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Multi Objective Optimization of Flux Cored Arc Weld Parameters Using Hybrid Grey - Fuzzy Technique

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Abstract: In the present work, an attempt has been made to use the grey-based fuzzy logic 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 grey-fuzzy reasoning grade. Based on the grey-fuzzy reasoning grade, optimum parameters are identified. The significant contributions of parameters are estimated using analysis of variance (ANOVA). This evaluation procedure can be used in intelligent decision making for a welding operator. The proposed and developed method has good accuracy and competency. The proposed technique provides manufacturers who develop intelligent manufacturing systems a method to facilitate the achievement of the highest level of automation.

Keywords: ANOVA, Deposition rate, Flux cored arc welding, Fuzzy, Hardness, Full factorial design.

أهداف مثلى متعددة لبارامترات فيض لحام القوس باستخدم المنطق الهجيني الرمادي الغيمي

م. ساتيش هوديا، ادون راجا داس

الملخص: في هذا البحث محاولة يتم تقديمها لاستخدام طريقة غيمية تعتمد على أساس رمادي لحل مشاكل تعددية الاستجابة المثلى في مجال لحام القوس. هذا النهج يحول الأهداف المتعددة المعقدة إلى هدف واحد غيمي رمادي منطقي. اعتمادا على هذا المنطق الرمادي الغيمي مستويات مثلى من البارمترات يمكن تحديدها. الإسهام المتميز للبارمترات يمكن تقديرها باستخدام طريقة تحليل التباين ANOVA. طريقة التقييم هذه يمكن استخدامها في صنع القرار الذكي لمشغل اللحام. الطريقة المقترحة و المطورة في هذا البحث تحقق كفاءة و دقة عالية. كما توفر التقنية المقترحة للمصنعين تطوير نظام تصنيع ذكي يحقق أعلى مستوى من الأتمتة.

الكلمات المفتاحية: معدل الترسيب، لحام القوس المعدني، الصلابة، تصميم مضروب كامل.

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1. Introduction

The flux cored arc welding process is a semi-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. The quality of the weld depends on mechanical properties of bead geometry, which in turn are controlled by the process parameters. The problem faced by the weld operator lies in controlling the process input parameters to obtain a good-quality welded joint with the required bead geometry and minimal detrimental residual stresses and distortion; hence, these parameters should be selected in a judicious manner to reach the desired target by the weldment's area of application. Traditionally, it was necessary to determine the weld input parameters for every new welded product to obtain a welded joint with the required specifications. To do so, weld input parameters were chosen by skilled engineers or machine operators, which required time-consuming trial and error. 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.

Common approaches to tackle the optimization problem in welding include multiple regression analysis, response surface methodology, artificial neural network modeling and the Taguchi method. In most cases, optimization has been performed using a single objective function. For a multi response process, while applying the optimal setting of control factors, it can be observed that an increase/improvement of one response may cause a change in another response which is beyond the acceptable limit. Thus, for solving a multi-criteria optimization problem, it is convenient to convert all the objectives into an equivalent single-objective function. This equivalent objective function, which is the representative of all the quality characteristics of the product, should be optimized.

2. Literature Review

Recent studies indicate that flux cored arc welding (FCAW) has a number of advantages over the common welding techniques available that use solid wires, such as manual metal arc welding (MMAW) and gas metal arc welding (GMAW) (Parmar 1999). As a semi-automatic process, FCAW also has cost advantages over other commonly used processes (Murugan *et al*. 1994). The toughness and strength of the weld bead depends on the hardness, and the weld is considered sound and economical if it achieves the maximum deposition rate (Nadkarni 1988; Houldcroft 1990). Selection of weld parameters to meet the above criteria is tedious and highly complicated due to the non-linear characteristics existing between the variables.

The Taguchi method, a systematic application in the design and analysis of experiments, is used for designing and improving product quality by reducing costs. However, the traditional Taguchi technique cannot solve multi-objective optimization problem efficiently and effectively. The most frequently used approach for multi-objective problems is to assign weights for every response. The weighted S/N ratio of each quality characteristics is used to compute performance characteristics (Sourav *et al*. 2008). In practice it is not practical because it uses past experiences and engineering judgment to optimize multi-responses.

