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Optimization of process parameters in friction stir welding of aluminium matrix SiC-Al_2O_3 composites by genetic algorithm

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Friction stir welding (FSW) grabs more attention since the past decade among the researchers worldwide due to its excellent characteristics such as no emission of fumes, no filler material, comparatively economical and so on. Friction stir welding is effectively used in bringing better joint without any appreciable defects in light materials such as Aluminium, Magnesium etc., Experiments in FSW of materials with high density such as steel, copper alloys etc., have also been tried out. The selection of proper welding parameters determines a good weldment. In this work, Aluminium matrix hybrid composite was manufactured through stir casting with the matrix AA7010 and reinforcements SiC and Al_2O_3. The hybrid composite workpieces were subjected to friction stir welding process by varying the process parameters such as tool rotation speed, welding speed and axial force using Taguchi L27 orthogonal array. Tensile strength of FS welded composite was examined and regression analysis was done. Genetic Algorithm technique was used to optimize the weld tensile strength within the design space of $5^3 = 125$ alternatives of parametric combinations. The study focuses on the improvement of the tensile strength of the welded specimens.

Keywords: Hybrid composite, Friction stir welding, Optimization, Genetic algorithm, Tensile strength.

Introduction

Composite materials gain more interest among the researchers across the globe due to their attractive properties that suit the requirements. The properties can be easily tailor-made according to the requirements in a specific application. The mechanical properties of any matrix can be modified by the addition of reinforcements with it thereby enhancing the effectiveness of the material for the application. The major advantage of composite materials over alloys is the incorporation of anisotropic nature that leads to different physical and mechanical properties of materials along different axes. Aluminium has many distinct properties such as light weight, good formability, ductile, malleable and castable and so on. Aluminium is used in many applications ranging from the household vessels to space vehicles. Aluminium in composite form is used widely in the skins of aircrafts' wing upper and lower structures. Aluminium alloys are used for both the structures which are primarily joined by the rivets that add up the total weight of the aircraft resulting in the higher fuel consumption. In order to reduce the weight of the wing structure, the welding process that does not affect the homogeneity of the structure is required [1]. The wings of aircraft carry the bending loads and moments, the direction of which subject to change during flight and idle conditions. The tensile strength is the key component for the wing structure to effectively transfer the load to the fuselage.

Ghosh et al. [2] fabricated LM6 Aluminium alloy reinforced with 7.5% SiC to observe the tribological characteristics that affect the surface integrity of the machined surface using Taguchi L27 design. The test results show that the wear parameters such as time, load and sliding speed have significant effects on the tribological behaviour. Li-na et al. [3], investigated the influence of stirring time and stirring temperature for the production of AA6061-ABOw—SiCp hybrid composite. The results show that there exists a homogenised reinforcement distribution and hence, better tensile strength was obtained at the decreased stir temperature and increased stir time (640 °C and 30 min respectively). A study on the wear behaviour of Coconut shell ash particulate (CSA) reinforced Aluminium Matrix composite reveals that the incorporation of the reinforcements opposes the forces causing wear on the composites [4]. When the load is increased, the CSA particles increase the wear resistance of the composite. Many researchers have tried out different techniques for the manufacturing of Aluminium matrix composites. Methods such as Powder metallurgy, Rheocast technique and in situ

