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Investigation of gas metal arc welding process parameters of aluminium alloy weldment using Taguchi-grey-fuzzy integrated approach

B.N. Sreeharan[a,*], J. Yoganandh[b], R. Sudhakar[b], and T. Kannan[c]

a. *Department of Mechanical Engineering, Kumaraguru College of Technology, Coimbatore, Tamil Nadu, India.*
b. *Department of Mechanical Engineering, Sri Ramakrishna Engineering College, Tamil Nadu, India.*
c. *Department of Mechanical Engineering, Amrita College of Engineering and Technology, Nagercoil, Tamil Nadu, India.*

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Abstract. Globally, aluminium alloys are used in many industries. Application of aluminium alloys is realized by many manufacturing processes in which joining processes are inevitable. Joining of aluminium alloys is achieved by various welding processes. One of the appropriate welding processes used to join aluminium alloy is Gas Metal Arc Welding (GMAW). This paper investigates the effect of process parameters of the GMAW process while welding AA 6351 aluminium alloy weldment with the help of an integrated Taguchi-grey-Fuzzy approach. Taguchi L-16 array was designed by using an orthogonal method to conduct the experiments. From the experimental results, Signal-to-Noise ratios (S/N ratio) were calculated from which Grey Relational Grades (GRG) were computed. These computed GRG were used as input for the fuzzy controller to find the Grey Fuzzy Relational Grades (GFRG), by which optimized process parameters were found and validated. Furthermore, Analysis of Variance (ANOVA) was used to identify the contributions of the GMAW process parameters over the responses. Subsequently, the effects of process parameters on the weldments were also discussed in detail. By identifying the optimized process parameters and contributing process parameters, the quality of weld joints is improved.

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1. Introduction

Aluminium is replacing steel in industries at a rapid pace. Current and future technological scenarios are more dependent on the application of artificial intelligence to perform tasks commonly associated with intelligence. Among the manufacturing processes, welding is one of the inevitable processes demanding enhancement from qualitative and quantitative perspectives. Weldments experience failure owing to the changes in weld bead characteristics such as Reinforcement Form Factor (RFF), Penetration Shape Factor (PSF), and percentage of dilution (%D), which are related to the thermomechanical variations that occur during welding. The relationship between weld beads and welding process parameters is always nonlinear and complicated, making it difficult for even experienced operators to easily fix the appropriate process parameters. The problems are related to theory-based assessment of

*. *Corresponding author. Tel.: +919790150825*
E-mail addresses: sreeharans@gmail.com (B.N. Sreeharan); jyogan@gmail.com (J. Yoganandh); sudhakar.ramasamy@srec.ac.in (R. Sudhakar); kannan_kct@yahoo.com (T. Kannan)

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input and output relationships of any welding process through various statistical investigations of the data obtained from the conducted experiments. Some of those approaches include non-linear and linear regression techniques, Taguchi technique, factorial design, RSM (Response Surface Methodology), and so on. In this work, a hybrid of Taguchi-grey-fuzzy is used to optimize the process parameters. Furthermore, investigations were carried out to explore the direct and interactive effects of process parameters on the welding process characteristics. The manufacturing of pipes used in the oil and gas industries is one of the more recent applications of aluminium welding investigated in this work.

In their paper, Benyounis and Olabi [1] concluded that evolutionary algorithms and computational techniques were developed and applied to many domains. Furthermore, they found that in recent years, the integration of various non-traditional optimization techniques such as Artificial Neural Networks (ANN), Genetic Algorithm (GA), Grey Relational Analysis (GRA), and fuzzy logic remained fascinating for researchers to express the input-response relationships of the joining process. Parida and Pal [2] proposed a fuzzy-based grey-Taguchi method to identify the optimum friction stir welding process parameters with multiple weld quality characteristics. Sahu et al. [3] presented the Fuzzy-grey Taguchi optimum technique for the optimization of process parameters of the friction stir welding process for Al/Cu joints with dissimilarity. Chandel et al. [4] studied the effects of submerged arc welding parameters on weld penetration, bead height, melting rate, and bead width. Kim et al. [5] utilized the Taguchi method. They determined the control settings that were optimum for the fuzzy controller. Kim et al. [6] determined the effect of measurement errors in parameters that were uncertain in nature while using the robotic Gas Metal Arc Welding (GMAW) process by sensitivity analysis and compared the experimental data with those obtained from the empirical formula. Satheesh and Dhas [7] proposed using a hybrid grey-fuzzy technique, a method that facilitates manufacturers in developing intelligent manufacturing systems and achieving the highest level of automation. Kumar and Maheshwari [8] implemented a hybrid method combining grey, fuzzy, and Taguchi approaches to integrate such properties as ultimate tensile strength and impact strength of the submerged arc weldments. Sarkar et al. [9] proposed an algorithm that was based solely on grey fuzzy. They also used the Taguchi method in that algorithm, which was used to identify the appropriate process parameters used in the welding of AISI 1518 grade steel by submerged arc welding. Saravanan and Pitchipoo [10] developed Taguchi-based GRA for multi-objective optimization of GMAW parameters for yielding better mechanical strength of welded joints. Hould [11] reported that for automated applications, process variables should be selected precisely to control the shape of the weld bead. Jeffus [12] stressed the importance of establishing relationships between the welding process parameters and the bead geometry so that prediction and control of the weld bead quality could be achieved. Özgörmüş et al. [13] proposed a method that could effectively deal with PSP and help a company establish a systematic and unbiased approach to the problem. Datta et al. [14] applied the Taguchi philosophy to optimize the process parameters with respect to bead geometry and width of Heat Affected Zone (HAZ) in Shielded Metal Arc welding (SMAW). Kannan and Yoganandh [15] studied the effects of GMAW process parameters on the geometry of clad beads and their shape relationships. Senthilkumar and Kannan [16] identified that heat input during the welding process played an important role in the determination of composition and microstructure of super duplex stainless steel while the cladding process began. They concluded that RFF was greatly influenced by factors like speed of the welding torch, arc length, melting rate, and resistance heating of the electrode. In their work, Ebrahimi Qazvini et al. [17] developed a two-stage approach based on Fuzzy Analytic Hierarchy Process (FAHP) and a Multi-Objective Mixed Integer Linear Programming (MOMILP) model under uncertainty and applied them to supplier selection and order allocation. Moghaddam et al. [18] addressed the idea of applying a multi-criteria optimization method for the GMAW process of API-X42 alloy. They conducted experiments based on the L36 Taguchi matrix and also employed Back Propagation Neural Network (BPNN), an ANN algorithm for predicting the geometry of weld bead and HAZ. Rostami et al. [19] developed ANN to forecast the thermal conductivity of a multi-walled carbon anotube (MWCNTs)-CuO/water nanofluid. Furthermore, they proposed an algorithm for finding the optimum for better performance. He et al. [20] developed an algorithm to predict the optimum neuron number from the trained ANN. Accordingly, they calculated the performance and correlation coefficient. In his work, Kurtulmuş [21] conducted the A-TIG welding process by covering a slim layer of activated flux deposited on the weld bead before the welding process. In doing so, he concluded that a high penetration depth was obtained. Kam et al. [22] optimized the Fused Deposition Modelling (FDM) process parameters to have better mechanical characteristics using the Taguchi method. They concluded that by using optimized FDM process parameters, the material properties were improved. Azadi Moghaddam and Kolahan [23] optimized the Electrical Discharge Machining (EDM) process parameters by training and developing ANN. Upon using the optimized process parameters, better material removal rate, surface roughness, and tool wear rate were obtained. Having gathered the experimental results as data points with respect to the volume fraction of various nanoparticles at different temperatures, Rostami et al. [24] developed an algorithm to predict the optimum neuron number that should be present in the hidden layer of the developed ANN. In their work, Garg and Kaur [25] presented an innovative multi-criteria cluster or group-based decision-making method under a cubic intuitionistic fuzzy environment by hybridizing the extended TOPSIS method. They demonstrated the feasibility of the proposed method by comparing the results obtained from various existing approaches. In their paper, Delir Nazarlou et al. [26] attempted to optimize the friction stir welding parameters. They employed the Taguchi L9 orthogonal array to design and conduct the experimental runs and to optimize the process parameters. By using ANOVA, they found the most influential parameter that affected the process. Toghraie et al. [27] investigated the dynamic viscosity of Ag/Ethylene glycol nanofluid. After conducting the experiments, the obtained data was used to develop an ANN model, which they later used to forecast the dynamic viscosity. In their study, Tavakkoil Nabavi et al. [28] addressed a technique to develop a model and optimize the process of Abrasive Water Jet Machining (AWJM). Taguchi and D-optimal techniques were used for the same purpose. They also employed regression modeling along with ANOVA to establish a relationship between the input process parameters and output responses.