To overcome this limitation, the combined Taguchi-based grey relational analysis approach was proposed and developed (Liao 2006). The grey relational analysis theory initialized by (Deng 1989) makes use of this to handle uncertain systematic problem with only partial known information. This approach converts multi-objective optimization into the optimization of a single grey relational grade. This method has been applied to optimize the multi-objective problems in laser cutting on light guide plates. The use of the Taguchi method with grey relational analysis as applied by Chiang and Hsieh (2009) was used to investigate the optimum condition of thin-film sputtering process in color filter manufacturing. Taguchi-based grey relational analysis method was successfully applied to optimize the input parameters in dissimilar friction stir butt welding of aluminum alloys (Kasman 2013). Ghosal and Chaki (2010) used a hybrid artificial neural network (ANN) technique to optimize the depth of penetration in CO_2-laser/MIG welding. Sait *et al*. (2009) used the Taguchi method in combination with desirability function to optimize machining parameters of glass fibre-reinforced plastic. A genetic algorithm along with the Taguchi method was used to optimize the parameters of submerged arc welding in the hard facing process (Patnaik *et al*. 2007). Recently, optimization of machining parameters for the milling operation and optimization of friction welding parameters was carried out using a particle swarm optimization algorithm (Baskar *et al*. 2005).

Usually the relationship among various factors in a complex multivariate system is unclear. Such systems are called 'grey'. The grey system theory analyzes uncertain relationship between the main influential factors and all other factors. The grey relational analysis is further improved with the implementation of the fuzzy logic theory in the multivariate system to obtain better system performance (Chiang *et al*. 2008). The theory of fuzzy logics initiated by (Zadeh 1965) has proven useful for dealing with uncertain and vague information. The definitions of objectives such as lower-the-better, higher-the-better and nominal-the-best contain a certain degree of uncertainty and vagueness. Hence, fuzzy logic is applied to establish the optimal setting of parameters for multiple objectives. The grey-based fuzzy logic approach has the advantage of both grey relational analysis and fuzzy logic methods. Optimization of complicated multi-objectives can be converted into a single objective through the grey-fuzzy reasoning grade.

The optimum level of process parameters is the level with the greater value of mean grey-fuzzy reasoning. This method has been applied successfully to optimize the multiple objectives of complicated problems having to do with the manufacturing process (Lin and Lin 2005), the optimization of drilling parameters of composites (Krishnamoorthy *et al*. 2012) and the optimization of the computer numerical control (CNC) turning process (Ahilan and Kumanan 2009). Ankita *et al*. (2013) investigated the optimization of the bead geometry of a submerged arc weld using the fuzzy-based desirability function approach for SAIL Steel, IS 2062.

In the present paper, the effects of the flux cored arc welding parameters on hardness and deposition rate are reported using grey-based fuzzy logic. The significant contribution of each cutting parameters to the multiple objectives are calculated by using analysis of variance (ANOVA) (Fisher 1925).

3. Hybrid Taguchi-Fuzzy Optimization Method

3.1 Grey Relational Analysis

The grey relational analysis is based on the grey system theory used to solve complicated interrelationship, multiple performance characteristics problems effectively. A grey system has a level of information between black and white. Black represents having no information and white represents having all information. Depending upon the characteristics of a data sequence, there are various methodologies of data preprocessing available for this analysis. Experimental data y_{ij} is normalized as Z_{ij} ($0 \leq Z_{ij} \leq 1$) for the i^{th} performance characteristics in the j^{th} experiment can be expressed as Eqns. (1)-(3).

