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Research Article

Optimization of friction stir welding process parameters using RSM based Grey–Fuzzy approach

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Abstract: Friction stir welding (FSW) is proved as a promising welding technology for joining dissimilar aluminium alloys. Aluminium alloys are used extensively within the aerospace industry for applications such as fuselage and wing skin panels due to their high strength to weight ratio. Therefore, an attempt is made to optimize the process parameters of friction stir welding using AA2024 and AA6061 age hardenable aluminum alloys in order to improve the tensile properties such as ultimate tensile strength (UTS) and tensile elongation (TE). A response surface method (RSM) based fuzzy grey relational approach (Fuzzy - GRA) is applied using four factors with three levels. The process parameters namely rotational speed (N), welding speed (F), axial load (P) and pin shape (PS). The results indicate a RSM based fuzzy grey relational approach improving tensile properties of FS welded AA2024 and AA6061 aluminum alloys when comparing to conventional grey relational approach. A quadratic relationship was also established between the process parameters and fuzzy grey relational grade.
Keywords: friction stir welding, fuzzy, response surface method, grey relational approach, tensile, elongation.

INTRODUCTION

Age hardenable aluminium alloy's 2XXX, 6XXX and 7XXX grades are difficult to weld using fusion welding techniques due to its high strength to weight ratio, sensitive to cracking, etc. Friction stir welding (FSW) has become a viable and alternative welding technique in fabrication of age hardenable aluminum alloys, especially to aerospace, automobile industries. Since, FSW process does not involve melting, solidification, porosity, segregation, etc [1]. A dynamic recrystallization using a rotating tool that permits super plastic deformations, bonds the weld zone of similar and dissimilar materials. Although, friction stir welding has numerous benefits, certain defects, such as an imperfect stirred zone during processing, inadequate heat causing poor material flow, lack of probe penetration, non-uniform material forging pressure throughout the material thickness, residual stress and voids on the advancing side, may still arise [2]. In general, age hardernable aluminum alloys required high fatigue performance, tensile strengths and elongations. So these defects should be eliminated by selecting appropriate process parameters. In the proposed investigation two age hardenable aluminum alloys namely AA2024 – T3 and AA6061 – T6 are considered to select an appropriate process parameter of FSW.

Experimental setup

A computerized friction stir welding (FSW) machine is used to fabricate the weld joints of dissimilar AA2024 and AA6061 aluminum alloys. Fig.1 shows the arrangement of AA2024 – T3 and AA6061 – T6 aluminum alloy plates on the FSW machine during a welding process. T3 represents the AA2024 alloy, which was solution heat-treated, cold-worked and naturally aged to be stable. The alloy was a solution heat treated to improve the strength, and the mechanical properties stabilized during room-temperature aging. T6 denotes AA6061 alloys that were solution heat-treated and artificially aged. These products were not cold worked after the solution heat treatment [3]. The mechanical and chemical compositions of each alloy are shown in Table.1. Aluminum alloy plates 300mm × 150mm × 6. 25mm were used to fabricate the butt joints. The tool rotates perpendicular to the longitudinal plate surface. The process parameters, such as tool rotational speed (N), welding speed (F), axial force (P) and pin shape (PS), were selected based on a thorough literature [4-7]. Three major pin shapes were assessed: taper (TA), square (SQ) and straight cylinder (SC).

Table-1: Mechanical properties and chemical composition of AA2024 and AA6061 aluminum alloys

Aluminum alloy (%)	Cr	Cu	Fe	Mg	Mn	Si	Tensile Yield Strength (MPa)	Elongation %
2024	0.10	4.90	0.90	1.80	0.90	0.50	324	20
6061	0.35	0.40	0.70	1.20	0.15	0.80	276	17

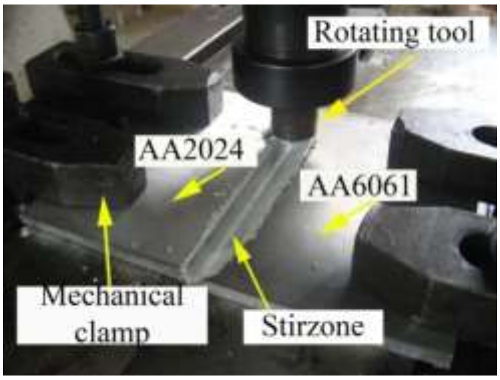

Fig-1: Arrangement of arrangement of AA2024-T3 and AA6061-T6 aluminum alloy plates

Fig-2: Fabricated FSW tools

SKD – 61 tool steel is used to fabricate the rotating tools. SKD - 61 tool steel is a chromium-molybdenum hot-worked air-hardened steel with good wear resistance, elevated-temperature strength, and thermal fatigue resistance [8]. The fabricated FSW tools are shown in Fig.2. The process parameter and their corresponding levels are presented in Table 2. The fabricated weld samples were kept for further mechanical and metallurgical characterization.

