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Using hybrid ANN-GA to refine parameters of the underwater friction stir welding process parameters for tensile strength enhancement

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Abstract—**The properties of additive underwater friction stir welding (UWFSW) practical components are strongly dependent on the different process parameters of standard friction stir welding (FSW). Hybrid computational methods to improve the objective feature will maximize the method parameters. The present research discusses the tensile strength(UTS) of ASTM D3039 standardized components produced by UWFSW using Al 6063. Three parameters were used to produce the research specimens: rotational speed (1000, 1400, and 1800 rpm), travel speed (4, 8, and 10 mm/s), and shoulder diameter (10, 15, and 20 mm). Besides, hybrid optimization techniques such as the genetic algorithm-artificial neural network (ANN-GA) are applied to improve these process parameters. The optimum precision of 98.19% obtained with ANN-GA among these instruments results in tailored parameters such as rotational speed 1800 rpm, movement speed 4 mm/s, and shoulder diameter 15 mm to achieve the maximum UTS 199.0212 MPa. The hybrid models designed could be suggested to accurately predict and exploit certain process parameters and effects for certain industrial applications**

I. Introduction

Solid-state methods used in joining or manufacturing are friction stir welding (FSW) and the allied friction stir processing technique (FSP). Applications include the joining of structural aluminum parts in the aerospace industry, large tanks for the satellite launch vehicles, and the Littoral Combat Ship. A cylindrical, revolving tool with a shoulder and extending pin is pushed into the surface around the protruding edges of the components to be welded in FSW. Via frictional and adiabatic heating, the material is sufficiently softened to plunge the tool pin into the material before the surface is touched by the elbow [1-2]. UWFSW has now achieved mainstream attention. This groundbreaking technique is a variation of the process of FSW in which the workpiece and tool are fully submerged within the water. Since the heat dissipated in a method of FSW is seen to be comparatively lower than the process of arc welding, the primary purpose of the research group to examine the process of UWFSW is to reduce the heat produced and thus expect an improved mechanical weld joint characteristic. Two main disadvantages of commercializing the UWFSW process are complexity because of the weld path and fixture design[3-7]. SARUKADA et al[8] the UWFSW of 6061 aluminum alloy plate was studied by high-speed rotation tool and the result revealed that the joint had greater fatigue strength than that created in the air. Related, the UWFSW of precipitated hardened aluminum alloys, although the lower heat input generated during UWFSW does not melt the patterned metal, the thermal cycles can still exert a negative effect on the mechanical characteristics of the joints through coarsening or dissolving the strengthening precipitates [9-10]. A. M. El-Kassas [11] Study the UWFSW of Pipes. UWFSW of Pipes of Al 1050 pipes was successfully conducted by designing a new device that allows friction stir welded to the rotational motion of the pipe underwater. In the UFSWoP an important consideration is the cooling effect during the process on the surrounding water. An experimental design of the Box Behnken was employed with different levels of rotational speed, traverse speed, and diameter of the tool. The corresponding response considered was the tensile of the joints that were produced. Finally, a model focused on hybrid Answer Surface Methodology-Fuzzy was suggested and tested for predicting the UWFSW of Pipes process's considered reaction. This model shows findings expected more reliably than model centered on the Artificial Neural Network. Ibrahim Sabry [3] A contrast between UWFSW and conventional FSW has been conducted on AA 6063 pipe joints with specifically developed fixtures in this work. The outcome has exhibited a high UTS of 218 MPa and nugget zone hardness of 83 VHN compared to the FSW that has 201 MPa and 65 VHN respectively. Mohd A. Wahid[12] The influence of UWFSW process parameters on the mechanical properties of the 6082-T6 aluminum alloy joint is studied and this process is further simulated using various algorithms of evolutionary optimization. To simulate this UWFSW process, three evolutionary optimization algorithms, i.e. optimization of particle swarm, firefly optimization, and non-dominated genetic algorithm dependent sorting (NSGA-II), were used. The findings revealed that when simulation the variable response values compared to the optimization of particle swarm and NSGA-II, the simulation-based on firefly optimization performed the best with the least mean square error.