For a larger-the-better condition,

$$Z_{ij} = \frac{y_{ij} - \min(y_{ij}, i = 1,2,\ldots.n)}{\max(y_{ij}, i = 1,2,\ldots..n) - \min(y_{ij}, i = 1,2,\ldots..n)} \tag{1}$$

For a smaller-the-better condition,

$$Z_{ij} = \frac{max\left(y_{ij}, i=1,2,\ldots n\right) - y_{ij}}{max\left(y_{ij}, i=1,2,\ldots.n\right) - min\left(y_{ij}, i=1,2,\ldots.n\right)} \tag{2}$$

For a nominal-the-best condition,

$$Zij = \frac{(y_{ij} - \text{Target}) - \min(|y_{ij} - \text{Target}|, i = 1,2,\ldots\ldots n)}{\max(|y_{ij} - \text{Target}|, i = 1,2,\ldots..n) - \min(|y_{ij} - \text{Target}|, i = 1,2,\ldots\ldots n)} \tag{3}$$

Then the grey relational coefficients are calculated to express the relationship between the ideal (best) and the actual experimental results. The grey relational coefficient γ_{ij} is expressed in Eqn. (4).

$$\gamma_{ij} = \frac{\Delta min + \xi \Delta max}{\Delta_{oj}(k) + \xi \Delta max} \tag{4}$$

where, j=1,2…n; k=1,2…m, n is the number of experimental data items and m is the number of responses.

a. $y_o(k)$ is the reference sequence ($y_o(k)$=1, k=1,2…m), while $y_j(k)$ is the specific comparison sequence.
b. $\Delta_{oj} = \| y_o(k) - y_j(k) \| =$ the absolute value of the difference between $y_o(k)$ and $y_j(k)$
c. $\Delta_{min} = \min\limits_{\forall j \in i} \min\limits_{\forall k} \| y_o(k) - y_j(k) \|$ is the smallest value of $y_j(k)$
d. $\Delta_{max} = \max\limits_{\forall j \in i} \max\limits_{\forall k} \| y_o(k) - y_j(k) \|$ is the largest value of $y_j(k)$
e. ξ is the distinguishing coefficient which is defined in the range $0 \leq \xi \leq 1$ (the value is adjusted based on the practical needs of the system).

This grey relation coefficient γ_{ij} is applied to show the relationship between the optimal (best = 1) and actual normalized results. The higher value of γ_{ij} represents the fact that the corresponding experimental result is closer to the optimal (best) normalized value for the single response characteristics.

3.2 Fuzzy Logic Analysis

Fuzzy logic is a way of representing information that mimics human reasoning about information (Zimmermann 1985). The most interesting fact about fuzzy logic is that fuzzy inferences make it possible to deduce a proposition similar to the consequence from some proposition that is similar to the antecedent (Dubois and Prade 1980). Fuzzy logic is a mathematical theory of inexact reasoning that allows the modeling of the reasoning process of humans in linguistic terms (Antony 2010). It is very suitable for defining the relationship between system inputs and desired

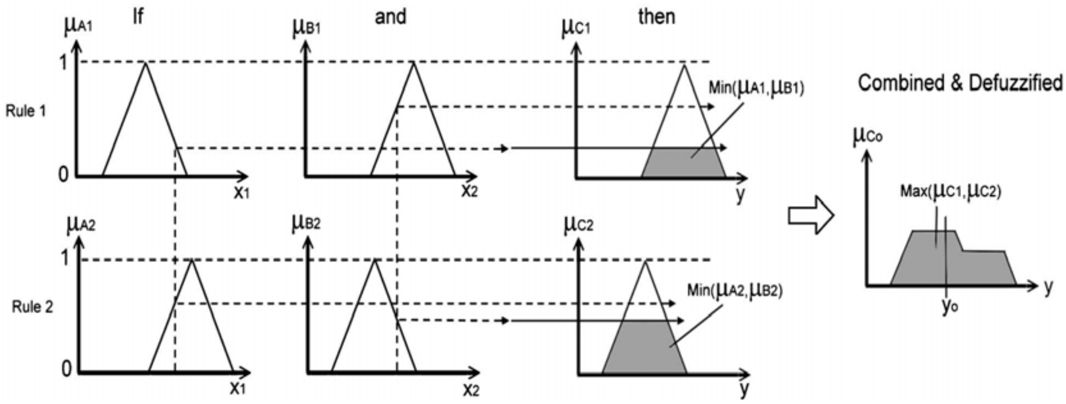

Figure 1. Mamdani implication methods with fuzzy controller operations.

outputs. Fuzzy controllers and fuzzy reasoning (Tsai 2011) have found particular applications in very complex industrial systems that cannot be modeled precisely even under various assumptions and approximations. A 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 (MF) to convert the 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 grey relational coefficients x_1, $x_2 ... x_n$ and a multi-objective output y is of the form if the following rules are adhered to:

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, *ie*. μ_{Ai} and μ_{Bi}.