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casting are used for the production of Al6061-AlN composites [5, 6]. Squeeze cast Al-Si-Mg matrix beryl composites show increase in the tensile strength and wear resistance compared to the gravity cast method. The optimum combination of weld speed reduction and rotary speed rise in the FS welding of AA7039 alloy was estimated and the mechanical properties are analysed with the different combinations in the work carried out by Sharma [7]. Lakshminarayananan et al. [8] employed Taguchi L9 orthogonal array during the welding of RDE-40 Aluminium alloy. The results indicate that the rotational speed, welding speed and axial force are the significant parameters in deciding the tensile strength of the joint. Al5186 and mild steel are joined through FSW by assigning the range of values for tool traverse speed, Plunge depth, tilt angle and tool pin geometry [9]. The results show that the intermetallic compounds tend to form during the low weld speed and get reduced during high weld speed. The work by Kasman et al., conclude that the process parameters have the greater influence over the strength of the weld [10]. Serio et al., used the infrared cameras to assess the correlation between the thermal behaviour of joints and the process parameters for monitoring of the quality of joints [11]. Vijayan and Rao [12] employed two computational approaches, genetic algorithm and simulated annealing algorithm in the dissimilar FSwelding of AA6061-AA2024. The results conclude that the use of the computational approaches influences the tensile properties significantly although considerable number of iterations and substantial amount of time were required to achieve the optimum parameter combinations. Hsieh and Chen [13] combined TRIZ methodology in friction stir welding and concluded that TRIZ in FSW will be used to establish correlation between parameters and will serve as references to subsequent designers which in turn shorten R&D duration. Ho et al. [14] proposed IHTGA (Intelligent hybrid Taguchi-genetic algorithm) that performed Taguchi method between the crossover operation of GA, where the genes for crossover are selected intelligently using Taguchi to get the enhanced performance results in the optimization of bearing offsets and shaft alignment in a marine vessel propulsion system. Parka et al. [15] fabricated WC-10% Co using SPS process which was utilized to improve the weld conditions of SS400 steel. Lina et al. [16] used Taguchi L18 array to optimize the machining parameters of EDM on zirconium dioxide and aluminum oxide. The results clearly indicAted the impact of peak current and pulse duration on material removal rate and surface roughness. Kamal et al. [17] arrived the better combination of friction stir welding process parameters in fabrication of aluminium alloy joints (cryorolled AA2219) using artificial neural network.

Methods and Materials

Preparation of composite

AA7010-SiC-Al_2O_3 Hybrid Composite is manufactured prior to the friction stir welding process. The composition and mechanical properties of AA7010 alloy are listed in Table 1 and 2. AA7010 is one of the heat treatable aluminium alloy with better properties in 7XXX alloys such as high strength-to-weight ratio, comparatively high strength, high fatigue strength, good resistance to corrosion and so on. The alloy is being replaced in the components of rib and wing structures in aircrafts. Stir casting technique was used to manufacture the composite. Aluminium billets placed in a graphite crucible were heated to temperature of around 730 ^{o}C to be melted. Meanwhile, the reinforcements SiC and Al_2O_3 each 10% were preheated to 900 ^{o}C in a Muffle furnace for a soaking time of one hour to remove the moisture content. Mg powder of 1% by weight was added into the melt to improve the wettability factor of reinforcements. The reinforcement particles were added using a feeder through the vortex created by stir action in the molten metal. The molten mix was poured into stainless steel mould of dimension 100 mm × 50 mm × 7 mm, which was preheated to around 250 ^{o}C to promote gradual heat dissipation from the melt.

Genetic algorithm

A genetic algorithm (GA) is an effective optimization tool for solving constrained and unconstrained optimization problems based on theory of natural genetics and natural selection process that replicates the biological evolution. GA is particularly suitable for deriving the better optimal combinations of process parameters in a potentially large space through navigation. GA differs from the conventional strategies and algorithms in obtaining the optimal solutions. Many conventional

Table 1. Chemical composition of AA7010.

Metal	Zn	Cu	Mg	Si	Ti	Cr	Pb	Sn	Ni	Ca, Mn	Aluminium
Composition %	55.84	2.04	1.65	0.05	0.04	0.03	0.02	0.02	0.02	Traces	Balance

Table 2. Mechanical Properties of AA7010.

Matrix material	Tensile strength (MPa)	Yield strength (MPa)	Elongation (%)	Fatigue strength (MPa)	Shear modulus (GPa)	Shear strength (MPa)	Poisson's ratio
AA7010	166	156	11%	180	26	320	0.32

