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Optimization of Operational Parameters in Friction Stir Welding of AA6061-TiO_2 Composite using Topsis Approach

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Abstract

The friction stir welding (FSW) process has been proven an efficient and effective welding technique to join hard-to-weld materials such as aluminium matrix composites (AMCs). However, the presence of reinforcement particles in the AMCs limits the range of process parameters that produce defect less joints. The present work focussed on friction stir welding of AA6061-TiO_2 composite at different operational parameters to analyse the effect of variables on joint quality. FSW tool and the operational parameters such as rotational speed and tool traverse speed has a vital role in controlling the grain size and joint strength. It is crucial to optimize the operational parameters to get superior joint properties. In this study, a Technique for Order Preference by Similarity to Ideal Solution (TOPSIS) technique is used to optimize the FSW operational parameters. The study indicates that the solution provided by the TOPSIS assists in achieving superior joint properties.

Keywords: *AA6061-TiO_2, Friction stir welding, TOPSIS, Optimization.*

1.0 Introduction

In recent times friction stir welding (FSW) process is proven to be an effective and efficient joining technique to join aluminium matrix composite, which falls under hard-to-weld materials (Mishra et al. 2016). The FSW process takes place at a temperature less than the melting temperature of the material, which makes FSW a solid-state welding process. The absence of melting of the workpiece during the welding process eliminates harmful effects associated with conventional fusion welding such as solidification and liquefaction cracking, agglomeration of reinforcement particles, and formation of brittle secondary phases in AMCs and thereby enhancing the weld quality (Avettand-Fènoël and Simar 2016). In FSW a non-consumable tool having pins of various profiles, rotating at sufficiently higher speed is plunged into the abutting edges of the workpiece to be joined until the shoulder surface of the tool touches the workpiece surface and then the tool is made to travel along the weld line. The combined motion (Transverse and Rotational) of the tool in the workpiece generates sufficient heat to plasticize the material in the weld region. As the tool advances in the weld region, softened material moves around the tool and gets solidified forming solid-state welding (Prabhu et al. 2019).

Variations in the thermal cycle and mechanical deformation caused by the rotating tool in the weld zone greatly affect the material flow around the tool periphery. FSW operational parameters and tool pin profile mainly affect the thermo mechanical variation in the weld area thereby affecting the softened material flow (Padhy et al. 2018). However material flow around the rotating tool while it is progressing in the weld zone is very complex and not fully understood as reported by (Heidarzadeh et al. 2020). Lots of research has been performed to understand the influence of operational

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parameters on the material flow, microstructure formation, and mechanical behaviour of friction stir welded joints (Subramanya et al. 2018). The impact of the operational parameters such as tool traverse speed (TTS), tool rotational speed (TRS), and tool pin profile (TPP) on the weld quality in terms of mechanical behaviour is an important field of research in recent times. Most of the researchers used the conventional method to understand the effect of operational parameters by changing one parameter at a time by keeping others constant, which turns out be an expensive and consumes a lot of time (Dinaharan and Murugan 2012). To reduce the number of experiments, few researchers adopted Taguchi's design of experiment method, to identify the major factors/parameters from many (Shojaeefard et al. 2013). But this approach ignores the interaction among various parameters involved in the study. These interactions are sometimes ignored to reduce the time and cost involved in the experimental work. It is necessary to consider all the operational parameters, their interaction among them, and their impact on the process responses to get superior weld qualities (Dhas and Dhas 2012). Selecting relevant operational parameters with their optimum values result in better weld quality with improved mechanical behaviour.