The fuzzy multi-objective output y is provided from those above rules by employing the max-min interfaced operation. Inference results in a fuzzy set with MF for y can be expressed as Eqn. (5).

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

where, $\wedge$ and $\vee$ are the minimum and maximum operation respectively. The above equation is illustrated in Fig. 1. 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 as in Eqn. (6).

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

The flow chart of the fuzzy logic controller coupled with grey based method used in the study is shown in Fig. 2.

4. Experimental Method

The experiments were conducted using a SUPRA INVMIG 500 welding machine (D & H Secheron, Mumbai, India) using DC electrode positive (DCEP). Test pieces 200 mm × 150 mm × 6 mm were cut from low carbon structural steel (IS: 2062) plate and surfaces were ground to remove oxide scale and dirt before cladding. A piece of flux cored mild steel electrode (E71T-1) measuring 1.2 mm diameter was used for welding. CO_2 gas at a constant flow rate of 15 L/minute was used for shielding. The experimental setup used consisted of a traveling carriage with a table for supporting the specimens. The welding torch was 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. A single pass welding bead on joint weld with a square butt weld was performed on the weld plates by varying the initial parameters. The working ranges for the process parameters were selected from the American Society Welding Handbook (1978). Each trial of the experiment was done twice and the average value was taken.

The photograph of the experimental set up is shown in Fig. 3. Deposition rate and hardness were considered as objectives. The metal deposition rate was calculated with the help of a stopwatch and the length of the electrode melt during the welding process. A hardness test was performed using a Brinell hardness testing machine. Based on the designed full factorial