From the above studies, it is noted that the exploration of GMAW aluminium weldments is very limited. Hence, an attempt is made in the current work to evaluate and optimize the GMAW process parameters for aluminium alloy AA 6351 weldment by integrating the Taguchi-grey-Fuzzy technique, which will provide a basis for machine learning in the future that can be applied in the industries.

2. Experimental method

The methodology adopted in the optimization of GMAW process parameters of aluminium weldments using the Taguchi-grey-fuzzy integrated approach is illustrated in Figure 1.

The experiments for the study were conducted using the experimental setup, as shown in Figure 2. 100% Argon was used as a shielding gas while welding. The base material composition is presented in Table 1. AA4043 with a wire diameter of 1.2 mm was used as

Table 1. Chemical composition of the base and filler metal (weight %).

Material	Al	Si	Mn	Mg
AA 6351 (base metal)	97.8	1.0	0.6	0.6
AA 4043 (filler metal)	94.8	5.2	—	—

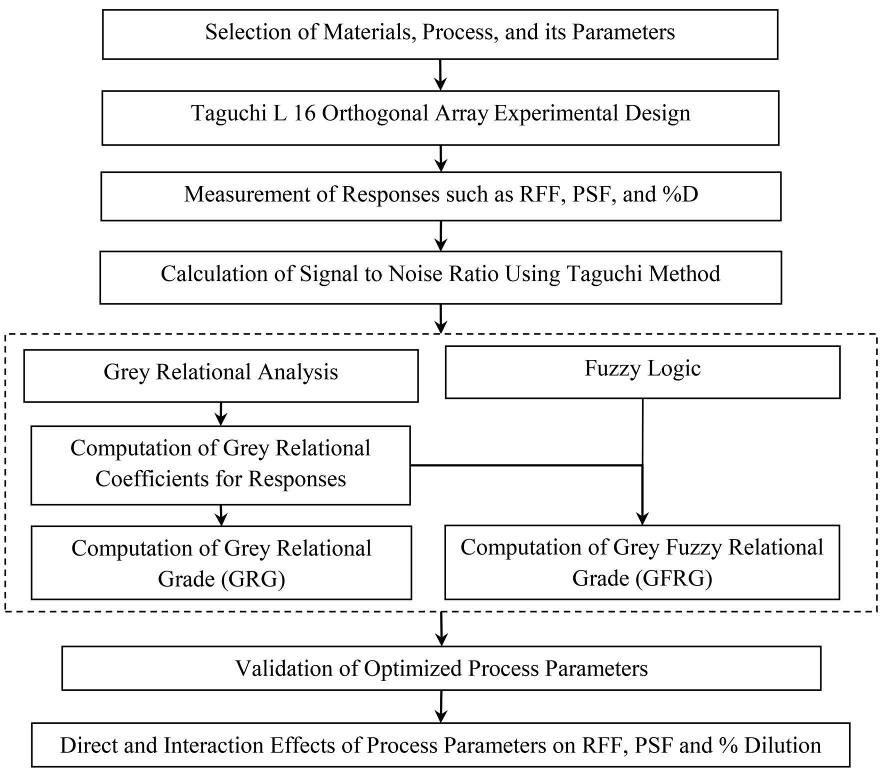

Figure 1. Methodology adopted in this paper.

Table 2. Process parameters and their levels.

Process parameters	Details		Levels			
	Units	Notation	1	2	3	4
Welding voltage	V	A	14	16	18	20
Welding speed	mm/min	B	150	160	170	180
Wire feed rate	inch/min	C	200	225	250	275
Nozzle to plate distance	inch	D	0.25	0.50	0.75	1.00

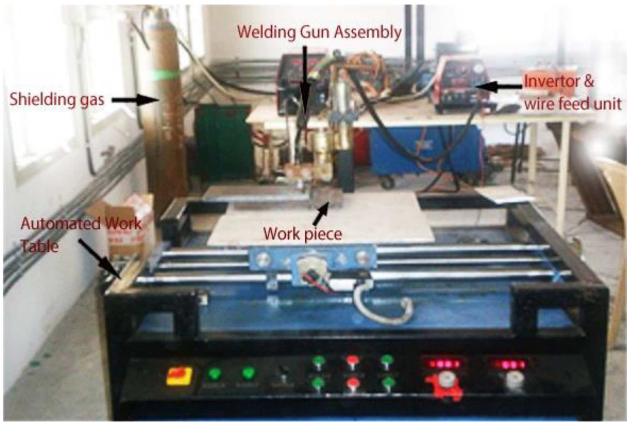

Figure 2. Experimental setup.