Table-2: Process parameters and their levels

S.No	Process Parameters	Unit	Range		
			-1	0	1
1	Rotational speed (N)	rpm	1500	1700	1900
2	Welding speed (F)	mm/min	0.5	1	1.5
3	Axial load (P)	kN	3	6	9
4	Pin Sapes (PS)		1(Tap)	2(Squ)	3(Cyl)

Test pieces were prepared from the welded samples for the joint strength estimations and metallographic examinations. The tensile specimens were cut perpendicular to their rolled direction. The tensile strength was tested using the American standard for testing of materials (ASTM) standard IX; the fracture samples are shown in Fig.3. The design matrix, including the experimental tensile strength and tensile elongation values, is shown in Table 3. The fractured test pieces were examined using a scanning electron microscope (SEM) to identify the fracture mode and poor joint strength root cause.

Table-3: Experimental results of ultimate tensile strength and tensile elongation

Std	Run	A:Rotational speed (RPM)	B:Welding speed (mm/min)	C:Axial load (kN)	D:Pin Shape	Ultimate Tensile Strength (UTS) (MPa)	Tensile Elongation (TE) (%)
1	7	1500	30	6	2	108.31	10.97
2	8	1900	30	6	2	109.33	9.23
3	11	1500	90	6	2	109.32	11.45
4	5	1900	90	6	2	101.06	9.45
5	25	1700	60	3	1	122.25	12.38
6	3	1700	60	9	1	127.09	10.16
7	4	1700	60	3	3	117.64	11.37
8	22	1700	60	9	3	124.31	9.72
9	18	1500	60	6	1	122.34	11.26
10	28	1900	60	6	1	119.06	10.54
11	6	1500	60	6	3	120.21	11.1
12	30	1900	60	6	3	115.37	9.11
13	21	1700	30	3	2	107.34	11.56
14	14	1700	90	3	2	106.13	11.77
15	23	1700	30	9	2	116.31	10.03
16	17	1700	90	9	2	112.31	10.49
17	20	1500	60	3	2	118.52	12.28
18	29	1900	60	3	2	115.98	10.12
19	19	1500	60	9	2	122.66	10.26
20	27	1900	60	9	2	124.22	9.37
21	31	1700	30	6	1	115.32	10.67
22	16	1700	90	6	1	104.34	11.67
23	26	1700	30	6	3	110.27	9.92
24	13	1700	90	6	3	108.31	10.89
25	24	1700	60	6	2	138.4	12.11
26	15	1700	60	6	2	143.64	12.25
27	2	1700	60	6	2	139.21	12.12
28	12	1700	60	6	2	139.28	12.48
29	1	1700	60	6	2	139.91	12.45
30	10	1700	60	6	2	141.34	12.38
31	9	1700	60	6	2	143.3	12.53

A ductile fracture mode was observed in the fractured zone when the test pieces were fabricated using a rotating tool with a square pin. A few fractured samples are shown in Fig.4 to demonstrate the fracture modes and identified the weld joint defects using scanning electron microscope (SEM). These weld defects drastically reduce the tensile strength versus the base material strength by 44% for AA 2024 and 51% for AA 6061 aluminum alloys.

Grey Relational Analysis (GRA)

Grey relational analysis (GRA) is a decision-making technique based on grey theory which is originally developed by Deng Julong [9]. According to grey theory, there are two kinds of data’s can be exist namely “known’ and “unknown” in the experimental investigation. These data are called in grey theory as ‘black’ and ‘white’ data’s respectively. The ‘black’ data’s represents unknown information, whereas ‘white’ data’s represents known information. Between the white and black data’s, there is an incomplete information exist in all experiments. This incomplete information is known as ‘grey system’.

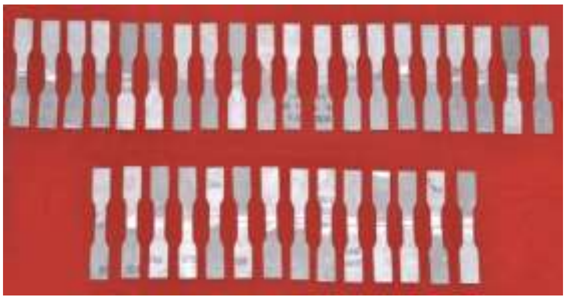

Fig-3: Tensile fractured samples

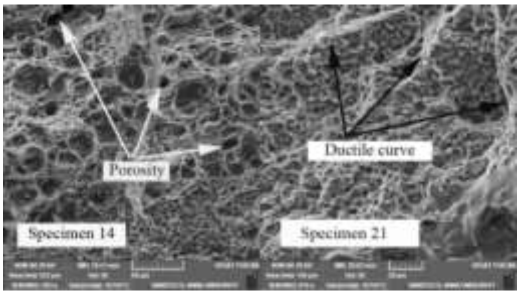

Fig-4: SEM Images of fractured zones

In the present investigation two responses are considered for maximization namely ultimate tensile strength (UTS) and tensile elongation (TE). Fig.5 provides a graphical illustration of the present grey fuzzy analysis. The range of each input and output factors and their respective units are different. Therefore, data's must be normalized. The data preprocessing transforms the original sequence to a comparable sequence. Hence, each response is normalized between 0 and 1.