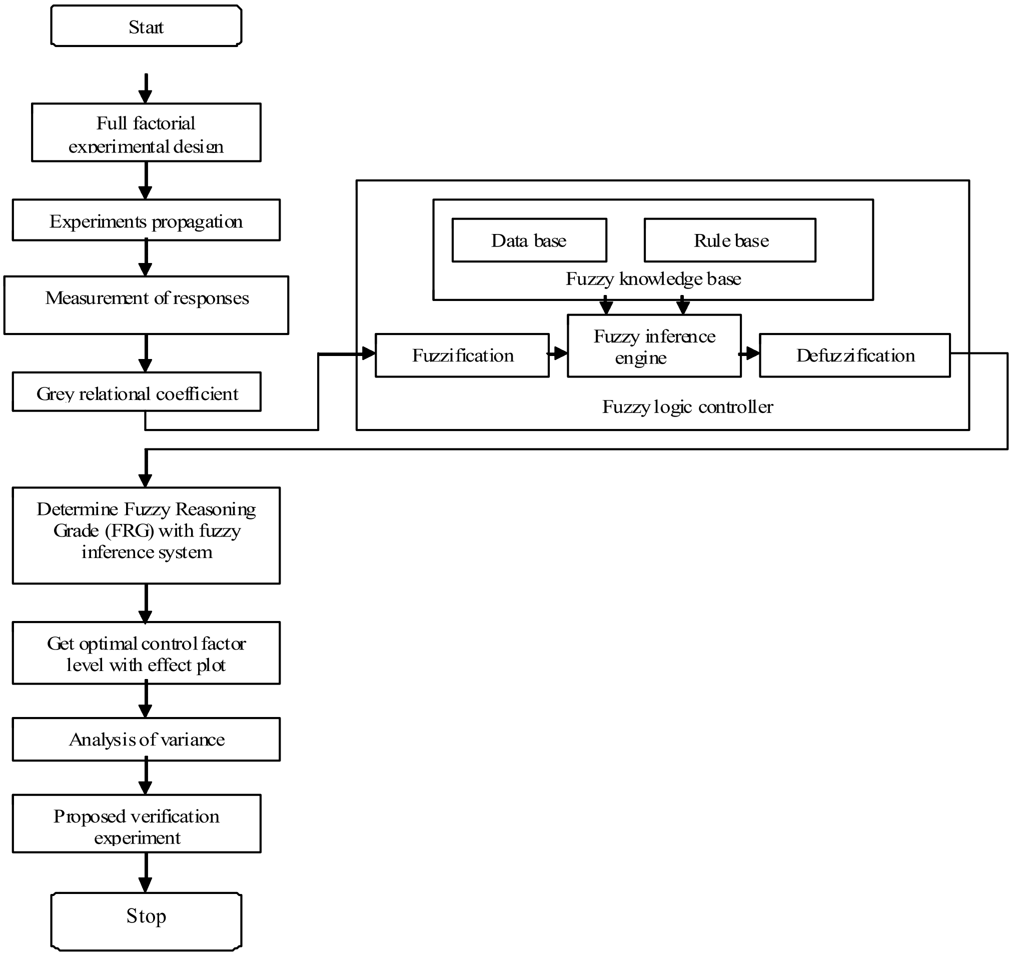

Figure 2. Flowchart of the fuzzy logic controller coupled with Taguchi methods.

Figure 3. Photographic view of experimental setup.

design combination, a series of joining processes were performed in the welding machine.

5. Results and Discussion

5.1 Design of Experiments

To perform the experiment as specified in the design, ascertaining three levels of welding parameters was necessary: welding current, arc voltage and electrode stickout (Table 1). An appropriate full factorial

Table 1. Process parameters and their levels.

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

design for the experiments requires a degree of freedom greater than or at least equal to those of the process parameters. In this study, an L27 (33) full factorial design was used because it has 26 degrees of freedom, which is more than the total degrees of freedom contributing to all welding parameters. The experimental combinations of the welding parameters using the L27 full factorial design are presented in Table 2.

5.2 Implementation of Grey-Fuzzy Based Method

Step 1: Normalize the value of given responses using Eq. (1) which results in values same as given in Table 2.

Table 2. Experimental design and 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

Step 2: Perform the grey relation analysis. Calculate grey relational coefficient using Eqn. (4). Since equal importance was given to both objectives, the value for was taken as 0.5 as in Eqn. (4) [Table 3].

Step 3: Compute the grey relational grade using fuzzy logic analysis. The grey relational coefficients of hardness and deposition rates were used as input to the fuzzy model and the output used was the grey-fuzzy reasoning grade. In this study, the most popular defuzzification method was the centroid calculation, which returns the center of the area under the curve. The defuzzifier can convert the fuzzy value into a non-fuzzy value which is defined as the grey-fuzzy reasoning grade.

The MF adopted in this was trapezoidal MF which has a flat top and really is just a truncated triangle curve. Figure 4 shows the five fuzzy sets of variables of grey relational coefficients: very small (VS), small (S), medium (M), large (L) and very large (VL). In the same way, in the output variable grey-fuzzy reasoning grade there were nine fuzzy sets shown in Fig. 5: tiny (T), very small (VS), small (S), small medium (SM), medium (M), medium large (ML), large (L), very large (VL) and huge (H).

Based on the above discussion, the larger the fuzzy reasoning grade, the better the multiple process responses. Table 2 shows the experimental results for the fuzzy reasoning grade using the experimental layout. Thus, the multi-criteria optimization problem has been transformed into a single objective optimization problem using the combination of the grey based approach and fuzzy reasoning analyses. The sequence with the largest fuzzy reasoning grade indicates that it is the closest to the desired values of the quality characteristics.

The fuzzy analysis procedure for the optimal conditions is graphically presented in Fig. 6, in which rows represent the 25 rules, and columns are the two inputs and one output variable. The locations of trapezoidal indicates the determined fuzzy sets for each input and output value. The height of the darkened area in each trapezoid corresponds to the fuzzy membership value for that fuzzy set.