Taguchi statistical design and empirical models are utilized by (Bhushan and Sharma 2019) to evaluate the relationship between FSW parameters and the output responses of the FS welded joints. (Kalaiselvan and Murugan 2012) used the Generalized Reduced Gradient (GRG) method to optimize FSW parameters to obtain better mechanical properties during FSW of Al-B4C composite. The desirability approach was espoused by (Periyasamy et al. 2013) to obtain optimized values for process parameters that give good quality welds in FSW of AA6061/SiC composite and shown that the weld quality is greatly enhanced by TRS whereas axial force and TTS have very less impact on the weld quality. (Kasman 2013) adopted the Taguchi-based Grey Relational Analysis (TGRA) approach to optimize the FSW of dissimilar aluminium alloys and proved that it can be effectively utilised for multi response optimization. Analysis of variance was used by (Palanivel et al. 2013) to detect the critical factors which controls the FSW process. Further, employed response surface methodology to visualize the influence of various parameters and concluded that weld quality can be enhanced by performing FSW process at optimum values of operational parameters. Genetic algorithm technique was adopted by (Sreenivasan et al. 2019) to optimize the FSW of AA7075/SiC composite to obtain better mechanical properties such as UTS and hardness. Taguchi technique assisted by the Fuzzy inference system was used by (Parida and Pal 2015) to optimize the FSW process parameters for multi-response optimization. Multi responses are transformed into single responses using a fuzzy inference system and further Taguchi technique was used to optimize the parameters. (Shojaeefard et al. 2014) employed an artificial neural network with a back propagation algorithm during FSW of dissimilar alloys and used particle swarm optimization technique for multi-attribute optimization. The artificial bee colony (ABC) algorithm was adopted by (Prasanth and Hans Raj 2018) to optimize the FSW parameters in case of the joining of dissimilar alloys.

Identifying optimal operational parameters to weld different materials through the FSW technique is an exigent task (Prabhu et al. 2022a). From the available literature, it can be concluded that various techniques have been employed by the researcher to optimize the FSW process variables. Most of the studies were carried out either with single-response optimization or algorithm-based multi-response optimization. The main drawback of the algorithm is that a lot of controlling parameters were used in the algorithm. A small change in these parameters results in a change in the effectiveness of these algorithms (Prabhu et al. 2022b). TOPSIS is a statistical tool that can effectively be employed in optimizing the process. In the present study multi-response optimization of FSW operational parameters to join AA6061/Rutile composite was discussed. Initial trial runs were carried out to fix the range of process parameters that provides defect less welds. Experiments were designed based on Taguchi's orthogonal array (OA). The influence of FSW operational parameters (TRS, TTS, and TPP) on the attributes (yield strength, UTS, and hardness) were studied. The efficacy of TOPSIS was tested by performing confirmation trials.

2.0 Experimentation

AA6061/3(wt%) rutile composite was fabricated using a bi-stage stir casting method (Prabhu et al. 2019). Chemical composition by wt%, of the material used in the study is Mg-0.8-1.2; Cu 0.15-0.4; Fe-0.7; Si-0.4-0.8; Cr-0.04-0.035; Mn-0.15; TiO_{2-3}; and remaining aluminium. Samples of size 100×50×5 mm for FSW were prepared from the composite by milling process. FSW was performed on CNC vertical milling center.

Figure 1: Experimental set up

Table 1: Details of operational parameters

Operational Parameters	Low	Medium	High
Tool traverse speed (TTS) in mm/min	60	75	90
Tool rotational speed (TRS) in rpm	750	1000	1250
Tool pin profile (TPP)	Threaded Cylindrical (TC)	Combined square and Threaded Cylindrical (CSTC)	Square (Sq)

2º tilt is given to the fixture concerning tool normal to avoid defects formation during the FSW process (Mathur et al. 2019). The set up used for the experiment was shown in Fig.1. Range of operational parameters is fixed by conducting trial runs which gave defect less weld joints. Taguchi L9 OA was employed to design the experiments as the selected OA should have equal to or higher degrees of freedom (DOF) than the total DOF required for the trials. Table 1 lists the operational parameters used in the study and their respective values.

Three types of pin profiles are used in the study namely threaded-cylindrical (TC), Square (Sq), and combined Square and Threaded Cylindrical (CSTC) profiles as schematically shown in Fig.2. UTS of the parent material and the FSW welded parts were measured according to the ASTM E8m standard (Prabhu et al. 2020). Three samples were taken from each of the experiments, machined in the direction normal to the weld line and the average of measured values are considered as response values. Tensile tests are performed on the Universal Testing Machine. The hardness of the joints was measured with an indentation load of 5kg for a duration of 15sec using a Vickers hardness tester. The test was performed across the joint at an interval of 3mm on either side of the weld line. Fig.3 depicts the UTS specimen and hardness measuring points on the FS welded sample. Experimental details and the output responses are listed in Table 2.