The following normalizing equation is used when the response needs to be maximized. The equation is as follows:

$$x_i^*(k) = \frac{x_i^o(k) - \min x_i^o(k)}{\max x_i^o(k) - \min x_i^o(k)} \qquad (1)$$

However, if there is a definite target value to be achieved, then the original sequence will be normalized in the form

$$x_i^*(k) = 1 - \frac{\left|x_i^o(k) - x^o\right|}{\max x_i^o(k) - x^o} \qquad (2)$$

where $x_i^o(k)$ denotes the original sequence, min $x_i^o(k)$ is the sequence after the data preprocessing, max $x_i^o(k)$ is the largest value of $x_i^o(k)$, min $x_i^o(k)$ is the smallest value of $x_i^o(k)$, and x^o is the desired value. The grey relational sequences in the analysis represent the grey relational coefficient. Generally grey relational coefficient is represented as ξ. It can be calculated as follows:

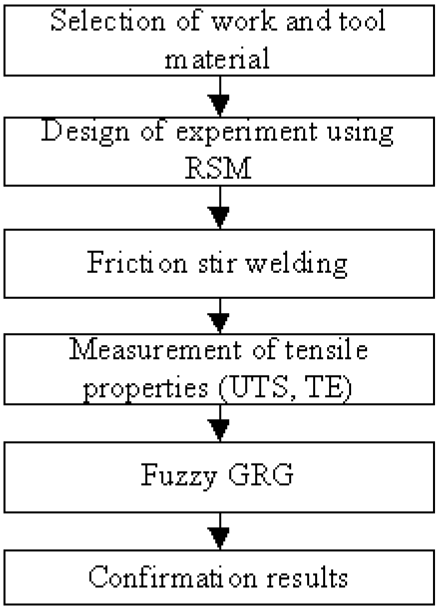

Fig-5: Graphical illustration of grey relational analysis

$$\xi(k) = \frac{\Delta_{\min} + \xi\Delta_{\max}}{\Delta_{oi}(k) + \xi\Delta_{\max}} \qquad (3)$$

where $\Delta_{oi}(k)$ denotes the absolute value of the difference between $x_i^o(k)$ and $x_i^*(k)$ and called the deviation sequence. ξ is known as the distinguishing coefficient. In general, ξ is assumed to be 0.5[10]. After the grey relational coefficient, the grey relational grade is calculated as follows:

$$x_i = \frac{1}{n}\sum_{k=1}^{n}\xi_i(k)\,. \qquad (4)$$

For practical applications, the weighting value can be varied based on the quality of responses considered in the experiment. Then the equation becomes

$$x_i = \frac{1}{n}\sum_{k=1}^{n}\omega_k\xi_i(k) \qquad (5)$$

where ω_k is the weighting factor of *k*. In the present investigation, equal weighting value ω_k of 1 is assigned. The grey relational grade (GRG) shows the level of association between the reference sequence and the comparability sequence. A larger grey relational grade means that the corresponding parameter combination is closer to the optimal. The significant process factors in the process can be identified using mean GRG values. The present investigation is to optimize the process parameters of FSW in order to improve the tensile properties of friction stir-welded AA2024 and AA6061 aluminum alloys. Therefore, the GRG for each experiment is estimated using equation (1) – (5) in the present study. The obtained GRG's are presented in table.4. A larger GRG is desirable irrespective of maximization and minimization. Accordingly 31st experimental run carries a larger GRG. Therefore it means 31st experimental run corresponding parameter levels are closer to optimal.

Table-4: Grey relational coefficients, grades and their respective rank

Std	Run	Grey relational coefficient		Grey relational grade	Rank
		Tensile Strength	Tensile Elongation		
1	7	0.19	0.23	0.208	23
2	8	0.19	0.17	0.180	30
3	11	0.19	0.25	0.222	17
4	5	0.17	0.18	0.171	31
5	25	0.25	0.32	0.283	8
6	3	0.28	0.20	0.239	11
7	4	0.23	0.25	0.237	12
8	22	0.26	0.18	0.222	16
9	18	0.25	0.24	0.246	10
10	28	0.23	0.21	0.221	19
11	6	0.24	0.23	0.236	13
12	30	0.21	0.17	0.191	29
13	21	0.18	0.26	0.222	18
14	14	0.18	0.27	0.226	14
15	23	0.22	0.19	0.206	26
16	17	0.20	0.21	0.205	27
17	20	0.23	0.31	0.269	9
18	29	0.22	0.20	0.206	25
19	19	0.25	0.20	0.226	15
20	27	0.26	0.17	0.217	21
21	31	0.21	0.22	0.215	22
22	16	0.18	0.27	0.220	20
23	26	0.19	0.19	0.192	28
24	13	0.19	0.22	0.206	24
25	24	0.40	0.30	0.348	7
26	15	0.50	0.31	0.403	2
27	2	0.41	0.30	0.355	6
28	12	0.41	0.33	0.371	5
29	1	0.43	0.32	0.374	4
30	10	0.45	0.32	0.384	3
31	9	0.49	0.33	0.412	1

Grey - Fuzzy Analysis

The grey relational grade is estimated on the basis of "larger the better", "smaller the better" and "nominal the better" characteristics. Hence, there is still some uncertainty is present in the obtained data. The theory of fuzzy logic provides a means for representing uncertainties associated with vagueness, imprecision and/or lack of information regarding the problem in hand. Zadeh [11] suggested a set of membership function when faced with uncertainty making a decision. Many investigators successfully implemented GRA fuzzy technique in various engineering discipline. For instance, Chiang et al [12] applied the grey fuzzy algorithm to predict the optimized input parameters of machining process and Rajmohan et al [13] applied the grey fuzzy algorithm to optimize the machining parameters of drilling hybrid MMC. Therefore, this technique is a globally accepted artificial intelligence technique which can be applied to obtain optimal process parameters irrespective of the manufacturing activity such as machining, welding etc. And an infinite number of membership functions that comprises onto the unit interval of 0 to 1. Thus the fuzzy logic approach can be handled various uncertainty situations involved in the output characteristics.