algorithms provide the limited solutions whereas GA searches in a huge search space and comes up with lot of local solutions arrives the best solution among them. Every optimization problem converges based on a fitness function that is dependent on a number of variables. In the present work, GA is designed to maximize the fitness function of the variables. To start the optimization, GA requires the encoding of real time parameters into genetic parameters. Once the genetic parameters are assigned, the required fitness functions will be evaluated from the final optimal parameters. GA starts with the evolution of population which usually starts from a population of randomly generated individuals. The population in each iteration is called as generation. The fitness of every individual in every generation is evaluated. The fitness is the desired value of the objective function in the optimization problem being solved. The fit individuals deserve to be selected to next generation and a few selected individual's genome is modified to form a new generation through genetic operations such as reproduction (selection), cross over and mutation. In selection or reproduction phase, a section of the existing population is selected to breed and a new generation is formed through the fitness function evaluation. The fit individual is more likely to be selected to next generation. Several methods provide the fitness value for every individual which is a time-consuming process, whereas GA picks the individuals in a generation randomly to come up with the best local solution for the particular generation.

The next phase, crossover operator is a genetic operator that combines coding of two parents to produce a new coding called as offspring. The strategy behind crossover is that the new offspring is better than both of the parents by taking the best characteristics from each of the parents. Crossover occurs during evolution according to a user definable crossover probability between 0.5-0.99. Cross over is designed in such a way to occur in the predefined site of the codings. For instance, cross over may be a Single point, N-point, Uniform, Arithmetic, Partially mapped, Order or Cycle cross over types. The third phase, mutation is one of the genetic operator which is used to change only one bit in a coding so as to provide the diversity in the generation. Mutation rate is generally selected a little lower to ensure that the variation of chromosomes bring much better offspring. The product of number of bits, number of experiments taken in the iteration and mutation rate is taken as the number of change of bits in that generation. Mutation can be classified as random, swap, scramble or inversion type.

Once the mutation is performed, the fitness function for the individuals is evaluated for the offspring. The better offspring in the current generation deserve to be selected mostly in the next generation. Thus the iteration process continues in a cycle and gets terminated until all the individual parameter settings are completed. The coding with the optimal setting is selected according to the fit value. As the GA is programmed in such a way to select the maximum fitness value, the optimal parameter setting will be obtained. Thus the GA gets terminated after the desired fitness is obtained in the cycles.

Experimental Procedure

Friction stir welding

Trial welds were tried out to find the range of FSW process parameters that fetch good welding results. The parameters and their range were selected as: Tool rotation speed (TRS) 1,200-1,400 revolutions/minute, Weld speed (WS) 30-50 mm/minute and Axial Force (AF) 2.5-3.5 kN. Butt joint configuration was selected to fabricate the FSW joints. A non-consumable square tool, made of high carbon high chromium steel, was used to fabricate FSW joints in vertical milling machine. The dimensions of the FSW tool are given in Fig. 1. Taguchi design is used to find the proper control factor settings against relatively uncontrollable noise factors. Signal-to-Noise ratio is the effective measure used to evaluate the robustness of the design that indicates the minimum variation against noise. The higher Signal-to-noise ratio indicates the effectiveness of control factor settings that minimize the noise factor effects. For the design of 3 parameters with each 3 levels, L27 orthogonal array is selected to carry out the experiments. The process parameters of FSW are shown in Table 3. The FSW machine and the weld specimen are shown in Fig. 2.

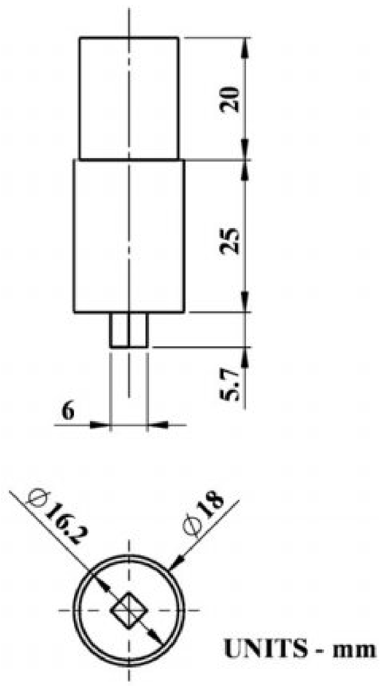
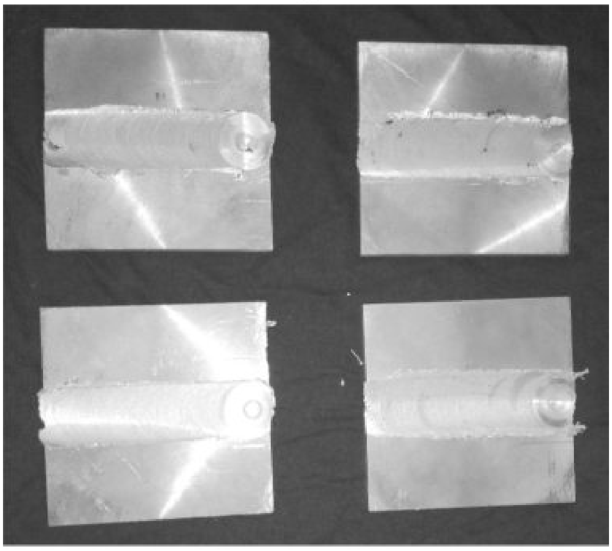