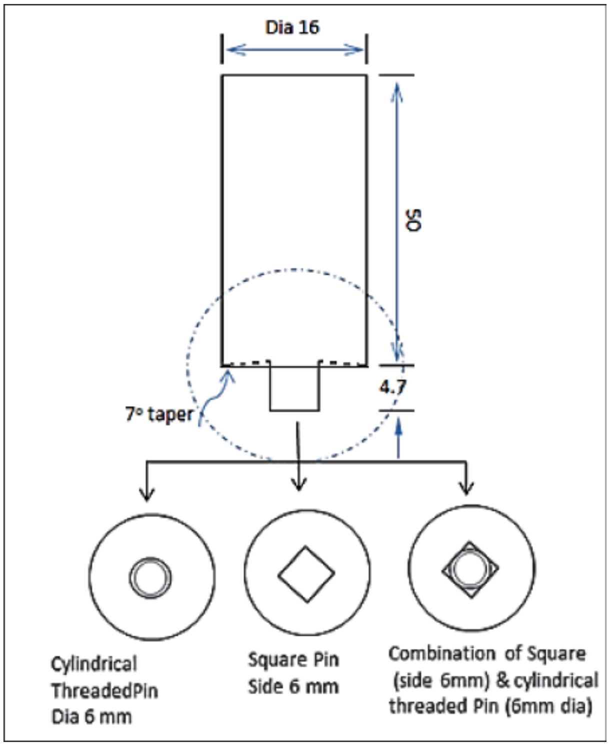

Figure 2: Schematic representation of FSW tool pin profile

Table 2: Operation parameters and responses

E.No.	Operation parameters			Responses		
	TRS (rpm)	TTS (mm/min)	TPP	YS (MPa)	UTS (MPa)	Hardness (VHN)
1	750	60	1	80	116	96
2	750	75	2	106	151	115
3	750	90	3	93	130	97
4	1000	60	2	110	158	115
5	1000	75	3	117	163	116
6	1000	90	1	101	145	110
7	1250	60	3	95	133	88
8	1250	75	1	99	142	100
9	1250	90	2	110	160	105

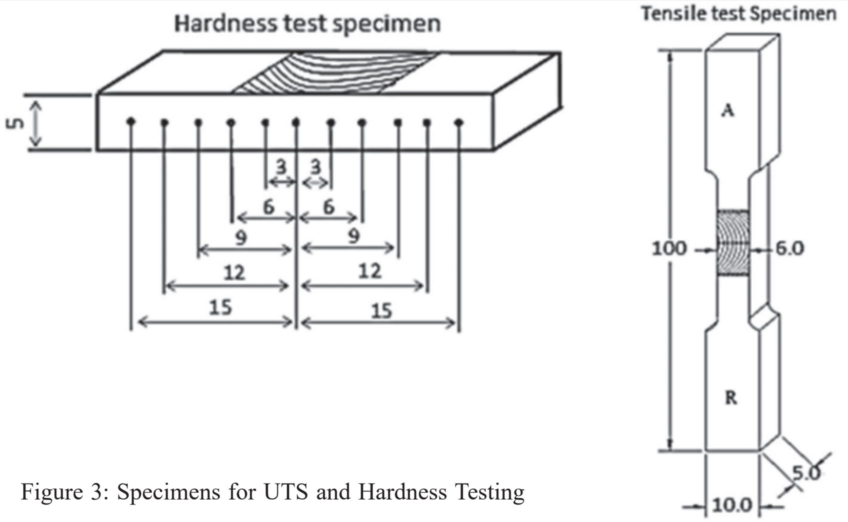

Figure 3: Specimens for UTS and Hardness Testing

$$n_{ij} = \frac{a_{ij}}{\sqrt{\sum_{i=1}^{m} a_{ij}^2}} \quad \text{... (1)}$$

i = number of different values varies from 1 to 9, j = number of responses, a_{ij} = Actual value of the j^{th} response in the i^{th} experiment. Table 3 lists the normalized values of responses.