The fuzzy logic approach consists of few steps namely fuzzification of input data, rule inference and defuzzification. Fuzzification is the process of making a crisp value using a linguistic variable. Expert systems use a set of linguistic variables or the fuzzified data in order to assign the membership function to each fuzzy variable. This process is based on the experience in the specific problem or involved by mathematical or logical operations. Many ways can be used for assigning the membership function. Namely the membership functions are called as triangular membership function, trapezoidal membership function, Gaussian and sigmoidal membership function. Depends upon the process suitability, membership function can be selected by the designers. For the present investigation, a well distributed triangular membership function is assigned to input and output variables. The assigned input membership function variables are as follows: rotational speed, welding speed, axial load and pin shape. Similarly, the output variable is grey relational grade. Based on input and output variables, fuzzy inference engine generates a fuzzy value based on IF – Then fuzzy rules. And sugeno, mamdani methods are commonly used to implicate fuzzy operations. In the present investigation mamdani's method of inference is used to implicate the fuzzy rules also it is called as a max - min method. Since it is intuitive, wide spread acceptance and well suited to human input Next step in the fuzzy logic is the defuzzification. It is the step of defuzzyfication from the fuzzified value of a fuzzy inference engine. This defuzzification method can be carried out by various ways like centroid method, max membership method, centroid method and mean - max membership method. For the present investigation centroid method is preferred. Centroid method is more prevalent and physically appealing of all methods [13]. Therefore, the defuzzifier can convert fuzzied value into a de fuzzified value which is called as a grey fuzzy reasoning grade. The grey relational grade reduces the uncertainty in the multiple number of the input characteristics further the fuzzy logic reduces if any remaining in the experiment. Therefore, the grey fuzzy reasoning grades may reduce uncertainties than the calculated grey relational grades. The following procedure is followed for the proposed grey fuzzy algorithm in order to minimize the uncertainties from the predicted grey relational grade.

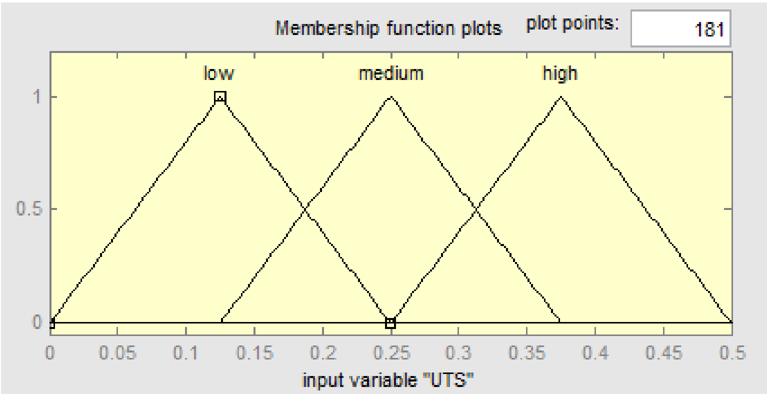

Fig-6: Triangular membership function

1. Selected an appropriate orthogonal array design to identify the level of each factor.
2. The experimental results of grey relational coefficients are predicted as per the recommended procedure of Deng Julong [9].
3. A weighting quality of multi response characteristic of each response is equally distributed to all responses such as ultimate tensile strength, and noise level.
4. For the desired weighting quality characteristics the multi response grades were estimated.
5. Established the triangular membership function to fuzzify the estimated grey

relational grades of multi responses. The Fig.6 shows the triangular membership function of each and combined responses. If-then rules are used to formulate conditional statements of multi response gray relational coefficients namely tensile strength (ξ_1), and noise level (ξ_2).

6. The only one multi response output (η) may be that is,
Rule.1 : if ξ_1 is A_{11} and ξ_2 is A_{12} and ξ_3 is A_{13} then η is D_1 else
Rule.2 : if ξ_1 is A_{11} and ξ_2 is A_{12} and $\xi 3$ is A_{13} then η is D_1 else
…
…
Rule.n : if ξ_1 is A_{11} and ξ_2 is A_{12} and ξ_3 is A_{13} then η is D_1 else (6)

7. There are nine fuzzy subsets are established as per if – then rules in order to estimate eighteen output of η. The fig.7 represents the nine fuzzy subsets and its ranges are presented in Table.5

Table-5: Fuzzy subsets and its ranges

Condition	Range	Membership function
Ultra small	0 - 0.05	Triangular
Very small	0 - 0.125	
Small	0.0525 - 0.158	
Low medium	0.125 - 0.25	
Medium	0.18 - 0.32	
High Medium	0.25 - 0.38	
Low	0.32 - 0.42	
Very low	0.38 - 0.5	
Ultra low	0.42 - 0.58	

8. The fuzzy multi response output is calculated by max – min interface operation. The Interferential output η can be expressed as,
$\mu_{DO}(\eta) = (\mu_{A11}(\xi_1)\wedge \mu_{A12}(\xi_2)\wedge \mu_{D1}(\eta)) \vee \mu_{A21}(\xi_1)\wedge \mu_{A22}(\xi_2)\wedge \mu_{D2}(\eta))$ (7)
Where $\wedge$ and $\vee$ represents the maximum and minimum operation respectively.