Fig. 1. FSW tool dimensions.

Table 3. Welding process parameters.

(a) Variable parameters	
Process Parameter	Value
Tool Rotational speed (TRS), rpm	1200, 1300, 1400
Weld Speed (WS), mm/min	30, 40, 50
Axial Force (AF), kN	2. 5, 3.0, 3.5
(b) Constant parameters	
Process Parameter	Value
Pin Length, mm	5.9
Pin diameter, mm	6
Shoulder diameter, mm	18
Shoulder diameter-Pin diameter ratio	3
Tool angle, deg	0^0

(a)



(b)

Fig. 2. (a) FSW machine and (b) welded specimens.

Table 4. Tensile strength of Welded specimen

S.NO	TRS (rev/min)	WS (mm/min)	AF (kN)	Ultimate tensile Strength (MPa)
1	1200	30	2.5	179.0
2	1200	30	2.5	176.0
3	1200	30	2.5	176.5
4	1200	40	3	169.3
5	1200	40	3	170.1
6	1200	40	3	170.0
7	1200	50	3.5	169.3
8	1200	50	3.5	171.7
9	1200	50	3.5	169.3
10	1300	30	3	149.0
11	1300	30	3	146.5
12	1300	30	3	144.3
13	1300	40	3.5	162.8
14	1300	40	3.5	163.8
15	1300	40	3.5	163.3
16	1300	50	2.5	148.0
17	1300	50	2.5	152.2
18	1300	50	2.5	154.0
19	1400	30	3.5	159.7
20	1400	30	3.5	160.0
21	1400	30	3.5	159.0
22	1400	40	2.5	174.0
23	1400	40	2.5	173.5
24	1400	40	2.5	169.9
25	1400	50	3	148.1
26	1400	50	3	148.6
27	1400	50	3	145.0

Results and Discussion

Taguchi design and ANOVA results

Tensile strength is the mechanical property considered in this investigation that describes the better FSW joint quality. As per the L27 orthogonal array design, the experiments were conducted in the machine and welding between the components was performed. The plates, after welding, were cut into the required size (50 mm × 50 mm × 6 mm) by power hacksaw and then machined as per the ASTM E8 standard. The observed tensile strengths for the 27 weld specimens are tabulated in Table 4. The schematic diagram of tensile specimen is shown in Fig. 3.

The adequacy of the experiments conducted is checked using ANOVA table using MINITAB V17 software shown in Table 5. ANOVA table shows the significance of each parameter involved in the process. The Probability value (or P-Value) for all parameters given shows values less than 5% or 0.05 thereby indicating that all three parameters of FSW are significantly influencing the tensile strength of the weld joint. Tool rotation speed is the most significant parameter affecting the response followed by axial force and welding speed. The R-Square and Adjusted R-Square values are greater than 95% stating that strong relationship exists between the response and the predictor. The regression formula for the ultimate tensile strength is obtained and shown below:

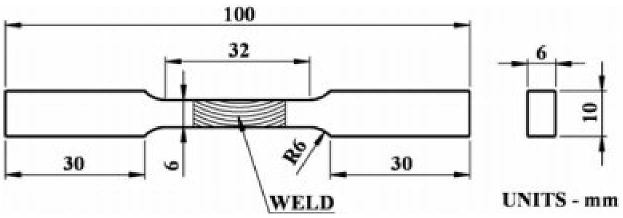


Fig. 3. Tensile specimen.