Step 2

To prioritize the responses, each response was assigned weights based on its importance in a given set of responses. Normalized response values multiplied with these weights as given in equation 2.

$$r_{ij} = w_j \times n_{ij} \quad \text{... (2)}$$

In the present work, all the responses are treated equally and assigned values as w_j = 0.33. Table 4 lists the normalized values assigned with weights.

Step 3

Depending on the characteristics of the responses, either larger is better or smaller is better is chosen as the best solution and the other extreme is taken as the worst solution. In the present study, "larger is better" is used for all responses. Positive/Best solution (S+) and negative/worst solution (S–) is calculated using equation 3a and 3b and tabulated in Table 5.

$$S+ = \{(\mathrm{Max}\,(r_{ij}) \mid j \in J \mid i = 1\ldots9\} \quad \text{... (3a)}$$

$$S- = \{(\mathrm{Min}\,(r_{ij}) \mid j \in J \mid i = 1\ldots9\} \quad \text{... (3b)}$$

J is a set of responses.

Step 4

The distance from the ideal solution for each alternative is calculated using equations (4a) and (4b) respectively.

3.0 Result and Discussion

3.1 Topsis

In the year 1995, Hwang and Yoon developed a multi-response optimization technique known as the Technique for Order Preference by Similarity to Ideal Solution (TOPSIS). Here alternatives are searched which are nearer to the best solution and at much far away from the worst solution. TOPSIS provides an optimized result that is not only away from the hypothetically worst but also closer to the best solution (Sudhagar et al. 2017). The procedural steps of TOPSIS as explained below.

Step 1

As the different responses are having different units and different value ranges, responses are normalized in the range of 0 to 1 using equation 1, after removing the units.

Table 3: Responses after normalization

E. No.	YS	UTS	Hardness
1	0.2620	0.2667	0.3045
2	0.3472	0.3472	0.3648
3	0.3046	0.2989	0.3077
4	0.3603	0.3633	0.3648
5	0.3832	0.3748	0.3679
6	0.3308	0.3334	0.3489
7	0.3112	0.3058	0.2791
8	0.3243	0.3265	0.3172
9	0.3603	0.3679	0.3330

Table 4: Normalized value assigned with a weight

E. No.	YS	UTS	Hardness
1	0.0873	0.0889	0.1015
2	0.1157	0.1157	0.1216
3	0.1015	0.0996	0.1026
4	0.1201	0.1211	0.1216
5	0.1277	0.1249	0.1226
6	0.1103	0.1111	0.1163
7	0.1037	0.1019	0.0930
8	0.1081	0.1088	0.1057
9	0.1201	0.1226	0.1110

Table 5: Best (S+) and Worst solution (S–)

Solution	YS	UTS	Hardness
S+	0.1277	0.1249	0.1226
S–	0.0873	0.0889	0.0930

The distance of each alternative from the best solution is computed as

$$D_i^+ = \sqrt{\sum_{j=1}^{3}\left(r_{ij} - S_j^+\right)^2} \quad \text{... (4a)}$$

The distance of each alternative from the worst solution is computed as

$$D_i^- = \sqrt{\sum_{j=1}^{3}\left(r_{ij} - S_j^-\right)^2} \quad \text{... (4b)}$$

Where, $i = 1\ldots9$, and j = number of response.

Step 5

The closeness coefficient of alternative (X_i) to the ideal solution is computed using equation 5

$$X_i = \frac{D_i^-}{(D_i^- - D_i^+)} \quad \text{... (5)}$$

Rank the alternatives based on the closeness coefficient value to identify the combination of operational parameters that provides the most and least preferred solutions. Table 6 lists the closeness coefficient of each alternative and the ranking of each alternative.

Table 6: Closeness Coefficient Value

E. No.	D_i^+	D_i^-	X_i	Rank
1	0.0581	0.0085	0.1271	9
2	0.0152	0.0484	0.7613	4
3	0.0416	0.0202	0.3267	7
4	0.0086	0.0541	0.8626	2
5	0.0000	0.0617	1.0000	1
6	0.0231	0.0395	0.6306	5
7	0.0445	0.0209	0.3198	8
8	0.0305	0.0314	0.5074	6
9	0.0141	0.0503	0.7811	3

Step 6

For each of the operational parameter levels, closeness coefficient values are computed and listed in Table 7. The optimal set of operational parameters that emerged from the study are TRS of 1000rpm, TTS of 75mm/min, and tool with CSTC pin.

