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Application of Multi-criteria Decision-making Methods in Parametric Optimization of a Friction Stir Welding Process

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Abstract

Friction stir welding (FSW) has become a popular manufacturing process used in joining of two dissimilar materials without melting the workpiece material. To operate the machine with its fullest manufacturing potential and to achieve the required target response values, it is necessary to operate the machine with its optimal parametric combination of various input parameters. However, it has been observed that the number of optimization methods used to find the optimal parametric combination of FSW process are only limited to a few. In this paper, a few unexplored multi-criteria decision-making methods like evaluation based on distance from average solution (EDAS) and weighted aggregated sum product assessment (WASPAS) methods are adopted to search out the best parametric combination for a FSW process for joining of two dissimilar AA6063-T6 and AA5083-O aluminium alloys. The identified optimal parametric setting is verified based on confirmation experimental trials which show a considerable improvement in the response values like tensile strength, grain size, and material hardness.

Keywords

Friction stir welding, Parametric optimization, EDAS, WASPAS, Responses

Introduction

FSW is well-known as a solid-state joining method used in joining two dissimilar work materials with the help of a non-consumable tool without melting the workpiece. In this process, heat is generated by friction produced in the contact region between the rotating tool and the workpiece, which moves along the line of joint weld subsequently forming a softened region close to the FSW tool. The welding tool used has an ended profile round in shape attached to a pin having different geometrical shapes. This pin is coupled to the rounded profile by the shoulder. In the process of welding, the shoulder scrubs with the top surface of the workpiece while the pin roles in to penetrate the joint of two workpieces. FSW has diverse applications, such as designing of different hulls, propellers, structures in aircraft vehicles, etc. [1, 2]. The operation of FSW process involves controlling of a large number of process parameters to attain desired performance measures (responses). It usually becomes challenging for a process engineer to choose the most suitable combination of those FSW process parameters to attain the preferred response values. On the other hand, an inappropriate selection may over and over again result in severe consequences as it is necessary for all engineering applications to produce defect-free, high-quality welding [3]. To operate the machine efficiently while obtaining the desired quality measures, it is our utmost priority to set the process parameter at the optimal combination of available input parameters. Most of the time, guidebooks issued by the manufacturers is looked at for the selecting the best possible combinations of the FSW parameters to fulfil the set quality requirements. But it is often observed that, the identified parametric combination does not always guarantee for the optimal combination of process parameters is achieved and many a times leads to near optimal combinations [4].

To attain the better welding potential and consistency, it is therefore of utmost importance to choose the optimal process parameters in the FSW. To counter this problem, different mathematical approaches in form of MCDM techniques, like grey relational analysis (GRA), additive ratio assessment, technique for Order of Preference by Similarity to Ideal Solution (TOPSIS), etc. have been efficiently applied to obtain the optimal parametric combination of FSW processes. Sahu and Pal [5] selected tool rotation speed, welding speed, plunging depth and shoulder diameter as four FSW process parameters and applied Taguchi-GRA method to optimize responses such as ultimate tensile strength, bending angle, percentage of elongation, yield strength, compressive stress, thermomechanical affected zone, average hardness at the nugget zone and heat affected zone. Sudhagar et al. [6] has employed GRA and TOPSIS to optimize three parameters such as welding speed, tool offset and rotational speed. The measured responses are tensile strength, impact toughness and hardness. Sahu et al. [7] developed FSW joints of Al/Cu dissimilar materials and applied fuzzy-GRA method for multi weld quality optimization of responses such as compressive strength, percentage of weld bead thickness, tensile strength, elongation, average hardness at the nugget zone and bending angle. Gupta et al. [8] combined artificial neural network and genetic algorithm (ANN-GA) methods to optimize response such as microhardness, tensile strength, and grain size. While selecting control parameters such as tool pin diameter, travel speed and tool rotational speed in FSW process, El-Kassas et al. [9] applied GRA and TOPSIS method to select the best parametric setting to maximize tensile strength and the hardness. Das and Chakraborty [10] compared four hybrid-Taguchi methods such as Taguchi-grey relational analysis, Taguchi-loss function, Taguchi-Super ranking, Mahalanobis-Taguchi and Taguchi-data envelopment analysis-based ranking to optimization the process parameters for FSW processes. However, it has been observed that the number of MCDM methods used to identify the optimal parametric setting of FSW process are only limited to a few.