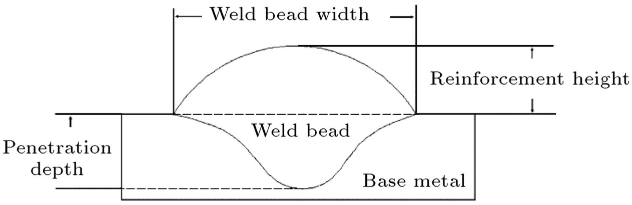

Figure 3. Weld bead geometry.

a filler material, whose composition is also given in Table 1.

For designing the experimental runs, the L16 Taguchi orthogonal array was utilized with welding voltage, welding speed, wire feed rate, and nozzle-to-plate distance as input process parameters. The input ranges identified are given in Table 2. During the experiments, experimental runs were randomized to reduce the environmental effects.

After initiating the experiments, weldments were sectioned in the transverse direction perpendicular to the weld line and the weld surfaces were prepared following the standard metallographic procedure. Keller's reagent was used as an etchant. Weld bead macrographs were characterized by an optical microscope, and the obtained images were imported to SolidWorks Drawing Editor, where the weld bead width, height, and penetration depth (as shown in Figure 3) were measured and RFF, PSF, and %D were calculated using Eqs. (1) to (3), as given by Bahrami et al. [29]:

$$RFF = W/R, \tag{1}$$

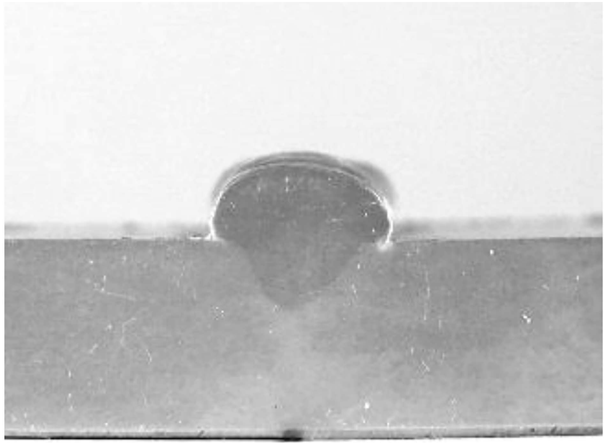

Figure 4. A sample macrograph (experiment no. 8).

where RFF is the Reinforcement form factor; W is the weld bead width (mm); and R is the reinforcement height.

$$PSF = W/P, \tag{2}$$

where PSF is the penetration shape factor; W is the weld bead width (mm); and P is the penetration depth.

$$\%D = \frac{Area\ of\ penetration}{Area\ of\ reinforcement + Area\ of penetration} \times 100. \tag{3}$$

A sample macrograph obtained is given in Figure 4.

2.1. Calculation of S/N ratios

The S/N ratio was calculated based on the larger the better criterion through Eq. (4). The calculated S/N ratio for the responses is tabulated in Table 3.

$$S/N = -10log\left[\frac{1}{n}\sum_{i=1}^{n}\frac{1}{y_i^2}\right], \tag{4}$$

where y represents the observed data and n is the number of tests in one trial.

2.2. Grey Relational Analysis (GRA)

Grey systems theory, developed by Deng, facilitates result prediction and decision-making with respect to uncertain systems. As per grey relational system modeling, grey relational coefficients were calculated

Table 3. Calculated S/N ratio for multiple responses.

Welding voltage (V)	Welding speed (mm/min)	Wire feed rate (inch/min)	Nozzle-to-plate distance (inch)	S/N ratio		
				RFF	PSF	%D
14	150	200	0.25	4.27	6.47	29.54
14	160	225	0.50	5.83	9.80	28.47
14	170	250	0.75	2.02	8.35	28.45
14	180	275	1.00	5.52	9.41	28.68
16	150	225	0.75	5.83	6.70	30.21
16	160	200	1.00	2.02	6.94	29.47
16	170	275	0.25	5.52	7.85	30.52
16	180	250	0.50	7.80	7.87	30.90
18	150	250	1.00	7.47	8.71	29.86
18	160	275	0.75	6.96	8.78	29.08
18	170	200	0.50	6.09	4.59	33.06
18	180	225	0.25	6.34	8.07	29.50
20	150	275	0.5	10.57	10.09	31.80
20	160	250	0.25	12.30	9.51	33.05
20	170	225	1.00	12.69	7.65	33.33
20	180	200	0.75	7.31	8.58	32.32

based on the 'larger the better' criterion through Eq. (5), after normalizing the data using Eq. (6) and computing the deviation sequence, which is calculated by Eq. (7). Furthermore, Grey Relational Grades (GRG) are calculated by taking the mean values of responses' grey relational coefficients, as presented in Table 4.

$$\xi_i(k) = \frac{\Delta_{\min} + \zeta\Delta_{\max}}{\Delta_{0i}(k) + \zeta\Delta_{\max}}, \tag{5}$$

where $\Delta_{0i}(k)$ is the deviation sequence; $X_0^*(k)$ is the reference sequence; $X_i^*(k)$ is the comparability sequence; and ζ is the identification or distinguishing coefficient.

If all the parameters are of equal importance, then 0.5 is considered. In this work, it is taken as 0.5.

$$X_i^*(k) = \frac{X_i(k) - \min X_i(k)}{\max X_i(k) - \min X_i(k)}, \tag{6}$$

where $X_i^*(k)$ is the sequence after data pre-processing; $X_i(k)$ is comparability sequence; and k is equal to 1 for the responses; $i = 1, 2, 3, \cdots, 16$ for experiment numbers 1 to 16.

$$[\Delta_{0i}(k)] = |[X_0^*(k)] - [X_i^*(k)]|, \tag{7}$$

where $\Delta_{0i}(k)$ is the deviation sequence; $X_0^*(k)$ is the reference sequence; and $X_i^*(k)$ is the comparability sequence.

Based on the GRG, rank is computed, which is also incorporated in Table 4.

Table 4. Grey Relational Grade (GRG) calculated from grey relational coefficient for responses.