9. Then the $\mu_{DO}(\eta)$ is transferred to predict the fuzzy – grey relational grade η_0 by using the formula,

$$\eta_0 = \frac{\sum y\mu_{DO}(y)}{\sum \mu_{DO}(y)} \qquad (8)$$

The obtained results by Grey – Fuzzy reasoning technique is shown in Table no. 6

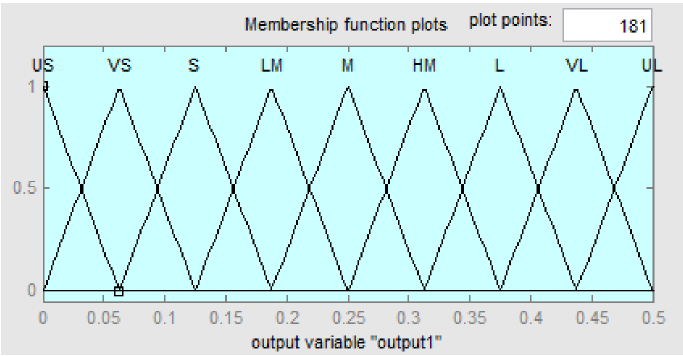

Fig.7- Fuzzy subsets

Table-6: Grey fuzzy reasoning grade

Std	Grey Fuzzy reasoning grade	Rank
1	0.238	19
2	0.211	30
3	0.250	11
4	0.215	29
5	0.254	8
6	0.254	9
7	0.250	12
8	0.229	23
9	0.245	17
10	0.231	21
11	0.241	18
12	0.209	31
13	0.250	13
14	0.251	10
15	0.220	27
16	0.230	22
17	0.250	14
18	0.226	24
19	0.226	25
20	0.223	26
21	0.235	20
22	0.250	15
23	0.220	28
24	0.248	16
25	0.360	2
26	0.350	7
27	0.360	3
28	0.357	4
29	0.357	5
30	0.355	6
31	0.387	1

10. In the present study there are two joint designs were considered and established to identify the various multi response feasibilities. The grey fuzzy reasoning grades are indicated that the modified butt joint configuration.
11. Identifying the optimal input parameters from the response table and response graph.
12. Finally, the verifying the optimal setting of input parameters respect to the decided factors.

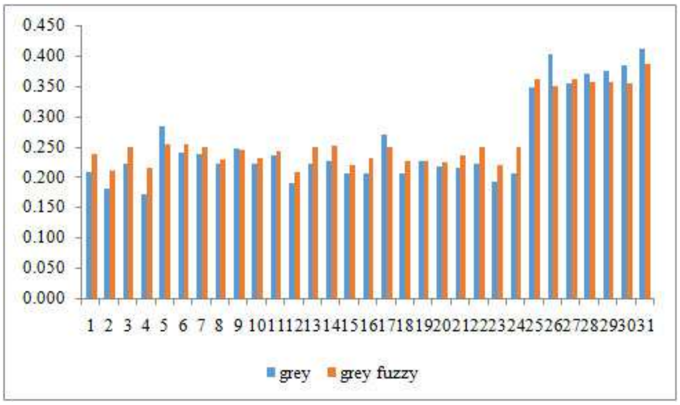

Fig-8: Comparison of GRG with fuzzy GRG

RESULTS AND DISCUSSION

In this section, the results obtained using grey fuzzy reasoning analysis and welding parameters, effect of grey relational coefficients, ANOVA for identifying significant parameters are presented.

MATLAB toolbox is used to perform the grey fuzzy reasoning analysis. A triangular membership function is used for the obtained two grey relational coefficients such as ultimate tensile strength (UTS) and tensile elongation (TE) with three membership function namely low, medium and high. A set of rules were written for each experiment therefore totally 31 rules were formulated for activating the fuzzy inference system (FIS). Fig.8 shows the comparison of grey relational grade with fuzzy grey relational grade. It is obvious that there is a significant improvement in obtained grey fuzzy grade when comparing to grey relational grade. Similar improvements can be observed by Rajmohan et al in optimizing the machining parameters in drilling of metal matrix composites. Lin et al [14] in optimization of EDM process using grey fuzzy relational analysis method. Fig.9 represents the effect of grey relational coefficients such as ultimate tensile strength (UTS) and tensile elongation (TE) on fuzzy grey relational co efficient. It is observed that, the increase in tensile properties of UTS and TE increases the cumulative performance of fuzzy GRG performance.