In order to strengthen the data base on the application of different MCDM methods applied towards parametric optimization of FSW process, in this paper, a few unexplored MCDM methods such as EDAS and WASPAS methods are adopted to search out the best parametric combination for a FSW process. The derived parametric setting is validated based on confirmation experimental trials which show a considerable improvement in the response values.

Materials and Methods

Experimental details

Selecting Taguchi's L_{27} orthogonal array design of experiments, Gupta et al. [8] performed 27 experimental trials to develop FSW joints of two dissimilar AA6063-T6 and AA5083-O aluminium alloys. For the experimentation four control parameters such as tool rotational speed (S), welding speed (W), shoulder diameter (D), and pin diameter (P) are considered. A three-level variation for each control parameter was considered based on the settings available in the FSW setup. The selected input parameters and their variation levels are provided in table 1. For quality performance measures, tensile strength (TS), material hardness (MH), and grain size (GS) were selected as the responses. The experimental plan details and the measured responses are given in table 2.

Table 1: Process parameters and levels [8].

Process parameter	Unit	Level		
		1	2	3
Tool rotational speed (S)	r/min	700	900	1100
Welding speed (W)	mm/min	40	60	80
Shoulder diameter (D)	mm	15	18	21
Pin diameter (P)	mm	4.5	5.0	5.5

EDAS method

EDAS method has become a popular method applied to sole different decision-making problems. It basically measures the positive and negative distances for the average of each experimental trial with respect to each response. It has been applied to solve parametric optimization problems for different manufacturing process [11, 12]. The steps involved in the application of EDAS method are detailed as follows:

Step 1: Development of the decision-making matrix (*X*)

For a problem having *m* alternatives (experimental trials) and *n* criteria (responses), the decision matrix can be defined as

$$X = \left[x_{ij}\right]_{m \times n} = \begin{pmatrix} x_{11} & x_{12} & \cdots & x_{1n} \\ x_{21} & x_{22} & \cdots & x_{2n} \\ \cdots & \cdots & \cdots & \cdots \\ x_{m1} & x_{m2} & \cdots & x_{mn} \end{pmatrix}$$

Where, x_{ij} represents the performance measures of i^{th} alternative with respect to j^{th} criterion.

Step 2: Estimation of average performance measures for all criteria using Eq. (1).

$$A = \left[X_j\right]_{1xn} \; (j = 1, 2, \ldots, n) \tag{1}$$

Where,

$$A_j = \frac{\sum_{i=1}^{m} x_{ij}}{m} \; (j = 1, 2, \ldots, n)$$

Step 3: Computation of the positive distance from average (*PDA*) and negative distance from average (*NDA*) with respect to the nature of quality characteristic.

For j^{th} beneficial criterion

$$PDA_{ij} = \frac{\max(0, (x_{ij} - A_j))}{A_j} \tag{2}$$

$$NDA_{ij} = \frac{\max(0,(A_j - x_{ij}))}{A_j} \quad (3)$$

For j^{th} non-beneficial criterion

$$PDA_{ij} = \frac{\max(0,(A_j - x_{ij}))}{A_j} \quad (4)$$

$$WSP_i = \sum_{j=1}^{n} w_j PDA_{ij} \quad (5)$$

Step 4: Estimation of weighted sum of *PDA* (*WSP*) and weighted sum of *NDA* (*WSN*) for all considered alternatives as given below:

$$WSP_i = \sum_{j=1}^{n} w_j PDA_{ij} \quad (6)$$

$$WSN_i = \sum_{j=1}^{n} w_j NDA_{ij} \quad (7)$$

Where, w_j is the weightage of j^{th} response.

Step 5: Normalization of W*SP* (*NSP*) and W*SN* (*NSN*) for all alternatives as detailed below:

$$NSP_i = \frac{WSP_i}{\max_i(WSP_i)} \quad (8)$$

$$AP_i = \frac{1}{2}(NSP_i + NSN_i) \quad (9)$$

Step 6: Computation of appraisal (*AP*) score for all considered alternatives as follows:

$$AP_i = \frac{1}{2}(NSP_i + NSN_i) \quad (10)$$

Where, $0 \le AP_i \le 1$. A higher *AP* score for an alternative indicates its preference over other considered alternatives.

WASPAS method

WASPAS method is a mix of two criteria of optimality, the weighted additive method and weighted multiplicative method [13]. The steps involved are as follows:

Step 1: Develop the initial decision matrix for a problem having *m* alternatives (experimental trials) and *n* criteria (responses) similar to EDAS method.

Step 2: Normalization of decision matrix using the following equations.

