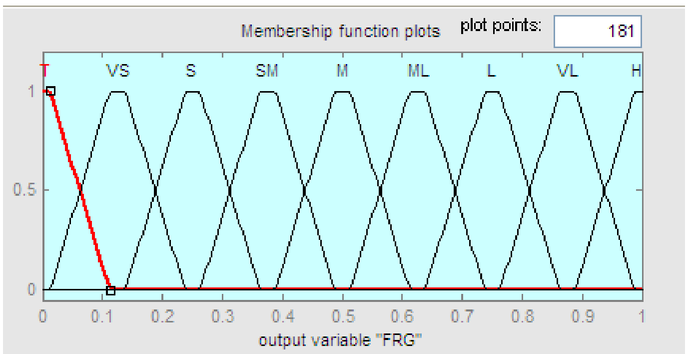


Fig. 5. Membership functions for desirability-fuzzy reasoning grade

Based on the above discussion, the larger the fuzzy reasoning grade, the better is the multiple process responses. Table 3 shows the experimental results for the fuzzy reasoning grade. Thus, the multi-criteria optimization problem has been transformed into a single objective optimization problem using the combination of desirability function fuzzy logic analysis. The sequence with largest fuzzy reasoning grade indicates it is the closest to the desired values of the quality characteristics. Fuzzy analysis procedure for the optimal conditions is graphically presented in Fig. 6, in which rows represent 25 rules and columns are the three inputs and one output variable. The locations of trapezoidal indicates the determined fuzzy sets for each input and output value. The reinforcement of the darkened area in each trapezoidal corresponds to the fuzzy membership value for that fuzzy set.

To determine the optimal process parameters, the effect of each weld process parameter on the ratio at different levels is separated out since the experimental design is orthogonal. To obtain the effect of each control factor on each quality characteristic for each level, the ratios with same level of control factor are averaged for 27 experiments. From Table 4, it is concluded that the parameter combination $I_3V_2S_2$ has the best performance for all the quality characteristics. The response plot for the overall fuzzy reasoning grade is represented graphically in Fig. 7.

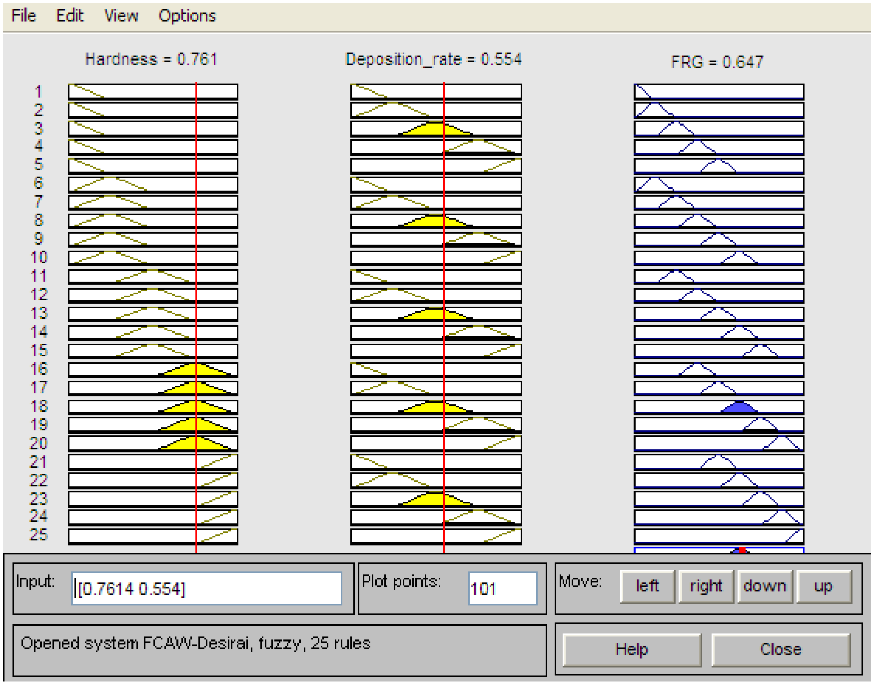


Fig. 6. Fuzzy logic reasoning procedure for the results by the optimal Conditions

### *c) Analysis of variance*

ANOVA is performed to identify the process parameters of flux cored arc welding that significantly affect the multiple performance characteristics. An ANOVA table consists of sums of squares, corresponding degrees of freedom, the F-ratios corresponding to the ratios of two mean squares, and the contribution proportions from each of the control factors. These contribution proportions are used to assess the importance of each factor for the interested multiple performance characteristic. The result of ANOVA for multiple quality characteristics (Table 5) shows that electrode stickout is the most significant control factor followed by welding current. The percentage contribution of each control factor to the total variance is electrode stickout 64.54 %, welding current 18.27 % and arc voltage 13.32%. Here, arc voltage is found to be a less significant factor in influencing the overall fuzzy reasoning grade.