Experiment no.	Grey relational coefficient			GRG	Rank
	RFF	PSF	%D		
1	0.39	0.43	0.39	0.40	15
2	0.44	0.90	0.33	0.56	6
3	0.33	0.61	0.33	0.43	14
4	0.43	0.80	0.34	0.52	9
5	0.44	0.45	0.44	0.44	13
6	0.33	0.47	0.39	0.40	16
7	0.43	0.55	0.47	0.48	11
8	0.52	0.55	0.50	0.53	8
9	0.51	0.67	0.41	0.53	7
10	0.48	0.68	0.37	0.51	10
11	0.45	0.33	0.90	0.56	5
12	0.46	0.56	0.39	0.47	12
13	0.72	1.00	0.62	0.78	3
14	0.93	0.82	0.90	0.88	1
15	1.00	0.53	1.00	0.84	2
16	0.50	0.66	0.71	0.62	4

2.3. Grey-fuzzy integrated approach

Fuzzy sets and systems concepts were introduced by Zedah [30]. Of the two fuzzy inference systems available, viz. Mamdani and Sugino, widely used Mamdani is preferred in this work because it is intuitive and appropriate for human inputs. The input values con-

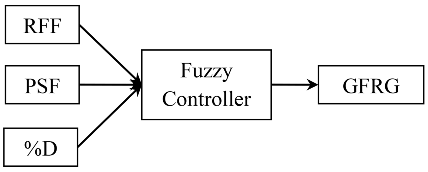

Figure 5. The Grey-Fuzzy model adopted.

Table 5. Fuzzy rules applied.

Fuzzy Rules	Input			Output
	RFF	**PSF**	**%D**	**GFRG**
1	L	M	L	VL
2	L	VH	L	VL
3	L	M	L	M
4	L	H	L	VL
5	L	M	M	LM
6	L	M	L	L
7	L	M	M	VL
8	M	M	M	LM
9	M	M	L	LM
10	M	M	L	LM
11	M	L	VH	LM
12	M	M	L	M
13	H	VH	M	LM
14	VH	H	VH	VH
15	VH	M	VH	VVVH
16	M	M	H	VVH

Note: L: Low; M: Medium, VL: Very Low; VH: Very High; H: High; LM: Low Medium, VVVH: Very Very Very High; VVH: Very Very High.

sidered in this work were the GRG values of responses, namely RFF, PSF, and %D, as shown in Figure 5. Fuzzification was done by converting the crisp input values into membership functions as "low, medium, high, and very high", whose values range between 0 and 1. The triangular method of defining membership functions was used. To increase the accuracy of the responses, nine membership functions were defined.

Fuzzy rules characterize the correlation among inputs and outputs in a fuzzy inference system by using a set of statements that are linguistic in nature. In general, the total number of fuzzy rules used in a fuzzy inference system depends directly on the number of fuzzy sets for each input variable. In this work, the bases of 16 possible rules were formed using fuzzy IF-THEN rules, as shown in Table 5.

In defuzzification, output values that were fuzzy were converted into crisp values. The centroid of area method was used in this work for defuzzification. Grey Fuzzy Relational Grade (GFRG) values were calculated using a Simulink model, which was also developed, as shown in Figure 6.

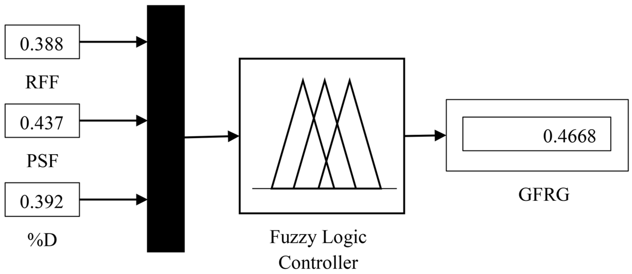

Figure 6. Simulink model for generating GFRG.

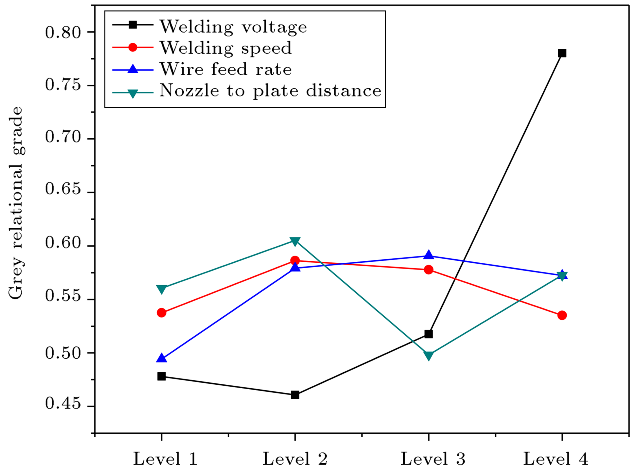

Figure 7. Response values on grey relational grades for process parameters.

From the calculated GRG values, parameter optimization is done by constructing the response tables. Given that the experiments were designed based on Taguchi's L16 orthogonal array, it is possible to separate out the effect of every control factor from the GRG at different levels, as shown in Table 6. A graph is drawn, which is shown in Figure 7 for different GRG obtained for the process parameters.

By using the grey-Fuzzy Inference system, GFRG values were computed and compared with GRG values computed through the grey relational technique, as shown in Table 7. In addition, rank is also computed based on GFRG values. Further, from the calculated GFRG values, parameter optimization is done by constructing the response table, as shown in Table 8. A graph is plotted, which is shown in Figure 8 for different GFRG obtained for the process parameters.

2.4. Comparison of the Taguchi-grey-fuzzy optimized values

For comparison, optimization was also done using the Taguchi method, which is included in the consolidated optimized values. The same is given in Table 9.

2.5. Conformity tests

Conformity tests were performed to verify the results of RFF, PSF, and %D with respect to the optimized process parameters, shown in Table 10.

Table 6. Response table for grey relational grade.

Symbol	Process parameters	Grey relational grade				Main effect (max-min)
		Level 1	Level 2	Level 3	Level 4	
A	Welding voltage	0.48	0.46	0.52	0.78*	0.32
B	Welding speed	0.54	0.59*	0.58	0.54	0.05
C	Wire fee rate	0.49	0.58	0.59*	0.57	0.10
D	Nozzle to plate distance	0.56	0.61*	0.50	0.57	0.18

*: Optimum level for grey relational grade (A4, B2, C3, D2).

Table 7. Comparison between Grey Relational Grade (GRG) and Grey Fuzzy Relational Grade (GFRG) calculated using fuzzy logic.