For beneficial criteria

$$\bar{x}_{ij} = \frac{x_{ij}}{\max_i x_{ij}} \quad (11)$$

For non-beneficial criteria

$$\bar{x}_{ij} = \frac{\min_i x_{ij}}{x_{ij}} \quad (12)$$

Step 3: Based on weigthed sum method (WSM), the relative importance of i^{th} alternative is calculated as:

$$Q_i^{(1)} = \sum_{j=1}^{n} \bar{x}_{ij} w_j \quad (13)$$

Where, w_j is weight (relative importance) of significance (weight) of j^{th} criterion.

Step 4: Based on weigthed product method (WPM), the relative importance of i^{th} alternative is obtained as:

$$Q_i^{(2)} = \prod_{j=1}^{n} (\bar{x}_{ij}) w_j \quad (14)$$

Step 5: A generalised criterion for WSM and WPM methods to get the weighted aggregation also termed as WASPAS (*Q*) score can be estimated as follows:

$$Q_i = 0.5Q_i^{(1)} + 0.5Q_i^{(2)} = 0.5\sum_{j=1}^{n} \bar{x}_{ij} w_j + 0.5\prod_{j=1}^{n} (\bar{x}_{ij}) w_j \quad (15)$$

The experimental trial with higher value of Q_i is recognized as the best trial among all considered experimental trials.

Results and Discussion

The experimental data presented in table 2 is taken into consideration for deployment of EDAS and WASPAS methods so as to find the best parametric setting for the considered

Table 2: L_{27} design matrix and recorded response values [8].

Exp. no.	T	W	S	P	TS (MPa)	MH (Hv)	GS (mm)
1	700	40	15	4.5	136.2	59.53	19.886
2	700	40	18	5.0	146.3	69.84	15.625
3	700	40	21	5.5	141.1	64.03	16.203
4	700	60	15	5.0	145	66.74	16.509
5	700	60	18	5.5	150.2	73.40	10.937
6	700	60	21	4.5	143.7	65.88	16.826
7	700	80	15	5.5	135.1	54.14	19.021
8	700	80	18	4.5	138.8	62.09	18.657
9	700	80	21	5.0	139.6	62.53	18.121
10	900	40	15	5.0	148.8	69.23	14.583
11	900	40	18	5.5	153.5	76.41	11.820
12	900	40	21	4.5	152.6	68.77	14.112
13	900	60	15	5.5	150.9	75.54	11.217
14	900	60	18	4.5	161.2	85.25	8.578
15	900	60	21	5.0	156.1	78.56	9.943
16	900	80	15	4.5	146.3	62.71	18.229
17	900	80	18	5.0	151.3	72.87	12.323
18	900	80	21	5.5	145.2	65.14	18.229
19	1100	40	15	5.5	145.4	69.92	13.257
20	1100	40	18	4.5	151.2	73.22	12.860
21	1100	40	21	5.0	143.9	72.43	12.152
22	1100	60	15	4.5	150.1	71.21	13.670
23	1100	60	18	5.0	157.5	79.39	9.720
24	1100	60	21	5.5	152.5	76.36	11.513
25	1100	80	15	5.0	137.5	66.54	17.156
26	1100	80	18	5.5	147.5	72.15	12.152
27	1100	80	21	4.5	142.5	62.45	17.500

FSW process for joining two dissimilar AA6063-T6 and AA5083-O aluminium alloys. Among the three measured responses, GS is the only response with lower-the-better quality characteristics. On the other hand, TS and TH are of larger-the-better quality characteristics. Now employing Eq. (1) - (5), and based on the type of quality measures, the PDA and NDA values are calculated for the considered responses as given in table 3. The WSP and WSN are then calculated considering equal weightage for the three responses along with their normalized values using Eq. (6) - (9) as provided in table 4. The final *AP* scores for each experimental trial are computed employing Eq. (10) and given in table 4. From the table it is observed that experimental trial number 14 with highest AP score and parametric setting as S = 900 r/min, W = 60 mm/min, D = 18 mm, and P = 4.5 mm also recognized as $S_2W_2D_2P_1$ is recognized as the best parametric setting among the 27 conducted experimental trials.

To find the optimal parametric combination of the considered FSW process using EDAS method, a response table as shown in table 5 is developed by taking the average of the calculated AP score attained at the corresponding parametric level of considered process parameters. From the table, it is observed that for all the considered control parameters the highest average AP score is obtained with level 2 (indicated in bold face). Hence, it can be understood that to attain better values of responses, the optimal parametric setting should be set as S = 900 r/min, W = 60 mm/min, D = 18 mm, and P = 4.5 mm ($S_2W_2D_2P_2$). A similar parametric setting was obtained by Gupta et al. [8] by employing hybrid ANN-GA.