Table 4. Response table for fuzzy reasoning grade

| Welding Parameters | Symbol | Fuzzy reasoning grade | | | |
|---|---|---|---|---|---|
| | | Level-1 | Level-2 | Level-3 | Max-Mini |
| Current (Ampere) | I | 0.397 | 0.430 | 0.518 | 0.121 |
| Voltage (V) | V | 0.396 | 0.502 | 0.448 | 0.106 |
| Stickout (mm) | S | 0.318 | 0.546 | 0.482 | 0.228 |
| Total mean of the fuzzy reasoning grade= 0.4489 | | | | | |

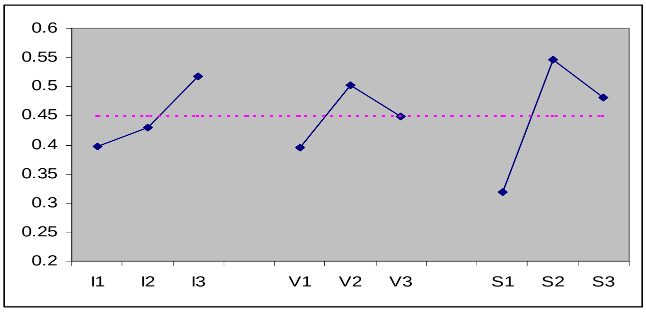


Fig. 7. Response graph for fuzzy reasoning grade

### *d) Confirmation test*

Confirmation test is a crucial step recommended by Taguchi to verify experimental conclusion. The improvements of the performance characteristic using the optimal level of weld parameters are verified. Estimated Grey relational grade (GRG) $\eta_{opt}$ is calculated as

$$\eta_{opt} = \eta_m + \sum_{i=1}^{q} (\eta_i - \eta_m) \tag{7}$$

Where $\eta_m$ is total GRG; $\eta_i$, mean GRG at optimum level; and $q$, number of process parameters having significant contribution in multiple performance characteristics. Table 6 shows the comparison of the multiple performance characteristics for initial and optimal welding parameters. The initial designated levels of welding parameters are $I_2$, $V_2$ and $S_2$. As noted from Table 6, the bead hardness increases from 438.52 to 515.09 and deposition rate increases from 2.89 Kg/hr to 3.75 Kg/hr. The estimated fuzzy reasoning grade is increased from 0.551to 0.647. It is observed that optimal design obtained from the desirability- fuzzy logic analysis has the largest experiential and predicted fuzzy reasoning grade with $R^2$ value of 0.9616. It is clearly shown that the multiple objectives of the weld process improved remarkably.

Table 5. Results from ANOVA

| Factors | Degrees of Freedom | Sum of Squares | Mean Squares | F value | P value | Contribution % |
|---|---|---|---|---|---|---|
| I | 2 | 0.069837 | 0.034918 | 47.51 | 0.000 | 18.27 |
| V | 2 | 0.050992 | 0.025496 | 34.69 | 0.000 | 13.32 |
| S | 2 | 0.247231 | 0.123615 | 168.20 | 0.000 | 64.54 |
| Error | 20 | 0.014699 | 0.000735 | - | - | 3.81 |
| Total | 26 | 0.382758 | - | - | - | 100.00 |

Table 6. Results of welding performance using the initial and optimal welding factors

| | Initial process parameters | Optimal process parameters | |
|---|---|---|---|
| | | prediction | experiment |
| Level | I2V2S2 | I3V2S2 | I3V2S2 |
| Hardness | 438.52 | - | 515.09 |
| Deposition rate | 2.89 | - | 3.75 |
| Fuzzy reasoning grade | 0.551 | 0.6682 | 0.647 |
| Improvement of Fuzzy reasoning grade | | 0.1172 | 0.096 |

## 5. CONCLUSION

In the present work, experiments are carried out to collect the data using Taguchi $L_{27}$ orthogonal array design. The hybrid, fuzzy-desirability technique has been introduced to optimize the multiple properties of flux cored arc welding. In this method, since the responses are linguistic in nature it is not essential to check interdependence (correlation) of the responses. Moreover, the individual priority weights need not be assigned. Fuzzy inference system takes care of that. From this analysis, it is revealed that electrode stickout and welding current are predominant factors which affect the weld quality of mild steel. The best performance characteristics are obtained with an optimum parameter setting of $I_3V_2S_2$ . Confirmation test proved that the determined optimum condition of welding parameters satisfies the real requirement. It is found that the proposed procedure employed in this study can resolve a complex parameter design problem with multiple responses. It could be applied to those areas where there are large data sets and a number of responses are to be optimized simultaneously.

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