Table-7: Summary of individual regression coefficient factors, interactions and their square terms

Term	Coeff	Se Coeff	T	P
Constant	0.355143	0.002391	148.554	0.000
Rotational Speed	-0.011250	0.001826	-6.161	0.000
Welding speed	0.005833	0.001826	3.195	0.006
Axial load	-0.008250	0.001826	-4.518	0.000
Pin shape	-0.006000	0.002366	-3.286	0.005
rotational speed * rotational speed	0.067613	0.002366	-28.852	0.000
welding speed * welding speed	-0.030988	0.002366	-25.781	0.000
axial load * axial load	-0.055363	0.002366	-23.403	0.000
pin shape * pin shape	-0.054988	0.002366	-23.245	0.000
rotational speed * welding speed*	-0.002000	0.003163	-0.632	0.536
rotational speed * axial load*	0.005250	0.003163	1.660	0.116
rotational speed * pin shape*	-0.004500	0.003163	-1.423	0.174
welding speed * axial load*	0.002250	0.003163	0.711	0.487
welding speed * pin shape*	0.003250	0.003163	1.028	0.319
axial load * pin shape*	-0.005250	0.003163	-1.660	0.116
*- insignificant R^2 = 99.22%		R^2 (adj) = 98.54%		

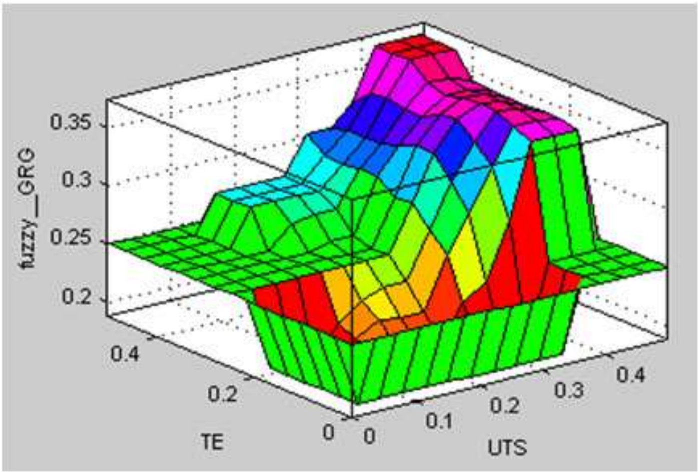

Fig-9: Effect of grey relational coefficients such as ultimate tensile strength (UTS) and tensile elongation (TE) on fuzzy grey relational co efficient

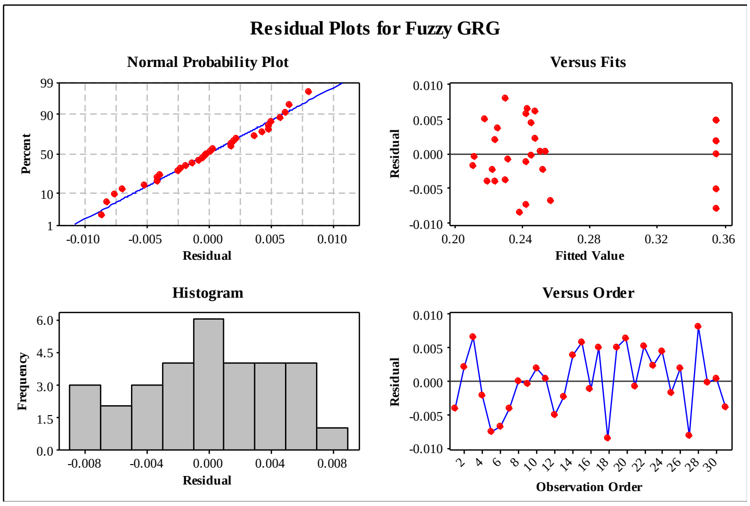

Fig-10: Standardized residuals and random distribution of fitted values

Table-8: Mean fuzzy GRG values

Parameters	Level 1	Level 2	Level 3
Rotational speed(N)	0.2417	**0.2851**	0.2192
Welding speed(F)	0.2290	**0.2823**	0.2407
Axial load(P)	0.2468	**0.2799**	0.2303
Pin Shape(PS)	0.2448	**0.2798**	0.2328

The polynomial coefficients were calculated using MINITAB statistical software. Table.7 shows the summary of individual regression coefficient factors, interactions and their square terms. The terms which are marked by '*' in the presented table.7 represents insignificant factors. Since their corresponding 'p' values are greater than 0.05 therefore these terms are said to be insignificant. These insignificant terms are excluded for further analysis. The backward elimination procedure is applied in order to eliminate the insignificant terms. Equation (9) shows the mathematical model developed excluding the insignificant terms in the present study.