Experiment no.	GRG	GFRG	Error percentage	Rank
1	0.40	0.43	–5.94	15
2	0.56	0.55	2.30	6
3	0.43	0.46	–7.73	14
4	0.52	0.52	0.18	7
5	0.44	0.47	–7.09	13
6	0.40	0.46	–1.38	16
7	0.48	0.48	0.90	12
8	0.53	0.50	4.84	8
9	0.538	0.49	7.05	9
10	0.51	0.48	4.77	10
11	0.56	0.58	–2.63	4
12	0.47	0.48	–1.37	11
13	0.78	0.76	2.51	3
14	**0.88**	**0.86**	**2.93**	**1**
15	0.84	0.827	2.92	2
16	0.62	0.56	8.77	5

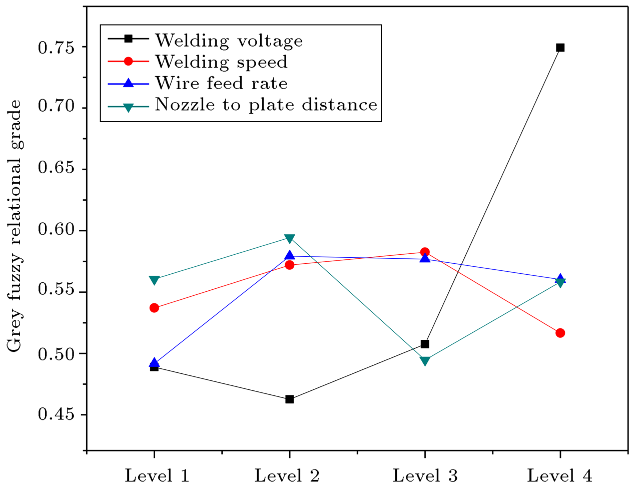

Figure 8. Response values on grey fuzzy relational grades for process parameters.

2.6. *ANOVA*

An ANOVA (Analysis of Variance) was employed to explore the significance of process parameters on the quality characteristics of weldments. Table 11 shows the detailed results of ANOVA for the responses.

3. Results and Discussion

3.1. *Significance of process parameters*

From Table 11, it was noted that the 'welding voltage' had the greatest influence (measured at 70.18%) over the RFF, followed by 'wire feed rate' at 12.83% and 'nozzle-to-plate distance' at 6.44%; however, the welding speed was of lower impact at 0.88%. For PSF, the impact of wire feed rate is 41.37% which is high, followed by welding voltage at 26.29%, welding speed at 20.22%, and nozzle-to-plate distance at 0.76%. In the case of %D, welding voltage had the highest impact at 67.62%, followed by welding speed at 10.22%, wire feed rate at 5.64%, and nozzle-to-plate distance at 5.20%.

Table 8. Response table for grey fuzzy relational grade.

Symbol	Process parameters	Grey fuzzy relational grade				Main effect (max-min)	Rank
		Level 1	Level 2	Level 3	Level 4		
A	Welding voltage	0.49	0.46	0.51	0.75*	0.29	1
B	Welding speed	0.54	0.57	0.58*	0.52	0.07	4
C	Wire fee rate	0.49	0.58*	0.58	0.56	0.09	3
D	Nozzle to plate distance	0.56	0.59*	0.49	0.56	0.10	2

*: Optimum level for grey relational grade (A4, B3, C2, D2)

Table 9. Consolidated optimized values.

Technique	Response	Welding voltage (V)	Welding speed (mm/min)	Wire feed rate (inch/min)	Nozzle to plate distance (inch)
Taguchi-grey-fuzzy	Multi-response	20	170	225	0.50
Taguchi-grey		20	160	250	0.50
Taguchi	Dilution	20	170	200	0.50
	PSF	20	160	275	1.00
	RFF	20	150	225	0.50

Table 10. Conformity test results.

Welding voltage (V)	Welding speed (mm/min)	Wire feed rate (inch/min)	Nozzle to plate distance (inch)	S/N ratios						Error (%)
				Actual value			Optimized value			
				RFF	PSF	%D	RFF	PSF	%D	
20	170	225	0.50	6.78	8.08	30.51	6.53	8.25	30.25	3.69
20	160	250	0.50				6.87	8.70	30.74	–1.33
20	170	200	0.50				5.98	8.13	30.52	11.80
20	160	275	1.00				6.90	8.78	30.27	–1.77
20	150	225	0.50				6.47	7.94	30.07	4.57

Table 11. Results of the ANOVA for Reinforcement Form Factor (RFF), Penetration Shape Factor (PSF), and percentage of dilution (%D).

Variables	Sum of squares	DoF	Mean of square	F characteristic	Contribution (%)
RFF					
Welding voltage	8.31	3	2.77	7.26	70.18
Welding speed	0.11	3	0.03	0.09	0.88
Wire feed rate	1.52	3	0.51	1.33	12.83
Nozzle to plate distance	0.76	3	0.25	0.67	6.44
Error	1.15	3	0.38	—	9.67
Total	11.85	15	3.95	—	100
PSF					
Welding voltage	0.62	3	0.21	2.31	26.29
Welding speed	0.48	3	0.16	1.78	20.22
Wire feed rate	0.98	3	0.32	3.64	41.37
Nozzle to plate distance	0.02	3	0.006	0.07	0.76
Error	0.27	3	0.09	—	11.36
Total	2.37	15	0.79	—	100
%D					
Welding voltage	490.7	3	163.57	5.97	67.62
Welding speed	74.18	3	24.73	0.9	10.22
Wire feed rate	40.95	3	13.65	0.5	5.64
Nozzle to plate distance	37.71	3	12.57	0.46	5.20
Error	82.14	3	27.38	—	11.32
Total	725.68	15	241.9	—	100

Table 12. Data means of the responses.

Level	Welding voltage	Welding speed	Wire feed rate	Nozzle to plate distance
		RFF		
1	1.69	2.33	1.81	2.43
2	1.89	2.39	2.57	2.45
3	2.17	2.37	2.55	1.94
4	3.53	2.18	2.35	2.46
		PSF		
1	2.69	2.55	2.18	2.52
2	2.33	2.76	2.55	2.61
3	2.42	2.30	2.70	2.55
4	2.82	2.66	2.84	2.58
		%D		
1	27.52	33.10	36.51	34.58
2	32.69	32.40	33.79	36.37
3	33.60	37.86	34.38	32.15
4	42.88	33.34	32.03	33.61

3.2. Optimized parameters using Taguchi-GREY

In general, the higher the grey relation grade, the higher the quality. Hence, a high GRG is the required optimum value. In this regard, from Figure 6, the optimum process parameters are A4, B2, C3, D2 and the corresponding values are welding voltage 20 V, welding speed 160 mm/min, wire feed rate 250 inch/min, and nozzle-to-plate distance 0.5 inch.

3.3. Optimized parameters using Taguchi-GREY-fuzzy

With reference to Figure 7, the computed optimum process parameters are $A4$, $B3$, $C2$, $D2$ and the corresponding values include welding voltage 20 V, welding speed 170 mm/min, wire feed rate 250 inch/min, and nozzle-to-plate distance 0.5 inch. It may be observed that the obtained optimized process parameters do not vary much as compared with the values derived from the ranks determined earlier.