Table 3: Calculated PDA and NDA values.

Exp. no.	PDA			NDA		
	TS	H	GS	TS	H	GS
1	0	0	0	0.0737	0.1434	0.3739
2	0	0.005	0	0.005	0	0.0795
3	0	0	0	0.0404	0.0786	0.1195
4	0	0	0	0.0139	0.0396	0.1406
5	0.0215	0.0562	0.2444	0	0	0
6	0	0	0	0.0227	0.052	0.1625
7	0	0	0	0.0812	0.2209	0.3141
8	0	0	0	0.056	0.1065	0.289
9	0	0	0	0.0506	0.1002	0.252
10	0.012	0	0	0	0.0038	0.0075
11	0.044	0.0995	0.1834	0	0	0
12	0.0378	0	0.025	0	0.0104	0
13	0.0263	0.087	0.225	0	0	0
14	0.0963	0.2267	0.4074	0	0	0
15	0.0616	0.1305	0.313	0	0	0
16	0	0	0	0.005	0.0976	0.2594
17	0.029	0.0486	0.1486	0	0	0
18	0	0	0	0.0125	0.0626	0.2594
19	0	0.0061	0.0841	0.0111	0	0
20	0.0283	0.0536	0.1115	0	0	0
21	0	0.0423	0.1604	0.0213	0	0
22	0.0208	0.0247	0.0556	0	0	0
23	0.0712	0.1424	0.3285	0	0	0
24	0.0372	0.0988	0.2046	0	0	0
25	0	0	0	0.0649	0.0425	0.1853
26	0.0031	0.0382	0.1604	0	0	0
27	0	0	0	0.0309	0.1014	0.2091

Table 4: Calculated WSP, WNP, NSP, NSN, and AP scores.

Exp. no.	WSP	WNP	NSP	NSN	AP
1	0	0.591	0	0.041	0.0205
2	0.005	0.0845	0.0068	0.8628	0.4348
3	0	0.2385	0	0.6131	0.3065
4	0	0.1941	0	0.6851	0.3425
5	0.3221	0	0.441	1	0.7205
6	0	0.2372	0	0.6151	0.3076
7	0	0.6163	0	0	0
8	0	0.4516	0	0.2673	0.1336
9	0	0.4028	0	0.3465	0.1732
10	0.012	0.0113	0.0164	0.9816	0.499
11	0.3268	0	0.4475	1	0.7237
12	0.0628	0.0104	0.086	0.9831	0.5346
13	0.3383	0	0.4632	1	0.7316
14	0.7304	0	1	1	1
15	0.5051	0	0.6916	1	0.8458
16	0	0.3621	0	0.4125	0.2063
17	0.2262	0	0.3097	1	0.6548
18	0	0.3346	0	0.4571	0.2286
19	0.0902	0.0111	0.1235	0.9819	0.5527
20	0.1934	0	0.2648	1	0.6324
21	0.2027	0.0213	0.2775	0.9654	0.6214
22	0.1011	0	0.1384	1	0.5692
23	0.542	0	0.7421	1	0.871
24	0.3405	0	0.4662	1	0.7331
25	0	0.2927	0	0.5251	0.2626
26	0.2018	0	0.2763	1	0.6381
27	0	0.3413	0	0.4462	0.2231

Table 5: Response table for AP score for EDAS method.

Process parameter	Level		
	1	2	3
Tool rotational speed	0.2710	**0.6027**	0.5671
Welding speed	0.4806	**0.6802**	0.2800
Shoulder diameter	0.3538	**0.6455**	0.4415
Pin diameter	0.4276	**0.5228**	0.4841

Similarly, to find the optimal parametric combination for the FSW process using WASPAS method, experimental data provided in table 2 is deployed. Employing Eq. (11) - (16), the normalized values, weighted additive and weighted multiplicative values ($Q^{(1)}$ and $Q^{(2)}$), and WASPAS scores are calculated and the results are provided in table 6. It can be observed similar to EDAS method, experimental trial number 14 with highest Q score of 3.8909 is recognized as the best parametric setting among the 27 experimental trials. To identify the optimal parametric setting, a response table is established given as table 7. From the table, it is observed that similar to EDAS method and Gupta et al. [8], WASPAS method identifies the optimal parametric setting as $S_2W_2D_2P_2$. A confirmatory test run as performed by Gupta et al. [8], shows that the obtained optimal parametric setting is able to improve quality of re-

Table 6: Calculated normalized values, $Q^{(1)}$, $Q^{(2)}$, and Q score values.