GRG - Fuzzy = 0.355143 - 0.011250N+0.005833F-0.008250P-0.006000PS-0.067613R^2-0.060988F^2-0.055363P^2-0.054988PS^2 (9)

Fig.10 represents standardized residuals and random distribution of fitted values. The plot reveals the adequacy of the developed model of the present investigation. The obtained points were close to straight line which defines the data follows normal distribution and on the residuals an independent patterns were observed. Fig.10 shows the histogram and observation order that shows numerous residual points are normally distributed and many lay between -0.01 to 0.01. This result confirms the errors are unevenly distributed. This finding which indicates the reduced model having high adequacy for the error variables. The response table and response graph are estimated from the obtained grey fuzzy reasoning grade in order to estimate the optimum level of each process parameter. For example, considering the first column in the response matrix, the ref order 1, ref order 2.., ref order 6 are the experimental runs at which rotational speed is set at level 1. The average sum of these values is corresponding to the average response value at that level. The obtained mean fuzzy grey relational grade are presented in table.8. The same is graphically represented in fig.11. The steep slope indicates the most influence level in the present investigation. It is understand that, the effect of rotational speed have the greater influence in the present process.

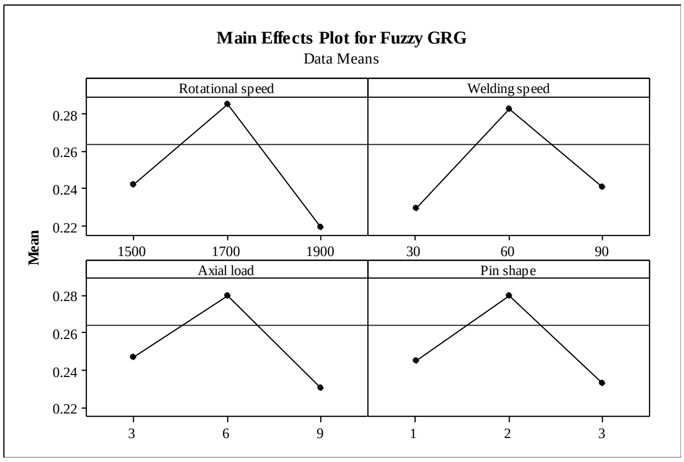

Fig-11: Mean of mean plot

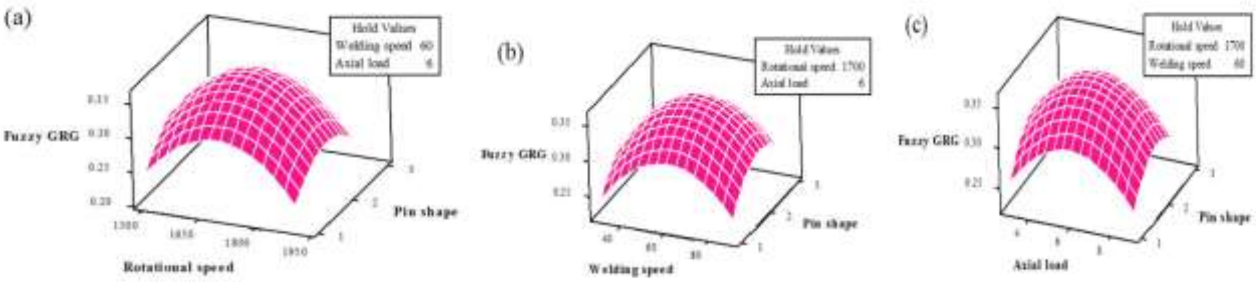

Fig-12: Surface plot of each process parameter vs. fuzzy GRG

Table-9: ANOVA results

Source	DF	Seq SS	adj SS	adj MS	F	P
Regression	8	0.081377	0.081377	0.010172	219.38	0.000
Linear	4	0.03176	0.03176	0.000794	17.12	0.000
Rotational speed	1	0.001519	0.001519	0.001519	32.75	0.000
Welding speed	1	0.000408	0.000408	0.000408	8.81	0.007
Axial load	1	0.000817	0.000817	0.000817	17.61	0.000
Pin shape	1	0.000432	0.000432	0.000432	9.32	0.006
Square	4	0.078201	0.078201	0.078201	421.63	0.000
rotational speed * rotational speed	1	0.020336	0.020336	0.032682	704.82	0.000
welding speed * welding speed	1	0.018522	0.018522	0.026591	573.47	0.000
axial load * axial load	1	0.017727	0.017727	0.021912	472.56	0.000
pin shape * pin shape	1	0.021616	0.021616	0.021616	466.18	0.000
Residual error	22	0.00102	0.00102	0.00102		
Lack of fit	16	0.000873	0.000873	0.000873	2.23	0.164
Pure error	6	0.000147	0.000147	0.000147		
Total	30	0.082397				
R^2 = 98.76%				R^2 = 98.31%		

Table-10: Confirmation experiment

Rotational speed (N)	**Welding speed (F)**	**Axial load (P)**	**Pin shape (PS)**	**Ultimate tensile strength (UTS)**	**Tensile elongation (TE_**
1700 rpm	60mm/min	6kN	Square	140.11 MPa	10.92 %