3.4. Validation

From Table 10, good agreement of S/N ratios between the calculated and actual values of responses is observed in the conformity test. The S/N ratios calculated from the validation experiments closely correlate with the experimental results.

3.5. Direct effects of process parameters

The direct and interactive effects of the process parameters affecting the weld bead properties are plotted using MINITAB 16, a statistics-based analysis software product. For analyzing the direct effects, the corresponding data means of the response for the respective input process parameters were used, as shown in Table 12. Figures 9–11 depict the direct impact of control factors on responses, namely RFF, PSF, and %D.

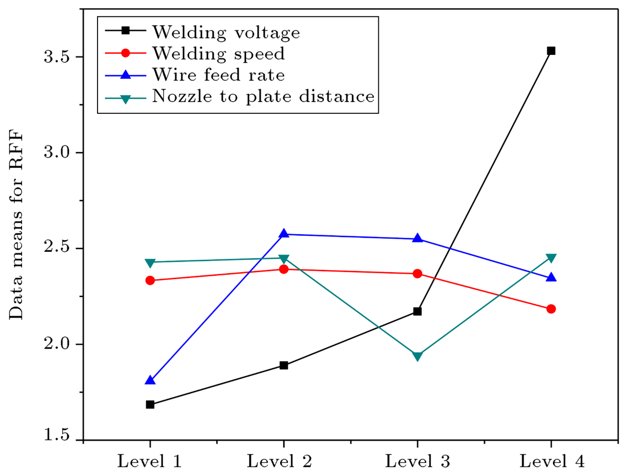

Figure 9. Direct effect over RFF.

3.5.1. Process parameters effects on RFF

From Figures 9–11, it is evident that RFF, PSF, and %D increase upon increasing welding voltage, which was also reported by Srihari [31]. It was shown that welding voltage directly affected the weld quality. As the wire feed rate increases, the reinforcement is achieved by greater deposition of weld material; hence, there is a reduction in RFF. Similarly, when welding speed increases, there is a reduction in RFF due to the

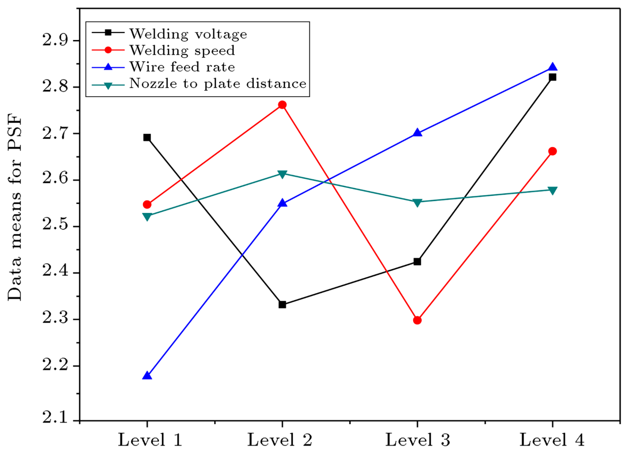

Figure 10. Direct effect over PSF.

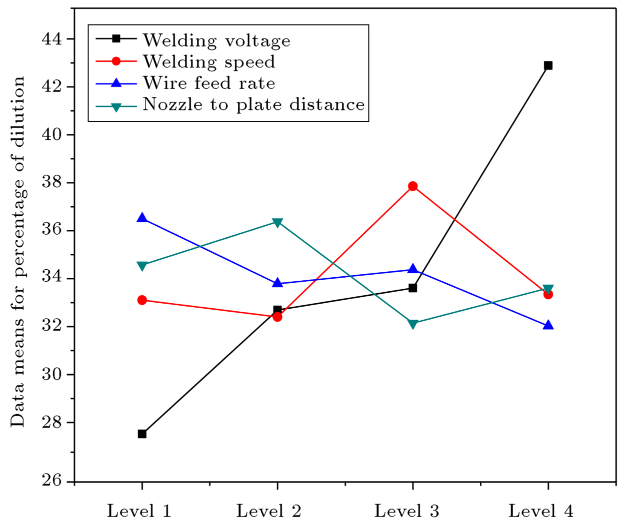

Figure 11. Direct effect over %D.

increased deposition of weld material, which increases the reinforcement. RFF is reduced when there is an increase in the nozzle-to-plate distance. This is because of the increase in the distance between the plate and the nozzle.

3.5.2. Process parameters effects on PSF
PSF increases when wire feed rate increases because a greater volume of material gets deeper penetration by enhancing power input through the filler wire. An increase in welding speed decreases PSF because at lower welding speeds, heat input will be greater and, hence, there will be increased bead width. Nozzle-to-plate distance increases PSF. This is because of the wider arc cone when there is an increase in the distance, as reported by Sowrirajan et al. [32].

3.5.3. Process parameters effects on %D
The dilution percentage increases with increase in welding voltage. This is because of a rise in the larger deposition rate of filler material, which is the result of better fluidity, and higher heat input, which was also reported by Hashmi et al. [33]. Other parameters reduce the dilution percentage because of a reduction in the area of penetration.

3.6. Interaction effects
ANOVA for GRG and GFRG is also performed to determine the significant parameters that affect the quality of weldment, as given in Table 13. From Table 13, it is evident that welding voltage affects the weld quality the most.

With reference to ANOVA performed over S/N ratios, GRG and GFRG, it was found that welding voltage predominantly affected the responses. Hence,

Table 13. ANOVA for Grey Relational Grade (GRG) and Grey Fuzzy Relational Grade (GFRG).

Process parameters	DoF	Sum of squares	Mean squares	F ratio	Contribution (%)
GRG					
Welding voltage	3	0.267	0.089	17.38	78.98
Welding speed	3	0.009	0.003	0.55	2.52
Wire feed rate	3	0.023	0.008	1.50	6.83
Nozzle to plate distance	3	0.024	0.008		7.12
Error	3	0.015	0.005		4.54
Total	15	11.846	0.113		
GFRG					
Welding voltage	3	0.211	0.070	10.70	74.59
Welding speed	3	0.011	0.004	0.57	3.96
Wire feed rate	3	0.020	0.007	1.02	7.13
Nozzle to plate distance	3	0.021	0.007	1.05	7.35
Error	3	0.020	0.007		6.97
Total	15	2.369	0.094		

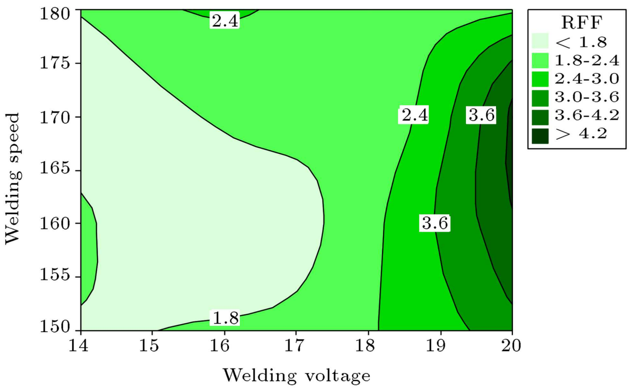

Figure 12. Interaction effect of welding speed and welding voltage over RFF.