Exp. no.	Normalized data			$Q^{(1)}$	$Q^{(2)}$	Q score
	TS	MH	GS			
1	1.5977	0.6983	0.4314	2.7273	2.7273	2.7273
2	1.7161	0.8192	0.549	3.0844	3.0844	3.0844
3	1.6551	0.7511	0.5294	2.9356	2.9356	2.9356
4	1.7009	0.7829	0.5196	3.0033	3.0033	3.0033
5	1.7619	0.861	0.7843	3.4072	3.4072	3.4072
6	1.6856	0.7728	0.5098	2.9682	2.9682	2.9682
7	1.5848	0.6351	0.451	2.6708	2.6708	2.6708
8	1.6282	0.7283	0.4598	2.8163	2.8163	2.8163
9	1.6375	0.7335	0.4734	2.8444	2.8444	2.8444
10	1.7455	0.8121	0.5882	3.1458	3.1458	3.1458
11	1.8006	0.8963	0.7257	3.4226	3.4226	3.4226
12	1.79	0.8067	0.6079	3.2046	3.2046	3.2046
13	1.7701	0.8861	0.7647	3.4209	3.4209	3.4209
14	1.8909	1	1	3.8909	3.8909	3.8909
15	1.8311	0.9215	0.8627	3.6153	3.6153	3.6153
16	1.7161	0.7356	0.4706	2.9223	2.9223	2.9223
17	1.7748	0.8548	0.6961	3.3257	3.3257	3.3257
18	1.7032	0.7641	0.4706	2.9379	2.9379	2.9379
19	1.7056	0.8202	0.6471	3.1728	3.1728	3.1728
20	1.7736	0.8589	0.667	3.2995	3.2995	3.2995
21	1.688	0.8496	0.7059	3.2435	3.2435	3.2435
22	1.7607	0.8353	0.6275	3.2235	3.2235	3.2235
23	1.8475	0.9313	0.8825	3.6613	3.6613	3.6613
24	1.7889	0.8957	0.7451	3.4296	3.4296	3.4296
25	1.6129	0.7805	0.5	2.8934	2.8934	2.8934
26	1.7302	0.8463	0.7059	3.2824	3.2824	3.2824
27	1.6716	0.7326	0.4902	2.8943	2.8943	2.8943

sponse values by 23.35%, 45.15% and 57.26% for TS, MH and GS compared to initial parametric setting. Hence, it can be understood that EDAS and WASPAS, being very simple methods are able to find the optimal parametric combination for enhanced FSW quality measures.

Conclusion

Thus, from the above analysis the following conclusion can be drawn:

- Using both EDAS and WASPAS methods, the optimal parametric setting is identified as tool rotational speed = 900 r/min, welding speed = 60 mm/min, shoulder diameter = 18 mm and pin diameter = 5 mm.
- The obtained optimal parametric setting is able to improve quality of response values by 23.35%, 45.15% and 57.26% for TS, MH and GS as compared to initial parametric setting.

EDAS and WASPAS being very simple methods are able to find the optimal parametric setting for enhanced FSW quality measures. As a future work, other popular yet to be explored methods, can also be adopted to check their effectiveness in identifying the optimal parametric setting of FSW processes.

Table 7: Response table for WASPAS method.

Process parameter	Level		
	1	2	3
Tool rotational speed	2.9397	**3.3207**	3.2334
Welding speed	3.1373	**3.4023**	2.9542
Shoulder diameter	3.0200	**3.3545**	3.1193
Pin diameter	3.1281	**3.2019**	3.1602

Table 8: Confirmation test run.

Method	Parametric setting	TS (MPa)	MH (Hv)	GS (mm)
Initial Combination	$S_1W_1D_1P_1$	136.2	59.53	19.886
EDAS, WASPAS, and ANN-GA [8]	$S_2W_2D_2P_2$	168	87	8.5
Improvement (%)		23.35	46.15	57.26

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None.

Conflict of Interest

The authors declare no conflict interest.

Credit Author Statement

Ningseng Singphow: Calculation, Analysis; Partha Protim Das: Manuscript - original draft preparation, Writing - review and editing. All the authors read and approved the manuscript.

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