Table 5. ANOVA Test Results for tensile strength (S/N ratio).

Source	DF	Seq.SS	Adj.SS	Adj.MS	F	P-value
TRS	2	1.56127	1.56127	0.780635	49.63	0.020
WS	2	0.69224	0.69224	0.34612	22	0.043
AF	2	0.77273	0.77273	0.386365	24.56	0.039
Error	2	0.03146	0.03146	0.01573		
Total	8	3.05771				

$$\begin{aligned} \text{UTS} = {} & 261.7 - (2.69 * \text{AXIAL FORCE}) \\ & - (0.063 * \text{TOOL ROTATION SPEED}) \\ & - (0.244 * \text{WELD SPEED}) \end{aligned} \qquad (1)$$

Genetic algorithm methodology

The methodology used in the study are summarised as flowchart in Fig. 4. The regression formula derived from the Taguchi design comprises the simple terms of process parameters. As the adequacy is safe, the fitness function for the GA analysis can be taken as the maximisation of Ultimate tensile strength in the design space. The design space selected in GA is similar to the levels used in Taguchi design but to find the best solution that maximizes the UTS requires a lot of time, man power, utilization of resources etc., in the conventional way. The best solution can be predicted through GA using the regression formula as GA explores the desired output within the space through iterations. Programming for the Genetic Algorithm is prepared in C package. Here, the fitness function is written as shown below:

$$\begin{aligned} F(x) = {} & 261.7 - (2.69 * \text{AXIAL FORCE}) \\ & - (0.063 * \text{TOOL ROTATION SPEED}) \\ & - (0.244 * \text{WELD SPEED}) \end{aligned} \qquad (2)$$

The levels of process parameters are increased from 3 to 5 considering the flexibility in the machine settings. The levels are decoded accordingly as shown in Table 6. The design space for the optimization is thus increased from $3^3 = 27$ to $5^3 = 125$.

The population size, Cross-over probability rate and Mutation probability rate are specified as 10, 0.70 and 0.033 respectively. Cross-over rate is selected to 0.70 to ensure that the better combination of parameters with good fitness value is retained to the next generation. In order to get the desired variability in the population, mutation rate is selected to 0.033 to change one bit in the population of 10 using the formula given below.

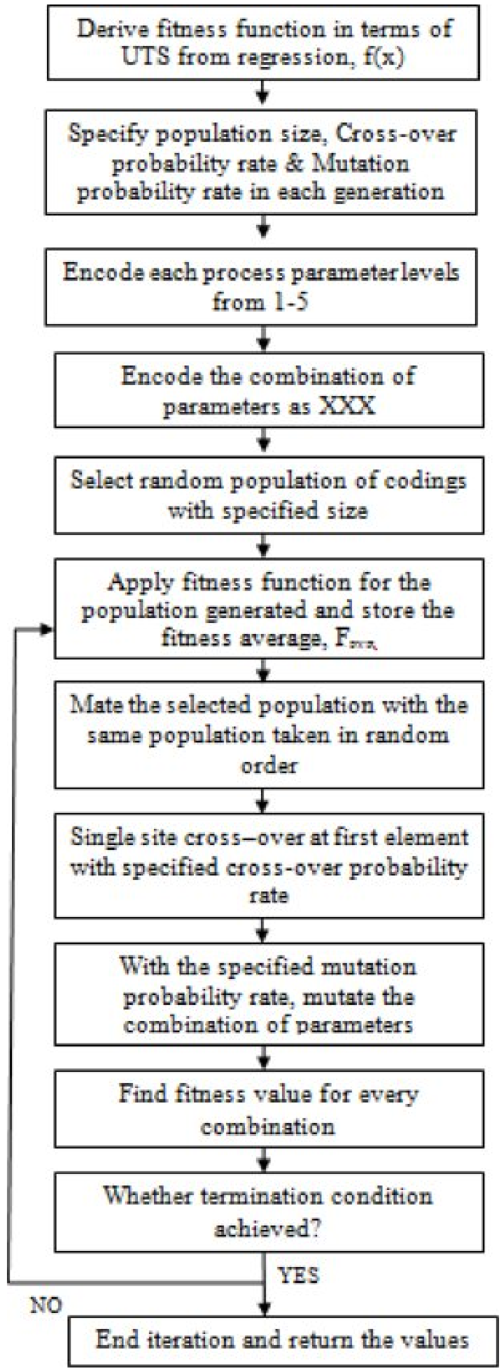


Fig. 4. Genetic algorithm methodology.