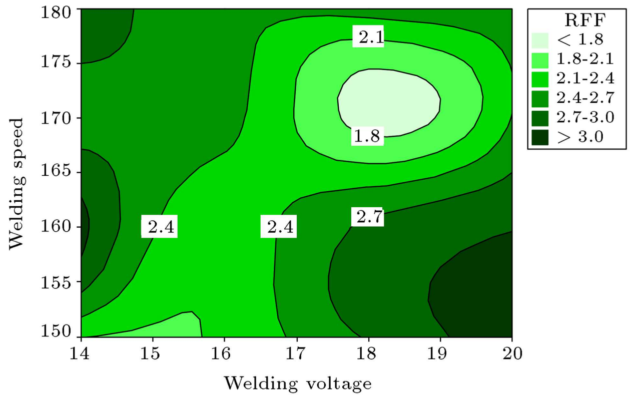

Figure 13. Interaction effect of welding speed and welding voltage over PSF.

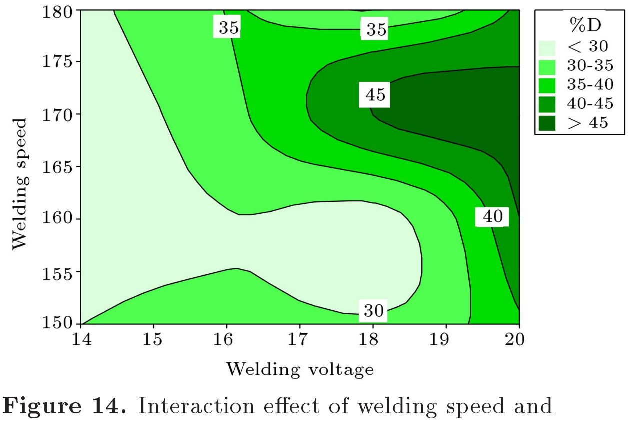

Figure 14. Interaction effect of welding speed and welding voltage over %D.

the interactive effects of welding voltage with other parameters over RFF, PSF, and %D are plotted in Figures 12-20 and analyzed.

According to Figures 12–14, when welding voltage increases in conjunction with the welding speed, RFF and %D increase, whereas in PSF, an interestingly high PSF is obtained at a low welding speed with high voltage. The reason for this is the reduction of weld bead width and increase of bead height.

From Figures 15–17, it is observed that RFF

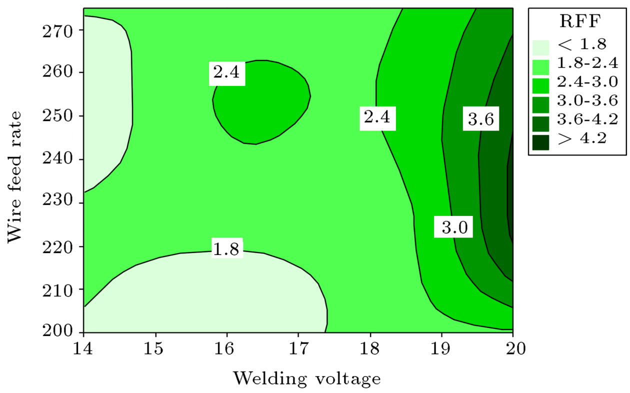

Figure 15. Interaction effect of wire feed rate and welding voltage over RFF.

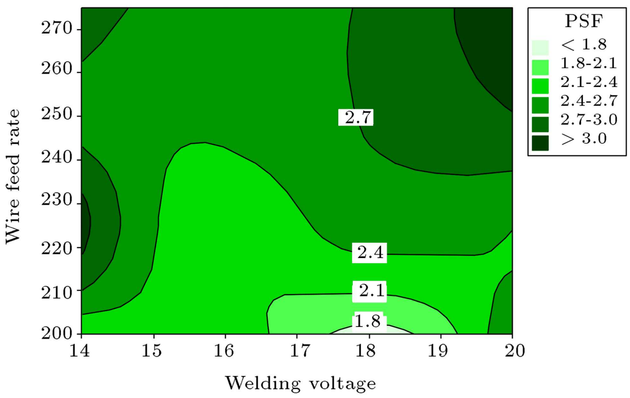

Figure 16. Interaction effect of wire feed rate and welding voltage over PSF.

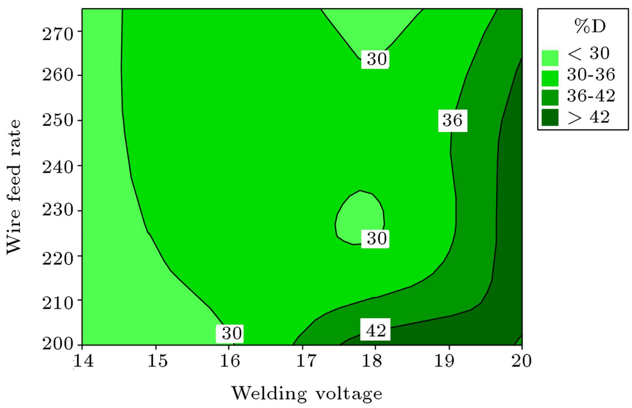

Figure 17. Interaction effect of nozzle-to-plate distance and welding voltage over %D.

increases as both welding voltage and wire feed rate increase. This is due to their combined effect of increasing the weld bead width, leading to the greater deposition of molten material due to the heat produced, which was also reported by Samir et al. [34].

Further, it is evident that when welding voltage increases with wire feed rate, PSF also increases. The reason behind this is that these parameters increase the effect of fusion in the weld joint, where molten material

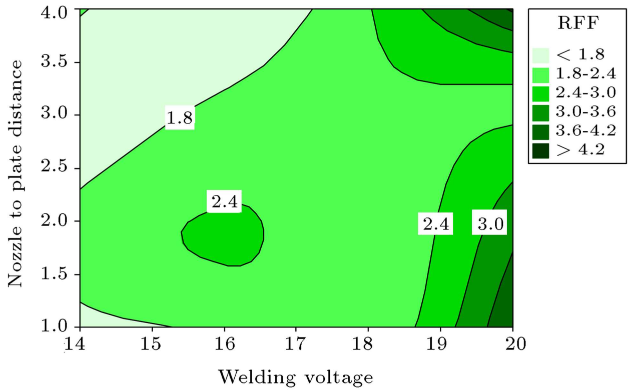

Figure 18. Interaction effect of nozzle-to-plate distance and welding voltage over RFF.