To obtain the effect of each control factor on each quality characteristic for each level, the ratios with the same level of control factor were averaged for 27 experiments. The mean response table for the fuzzy reasoning grade is shown in Table 4 and represented

Table 3. Values of normalized, grey relational coefficient and fuzzy reasoning grade.

Ex. No	Normalized values		Grey relational coefficient		Fuzzy reasoning grade
	Hardness	Deposition rate	Hardness	Deposition rate	
1	0.182	0.163	0.3795	0.3740	0.121
2	0.706	0.170	0.6295	0.3760	0.256
3	0.626	0.185	0.5724	0.3801	0.217
4	0.613	0.010	0.5639	0.3355	0.172
5	0.984	0.115	0.9697	0.3610	0.498
6	0.776	0.185	0.6906	0.3801	0.295
7	0.519	0.000	0.5097	0.3333	0.125
8	0.958	0.010	0.9225	0.3355	0.442
9	0.776	0.173	0.6902	0.3767	0.292
10	0.209	0.273	0.3874	0.4076	0.146
11	0.000	0.916	0.3333	0.8563	0.383
12	0.553	0.341	0.5277	0.4312	0.214
13	0.567	0.242	0.5360	0.3975	0.200
14	1.000	0.137	1.0000	0.3668	0.520
15	0.016	1.000	0.3368	1.0000	0.500
16	0.388	0.223	0.4497	0.3915	0.160
17	0.865	0.209	0.7879	0.3872	0.382
18	0.597	0.197	0.5535	0.3836	0.208
19	0.030	0.633	0.3402	0.5768	0.183
20	0.672	0.468	0.6038	0.4843	0.329
21	0.254	0.691	0.4014	0.6178	0.265
22	0.490	0.376	0.4951	0.4450	0.211
23	0.761	0.554	0.6770	0.5285	0.389
24	0.682	0.573	0.6111	0.5395	0.362
25	0.179	0.607	0.3786	0.5597	0.207
26	0.609	0.657	0.5615	0.5932	0.367
27	0.567	0.544	0.5358	0.5232	0.284

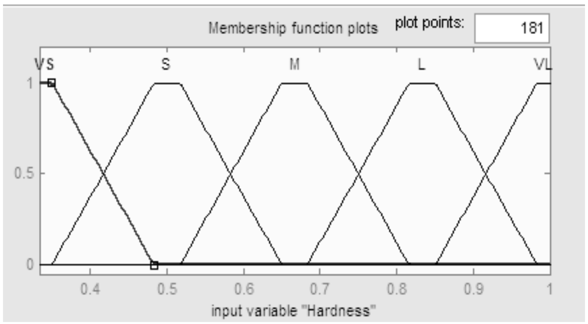

Figure 4. MFR for grey relational coefficient of hardness.

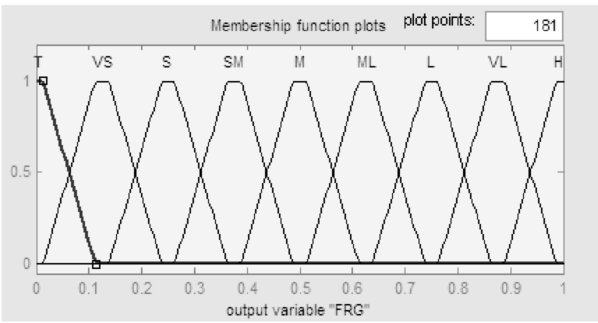

Figure 5. MF for grey-fuzzy reasoning grade.

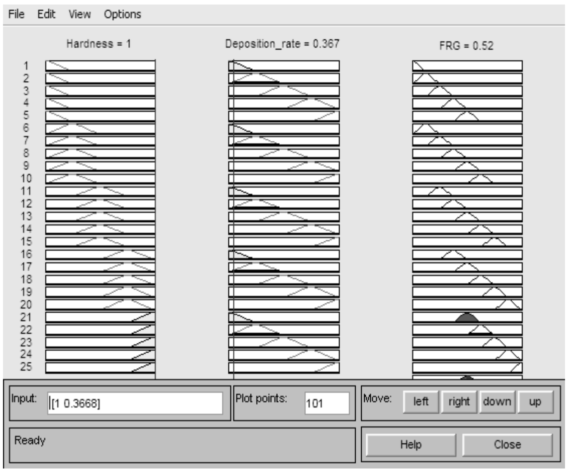

Figure 6. Fuzzy logic reasoning procedure for the results by the optimal conditions.

graphically in Fig. 7. With the help of the response table and graph, it was concluded that parameter combination I_3 V_2 S_2 had the best performance for all the quality characteristics.