Table 7: Average Closeness Coefficient Value

	TRS	TTS	TPP
Low	0.4050	0.4365	0.4217
Medium	0.8310	0.7563	0.8017
High	0.5361	0.5794	0.5488

3.2. Mathematical model for TOPSIS

A regression analysis was carried out to develop a mathematical model for TOPSIS using uncoded operational parameters (TRS and TTS) and coded parameters (TPP-TC=1; CSTC=2 and Sq=3) at a 95% confidence level. A quadratic model with a linear term of parameters and interaction terms was developed as given below.

Closeness Coefficient
= 4.251 - 0.00950 * TRS - 0.1080* TTS +
5.777*TPP + 0.000175*TRS*TTS - 0.002312* ... (6)
TRS*TPP - 0.04096 *TTS*TPP

The mathematical model was expressed in terms of the main process variables and the interaction among them. A data set (predicted value) was generated using this equation. The actual and predicted values was shown in Fig.4. The % error arises from 2 to 16%. The suitability of the model is tested using the R^2 value which exhibits the strength of the mathematical model which varies from 0 to 1 (Chen 1988). The correlation between the predicted and actual values is considered as best if the R^2 value is closer to 1. The R^2 value of the developed mathematical model by the TOPSIS approach is 98.39%

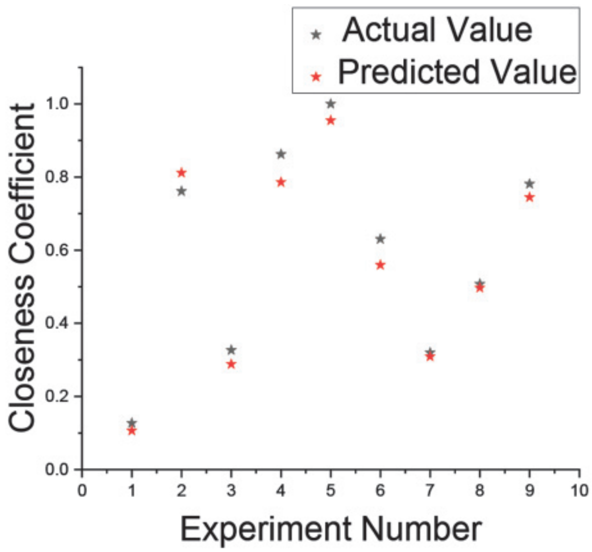

Figure 4: Actual and predicted values of TOPSIS closeness coefficient

3.3 Confirmation Test

Experiments were conducted using operational parameter combinations obtained from the TOPSIS to find out the competency of the optimization process. Three trials are conducted at TTS of 75 mm/min, and TRS of 1000 rpm using a tool having a CSTC pin profile, and the output responses (YS, UTS, and Hardness) are measured in each of the welded samples. The average values of each response are calculated. The response values obtained from the confirmation trials were improved by 10.25% in YS, 8.6% in UTS, and 10.3% in hardness in comparison with the best results obtained from L9 OA experimental set. It can be concluded that TOPSIS can be successfully utilized to optimize the FSW process.

4.0 Conclusion

FSW rutile reinforced AA6061matrix composite was performed by varying operational variables namely tool traverse speed, tool rotational speed, and tool pin profile. The joint quality was evaluated by measuring responses like yield strength, UTS, and hardness. The impact of operational parameters on responses is evaluated by conducting a set of experiments based on L9 OA. Multi-response optimization was carried out using the TOPSIS technique. A solution obtained from the TOPSIS was tested by conducting confirmation trials. The analyses performed indicated that the TOPSIS technique successfully optimized friction stir welding of AA6061/rutile composite. The optimal combination of operational parameters is TRS of 1000 rpm. TTS of 75 mm/min and tool with combines square and threaded cylindrical pin.

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