The optimal setting of process parameter is to achieve the higher grey fuzzy relational grade. Since the optimal setting of process parameter represents the relationship between the reference sequence and objective sequence, therefore greater fuzzy grey relational grade reveals the objective sequence has a stronger relationship than the reference sequence. Accordingly, the optimal setting of process parameters are larger fuzzy – GRG is desirable for obtaining larger UTS and TE of fabricated FS welded specimen. According to the estimated fuzzy – GRG, 31st experimental run have larger GRG. Therefore, 31st experimental run is the experimental run which is closer to optimum. Addition to that, the fuzzy grey relational grades assigned with two process variable at their center level to examine the tensile behavior of FS welded specimen as shown in fig. 12(a) to 12(c). it is observed that, a low or high level for a desired process parameter such as rotational speed(N), welding speed (F) and axial load (P), significantly decreased the tensile characteristics for FS-welded specimen irrespective of tool pin profiles. The FS welded joints fabricated using square pin had the highest fuzzy GRG. Since Pin profiles with flat faces are associated with eccentric material flow. This eccentricity of material flow allows an incompressible material flow to pass around the pin profile. The relationship between the static volume and dynamic volume decides the path for the flow of plasticized material from the leading edge to the trailing edge of the rotating tool. This ratio is equal to 1 for straight cylindrical, 1.09 for tapered cylindrical and 1.56 for square pin profiles. Addition to that, the square pins produces more pulsating effect causes higher GRG values whereas no pulsating effect to cylindrical and taper pins, which gave poor GRG values[15]. However, a continuous pulsating effect may lead severe wear at the edges of the square pin surfaces. The cylindrical and taper pins may be considered while considering longevity of rotating tool then tensile strength will be compromised. However, when considering higher tensile properties due to the requirement of product, factor of safety and durability, the longevity of square pin will be compromised.

The developed model is validated further validated using analysis of variance (ANOVA). ANOVA reveals the contribution of significant factors which are involved in the process. It is accomplished by separating the total variability of fuzzy grey relational grade which is measured by the sum of the squared deviations from the total mean of fuzzy grey relational grade into contribution by each welding process parameters and the error. A result of ANOVA is presented in table 9 and it is identified that, the square of the rotational speed (N^2) contributed 24.68 %, the welding speed (F^2) contributed 22.47 %, the axial load (P^2) contributed 21.51 % and the pin shape (PS^2) contributed 26.37 %. Furthermore, linear terms such as the rotational speed (N), welding speed (F), axial load (P), and pin shape (PS) contributed very little (3.85%) to the GRG and these ANOVA contributions are graphically presented in fig 13. Finally, the residual error contribution was 0.705% split into the lack of fit and pure error, which contributed 0.54 % and 0.16% respectively. This method yielded a simplified model with an R^2 of 98.76% which indicates its significance. The obtained R^2 value is lower than the full quadratic model which provides the real relationship between the response and input variables.

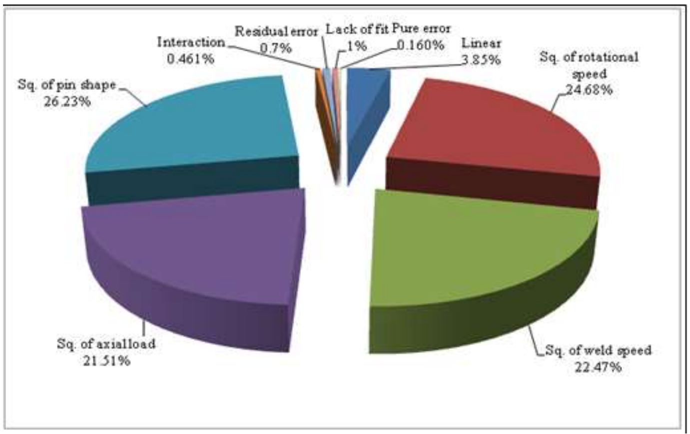

Fig-13: Percentage of contribution of each factor

Conformation experiment

Since the optimum parameters selected, the confirmation test is performed in order to validate the obtained optimum results. The optimal settings based on obtained fuzzy – GRG are as follows, Rotation speed(N) – 1700rpm, welding speed(F) – 60mm/min, axial load(P) – 6kN and pin shape(PS) – 1.9 Ω 2 i.e., Square pin shape. Table.10 shows the confirmation results obtained by the optimal setting of process parameters. This clearly evident that the grey fuzzy optimization improves the multiple performance characteristics of FS welded AA2024 and AA6061 dissimilar aluminum alloys.

CONCLUSION

The proposed systematic method of RSM based fuzzy GRG determined adequately optimal process parameters for FS welded AA2024 and AA6061 dissimilar aluminum alloys. The results of the present investigation can be summarized below,

1) It is observed that there is an improvement in the values of grey fuzzy reasoning grade compared to grey relational grade. Since the fuzziness is reduced very much that leads the reference value towards ‘1’.
2) A regression model was developed for the linear terms such as rotational speed, welding speed and axial load by varying pin shapes.
3) The square terms of the process parameters such as N^2, F^2, P^2, PS^2 are significant.
4) The optimal setting of process parameters are as follows,
    a) Rotational speed(N) – 1700rpm,
    b) Welding speed(F) – 60mm/min,
    c) Axial load(P) – 6kN
    d) Pin shape (PS) – 1.9 Ω 2 i.e., Square pin shape.
5) The UTS was 141 MPa with an elongation of 12%. It is due to a drastic reduction in strength of 44% and 51% for AA2024 and AA6061 aluminum alloys respectively.

Therefore combining the present investigation along with the mathematical model provides an effectiveness of application to achieve the desired tensile properties of FS welded AA2024 and AA6061 dissimilar aluminum alloys.

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