Table 6. Codings for the FSW process parameters.

Tool rotation speed (TRS), rpm	Welding speed (WS), mm/min	Axial Force (AF), kN	CODE
1200	30	2.50	1
1250	35	2.75	2
1300	40	3.00	3
1350	45	3.25	4
1400	50	3.50	5

No. of bits for formulation
= Population size ∗ no. of bits ∗ mutation probability rate (3)

The combination of first generation parameters are selected randomly as shown in Table 7. Then, the fitness functions for the first generation are computed as shown in the last column. Sum and average of the fitness values are also tabulated and saved as F_{sum} and F_{avg} respectively. The values for proportion (β) and Expected count (E) are tabulated from the following formulae:

$$\beta = F_i / F_{sum};\ E = \text{Population size} * \beta \tag{4}$$

Roulette wheel method of selecting the best parents for mating is used here for the cross-over phase. The values for the codes 1, 5, 7 and 9 are observed less than the F_{avg}.. These values have the less probability to get selected in the population pool while using Roulette wheel since the circumference of the wheel is linear with the expected count. Similarly, the values 2, 3, 4, 6, 8 and 10 with expected count greater than F_{avg} are likely to be selected in the population pool. The cumulative probability (C) is calculated from the expected count, E. Thus, the C value for the last row is 1. Programming is done in such a way that 10 random numbers are generated and the corresponding parents are selected based on the intervals of cumulative probability in terms of string, S. It is observed that the parents in rows 5, 8, 9 and 10 are not selected; 1, 2, and 6 are selected once; 3 and 7 are selected twice; 4 is selected thrice as tabulated. Correspondingly the new population pool is generated and are mated with the previous generation as shown in Table 8. It is also noted that any code providing high F_i value may also be neglected and vice versa thereby improving the F_{avg} value for every generation progressively.

It is noted that the number of bits for mutation are calculated as 1 and changed in the first bit of 5th row. The bit selected for mutation is programmed such that the old codes are not selected in order to explore the undiscovered design space. It is observed that F_{avg} value for the first iteration process has improved from 161.9 to 162.4. The same procedure is repeated until all the possible combinations are verified. It is observed

Table 7. First generation process parameters with codes.

CODE	TRS	WS	AF	FITNESS VALUE	Proportion, β	Expected count, E	Cumulative probability, C	Random number, R	String , S
432	1350	40	2.75	159.5	0.0985	0.9849	0.0985	0.5914	6
241	1250	45	2.50	165.2	0.1020	1.0204	0.2005	0.2787	3
123	1200	35	3.00	169.5	0.1047	1.0466	0.3052	0.6741	7
134	1200	40	3.25	167.6	0.1035	1.0349	0.4087	0.3308	4
553	1400	50	3.00	153.2	0.0946	0.9462	0.5033	0.3586	4
251	1250	50	2.50	164.0	0.1013	1.0129	0.6046	0.3491	4
552	1400	50	2.75	153.9	0.0950	0.9504	0.6996	0.6830	7
115	1200	30	3.50	169.4	0.1046	1.0459	0.8042	0.0678	1
555	1400	50	3.50	151.9	0.0938	0.9379	0.8980	0.2109	3
154	1200	50	3.25	165.2	0.1020	1.0199	1.0000	0.1354	2
Sum of fitness values, F_{sum}				1619.4					
Average of fitness values, F_{avg}				161.9					

Table 8. Population pool for mating.