5.3 Analysis of Variance (ANOVA)

ANOVA was performed to identify the process parameters of flux cored arc welding that significantly

Table 4. Response table for fuzzy reasoning grade.

Symbol	Welding Parameters	Fuzzy reasoning grade Level-1	Level-2	Level-3	Max-Mini
I	Current	0.2686	0.3014*	0.2885	0.0328
V	Voltage	0.2340	0.3496*	0.2741	0.1156
S	Stickout	0.1694	0.3962*	0.2930	0.2268
Total mean of the fuzzy reasoning grade= 0.2862					

Table 5. Results from ANOVA.

Factors	Degrees of Freedom	Sum of Squares	Mean Squares	F value	P value	Contribution %
I	2	0.004908	0.002454	0.77	0.478	1.350
V	2	0.061263	0.030631	9.57	0.001	16.91
S	2	0.232047	0.116023	36.25	0.000	64.04
Error	20	0.064013	0.003201	-	-	17.66
Total	26	0.362231	-	-	-	100.00

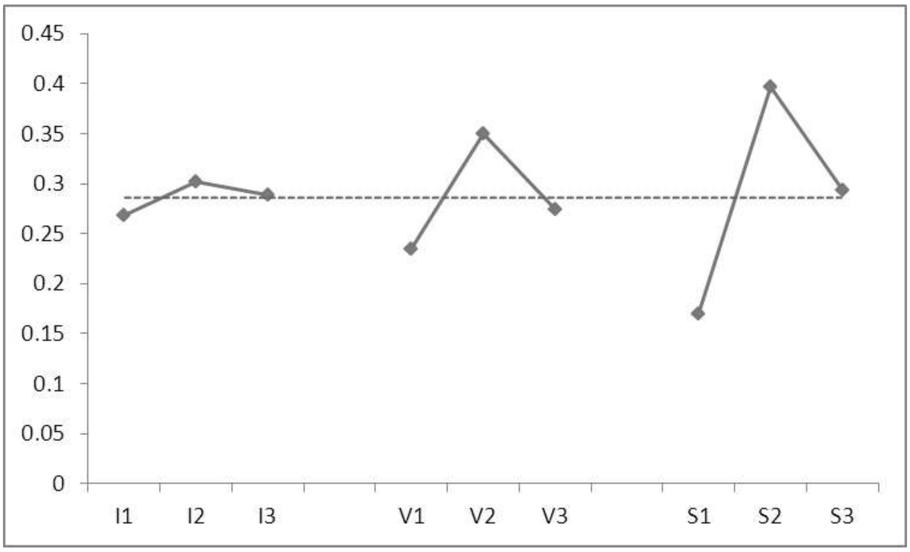

Figure 7. Response graph for fuzzy reasoning grade.

affect the multiple performance characteristics. An ANOVA table consists of sums of squares, correspon-ding 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 can be used to assess the importance of each factor for the interested multiple performance characteristics. The results in Table 5 show that electrode stickout was the most significant control factor, followed by arc voltage. The each control factor varied in its contribution to the total variance: electrode stickout (64.04%), arc voltage (16.91%) and welding current (1.06%). In this study, welding current was found to be an insignificant factor in influencing the overall fuzzy reasoning grade.