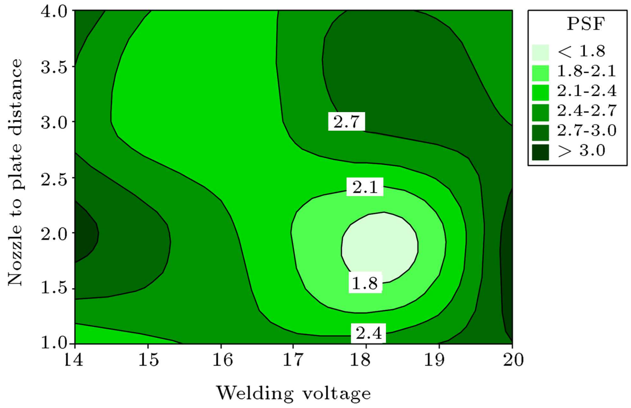

Figure 19. Interaction effect of nozzle-to-plate distance and welding voltage over PSF.

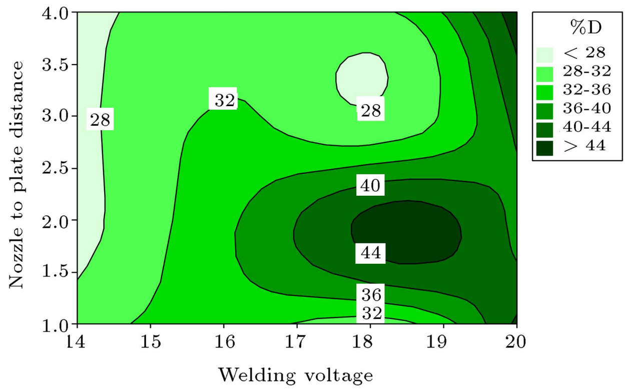

Figure 20. Interaction effect of nozzle-to-plate distance and welding voltage over PSF.

is accumulated, resulting in bead width increase, according to Srihari [31]. Hence, if there is an increase in welding voltage and wire feed rate, it greatly influences the PSF. In the case of %D, when the above parameters increase in value, the value of %D increases, as well. A linear relationship exists for %D when welding voltage and wire feed rate interact.

With reference to Figures 18–20, when welding voltage interacts with a short nozzle-to-plate distance, RFF increases. This is due to the arc length increment, which results in wider bead width. PSF also increases when higher wire feed interacts with a short nozzle-plate distance. This is due to more material penetrating the base material and the shape of the arc cone. The increasing trend in %D is observed when welding voltage increases along with the nozzle-to-plate distance up to a certain limit because of the presence of low penetration patterns.

4. Conclusion

This study investigated the effects of Gas Metal Arc Welding (GMAW) process parameters while welding AA 6351 aluminium alloy. Optimized parameters were effectively determined by applying an integrated Taguchi-grey-Fuzzy approach, which was validated by conformity tests. The following are the conclusions:

- Investigation with the help of ANOVA revealed that welding voltages along with wire feed rate dominated the characteristics of weld bead;
- When welding voltage increased, Reinforcement Form Factor (RFF), Penetration Shape Factor (PSF), and percentage of dilution (%D) raised;
- RFF decreased when there was an increase in welding speed, wire feed rate, and nozzle-to-plate distance;
- In the case of PSF, PSF increased when wire feed rate and nozzle-to-plate distance increased, but decreased while there was an increase in welding speed;
- %D decreased while increasing the other process parameters other than the welding voltage;
- RFF and %D increased with welding voltage and welding speed;
- High PSF was obtained at a low welding speed;
- RFF, PSF, and %D exhibited an increasing trend when welding voltage interacted with wire feed rate;
- When high welding voltage increased with short nozzle-to-plate distance, RFF and PSF increased, whereas %D increased up to a certain limit.

Nomenclature

GMAW	Gas Metal Arc Welding
S/N ratio	Signal to Noise ratio
GRG	Grey Relational Grades
GFRG	Grey Fuzzy Relational Grades
ANOVA	Analysis of Variance
PSF	Penetration Shape Factor
RFF	Reinforcement Form Factor

%D	Percentage of dilution
RSM	Response Surface Methodology
ANN	Artificial Neural Network
GA	Genetic Algorithm
GRA	Grey Relational Analysis
W	Weld bead width
R	Reinforcement height
P	Penetration depth
$\Delta_{0i}(k)$	Deviation sequence
$X_0^*(k)$	Reference sequence
$X_i^*(k)$	Comparability sequence
ζ	Identification or distinguishing coefficient
$X_i^*(k)$	Sequence after the data pre-processing
FAHP	Fuzzy Analytic Hierarchy Process
MOMILP	Multi-Objective Mixed Integer Linear Programming

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Biographies

Boluvampatti Nagamani Sreeharan completed his PhD under Mechanical Engineering stream and Post graduated in CAD/CAM from Kumaraguru College of Technology under Anna University, Coimbatore. His research areas include optimizing process parameters and MCDM techniques. He published 11 papers in international journals and 3 in national journals.

Jayaraman Yoganandh received his PhD degree from National Institute of Technology, Tiruchirappalli. He did his Post graduate studies specializing in CAD/CAM Engineering from Kumaraguru College of Technology, Coimbatore. He was sponsored by the Department of Science & Technology, India under Young Scientist Scheme to present his paper in the International Conference on Surface Modification Technology held at Ecully Centrale De-Lyon, France. His areas of interest include tribology, surface engineering, weld cladding composite materials, and advanced manufacturing process.

Ramasamy Sudhakar received his PhD in Mechanical Engineering from Anna University, Chennai and his Masters' degree in Advanced Manufacturing Technology from Coimbatore Institute of Technology, Anna University Chennai. His research interests include welding processes, mechatronics system design, fluid power automation, manufacturing, and simulation.

Thankappan Kannan is a Teacher, Researcher, and Administrator. His areas of specialization and interest in Mechanical Engineering include manufacturing, optimization, and surface engineering. He has published more than 175 technical papers in reputed international and national journals and edited books besides presenting several papers in conferences. He was the Principal Investigator of a sponsored project on 'Studies on Pitting Corrosion and Ferrite Number of Duplex Stainless Steel Clad Metals Deposited by Pulsed GMAW' funded by AICTE.