Population pool	Cross over site	New generation	Random bits for mutation	Modified new generation	Fitness value	
432	251	1	451		451	158.1
241	552	-	241		241	165.2
123	115	2	125		125	170.1
134	555	1	155		155	169.4
134	154	-	134	1	334	167.5
134	432	2	132		132	168.9
552	241	-	552		552	153.9
123	123	1	123		123	168.3
251	134	2	254		254	162.6
552	553	2	553		553	152.5
				Sum of fitness values, F_{sum}		1636.6
				Average of fitness values, F_{avg}		163.7

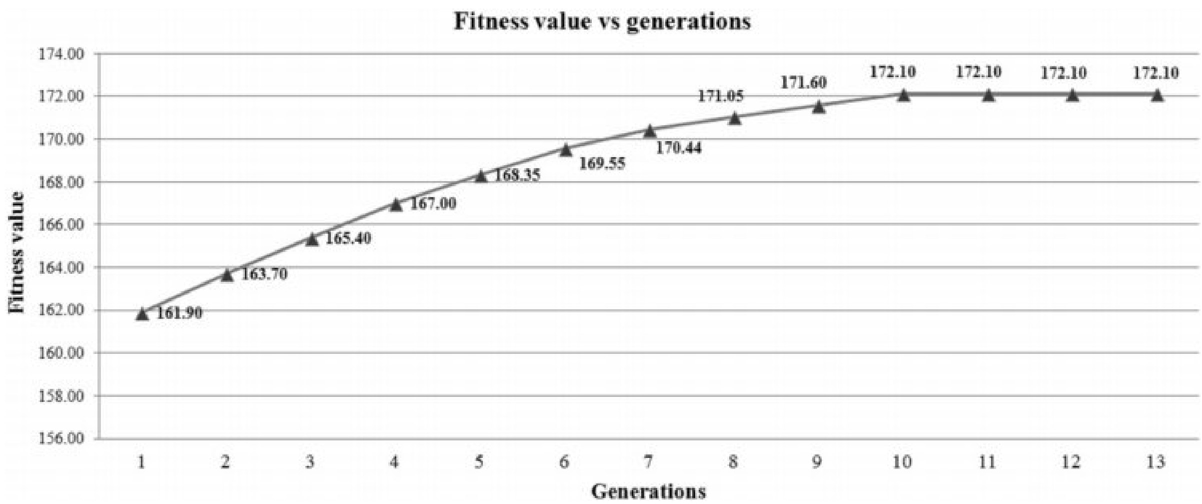


Fig. 5. Plot between fitness value vs generations.

that fitness value, F_{avg} value increases and reaches the maximum value of 172.10 MPa shown in Fig. 5.

Confirmation test

The final F_{avg} value after the program run obtained is to be verified with the experimental results in order to validate the GA methodology. The corresponding parameters for the maximum ultimate tensile strength are obtained as code 111 indicating TRS – 1,200 rpm; WS – 30 mm/min; AF – 2.5 kN. The code 111 is set with the vertical milling machine and five trial welds are carried out in order to eliminate any unwanted noise in the run. The average value of the trial welds results for the confirmation test obtained is 176.8 MPa with 1.22% error at 95% confidence level.

Conclusion

Genetic Algorithm is effectively used to optimize the Friction stir welding parameters. The stir cast hybrid composite AA7010-SiC-Al_2O_3 was friction stir welded by varying the Tool rotation speed, Weld speed & Axial force and keeping the other key FSW parameters constant. Taguchi L27 orthogonal array design was used to conduct the experiments. GA way of optimization was used to investigate the maximum ultimate tensile strength of the hybrid composite. Friction stir welding of aluminium matrix composites is used efficiently for joining of aluminium alloys. The tensile strength of the weldment of composites depends upon the Friction stir welding parameters. Every parameter has its effect over the tensile strength. The maximum tensile strength is optimized from the design space by genetic algorithm through C programming. The optimum parameters for Friction stir welding of AA7010-SiC-Al_2O_3 hybrid composite are: Tool rotational speed (TRS) – 1200 rpm; Axial Force (AF) – 2.5 kN and Weld Speed (WS) – 30 mm/min. The tensile testing in trial welds also confirms that the optimized results by GA are agreeable with the experimental results.

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