5.4 Confirmation Test

Once the optimal level of the process parameters was determined, the final step was to predict and verify the improvement of the performance characteristics using the optimal level of weld parameters. 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_1, V_3, and S_2. The estimated fuzzy reasoning grade $\hat{\gamma}$ using the optimal level of the welding parameters is calculated using Eq. (7).

$$\hat{\gamma} = \gamma_m + \sum_{i=1}^{q} (\bar{\gamma}_i - \gamma_m) \quad (7)$$

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

	Initial process Parameters	Optimal process parameters Prediction	Experiment
Level	I1V3S2	I2V2S2	I2V2S2
Hardness	580.99	-	595.07
Deposition rate	1.48	-	2.01
Fuzzy reasoning grade	0.442	0.4596	0.520
Improvement of Fuzzy reasoning grade		0.0176	0.078

where γ is the total mean of the fuzzy reasoning grade, γ is the mean of the fuzzy reasoning grade at the optimal level, and q is the number of the welding parameters that significantly affects the multiple performance characteristics. As noted from Table-6, the deposition rate is increased from 1.48 Kg/hr to 2.01 Kg/hr and the hardness is increased from 580.99 to 595.07. The estimated fuzzy reasoning grade is increased from 0.442 to 0.4596. Also it is observed that optimal design obtained from the fuzzy logic analysis has the largest experiential and predicted fuzzy reasoning grade with R^2 value of 0.823. It is clearly shown that the multiple objectives of the weld process are together improved remarkably.

5.5 Predicted Means

The 95% confidence intervals of confirmation experiments (CICE) and population (CIPOP) were calculated by using Eqns. (8) and (9).

$$CI_{CE} = \sqrt{F_\alpha(1, f_e) V_e \left[\frac{1}{n_{eff}} + \frac{1}{R}\right]} \tag{8}$$

$$CI_{POP} = \sqrt{\frac{F_\alpha(1, f_e) V_e}{n_{eff}}} \tag{9}$$

where, F_α (1, f_e) = The "F" ratio at the confidence level of (1 - α) against DOF 1 and error degree of freedom f_e.

$$n = \frac{N}{1 + [DOF\ associated\ in\ the\ estimate\ of\ mean\ response]}$$

= 27 / (1+4) = 5.4

Total number of results (N) = 27
Error variance (V_e) = 0.0032 [Table 5]
Error DOF (f_e) = 20 [Table 5]
Sample size for confirmation experiments (R) = 1
Tabulated F value (F0.05) (1, 20) = 4.35
So, CICE = ±0.1284 and
CI_{POP} = ±0.274

Therefore, the predicted CI for confirmation experiments is:

Mean $\hat{\gamma}$ - CI_{CE} < $\hat{\gamma}$ < Mean $\hat{\gamma}$ + CI_{CE}
0.331< $\hat{\gamma}$ < 0.588

The 95% CI_{POP} is

Mean $\hat{\gamma}$ − CI_{POP} < $\hat{\gamma}$ < Mean $\hat{\gamma}$ + CI_{POP}
0.135 < $\hat{\gamma}$ < 0.7336

6. Conclusions

In the present work, experiments were carried out to gather data as per full-factorial design to establish the relationships between the welding process parameters and various features of their responses. The following conclusions were obtained:

- The welding parameters were optimized with respect to multiple performances in order to achieve good quality;
- Optimization of the parameters was carried out using grey fuzzy analysis;
- It was identified that a welding current of 220 amperes, an arc voltage of 24 volts and an electrode stickout of 21 mm is the optimal combination of welding parameters to produce a high value of grey fuzzy reasoning grade (0.52).
- ANOVA statistics revealed that electrode stickout is the most influencing parameter in achieving good results, followed by arc voltage and welding current.

The developed methodology finds scope in the welding shop floor environment to set the initial weld process parameters and also the process planners to facilitate effective decision making in choosing the process parameters for consistent weld quality. Proof of characteristics of fuzzy systems is difficult or impossible in most cases because of a lack of mathematical descriptions. Especially in the area of stability of control systems, this is an important research area. On the other hand, when solving practical problems, this is often not a very severe restriction because when the system is tested the characteristics will also be found.

The present work might be extended in a number of ways:

1. To establish input-output relationships in the FCAW welding process, an expert system should be developed in the future which also might be useful for online control of the process.
2. In the present work, only parameters related to hardness and deposition rate were considered but the other mechanical and metallurgical properties were neglected. In the future, a more realistic model involving mechanical and metallurgical properties may be developed.

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