I. Sabry[13] This work-study compared the parameters of FSW and UWFSW on the weld joint, such as tool rotation speed, transverse speed, and wall thickness, and compare the ultimate tensile strength (UTS) weld joint using ANOVA analysis. From the study, it was observed that with minimal tool transverse speed, high tool rotation speed for UWFSW, maximum tensile strength is given, and that of traditional FSW. Using ANN and GA, the various evolutionary algorithms are exercised to maximize UTS at optimum process conditions, the UTS of all produced materials. To find the optimal method parameters for maximum tensile power, ANN was then utilized to suggest the for the highest correlation coefficient (R), and GA, fitness function was used. Evolutionary algorithms such as GA-ANN have been used to learn/train data and sketch the relevance inter UWFSW input parameters and performance, leading to precise optimization of goals. Eventually, on the tailored test parameters for the predicted model, experimental tests were conducted. We suggest the use of hybrid algorithms in the simulation and optimization of UWFSW method parameters, where there is a nonlinear relationship.

II. MATERIALS AND METHODS

A. Materials

In general, the UFSW pipe cycle begins by placing the device pin in the space between the two opposing pipes before the shoulder meets the surfaces of the two pipes (Figure 1(a)). As well as being done underwater, the UFSWoP has the same technique as the FSW of pipes. The UFSWoP process was conducted to join two pieces of Al 6082-T6 pipes. Could pipe had an outer diameter of 30 mm, and thickness of 3 mm. The chemical structure of the pipes ' substance Al 6082-T6 is shown in Table 1. The Process main factors and their working levels is shown in Table 2.

TABLE I.

CHEMICAL COMPOSITION (WT. %) OF AL 6063

Wt. %	Al	Si	Fe	Cu	Mn	Mg	Cr	Zn
	Bal	0.8	0.5	0.1	0.7	0.9	0.25	0.2

TABLE II.
THEIR WORKING LEVELS PROCESS

Parameter	Unit	Level		
		-1	0	1
Shoulder Diameter (***D***)	mm	3	4	5
Rotation speed (***N***)	RPM	1000	1200	1800
Travel speed (***S***)	mm/min	10	16	20

The following dimensions were used for the non-consumable hard-edge steel tool: a shoulder with a diameter (D) and a height of 5 cm. The pin profile is tapered with an initial diameter of 5 mm and a final diameter of 3 mm with a length of 1 mm per pin[14-15]. In a central composite design matrix cantered on the surface reaction plan, a complete factorial experiment was carried out, in which the three factorial design variables were selected in three steps, consisting of 27 experimental coded conditions, as seen in Table 2. At three stages, these parameters varied, and other parameters were kept constant, as seen in Table 2. Using the QT-6201 type UTM test machine for UTS, the testing specimens were tested, As demonstrated in Fig. 1(c) as per usual examination stipulations of ASTM D3039. Therefore, In conjunction with the above, test runs were processed on the UTM norm to measure the tensile strength of parts and a measured average of 5 specimens is taken as the output value[15-18]. Table 3 displays the matrix of experimental input variables and their output values.

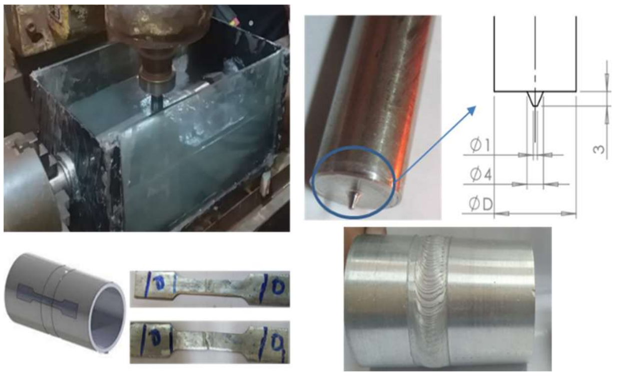

Fig. 1. (a) UFSW of AA 6061 pipes using EG-FSW-M1 equipment. (b) Conical friction stir welding tool (c) Test specimens fabricated with ASTM D3039 standards. (d) Underwater friction stir weld images of Al 6061 pipe

TABLE III.
DESIGN MATRIX AND EXPERIMENTATION FOR FULL FACTORIAL ANALYSIS.

Test Run	Process parameter			Experimental Values
	N (rpm)	F(mm/min)	S (mm)	Tensile strength
1	-1	1	-1	246.56
2	-1	-1	-1	256.32
3	1	-1	1	227
4	-1	1	1	242.58
5	0	0	0	246.25
6	1	1	1	228.6
7	1	1	-1	239
8	-1	-1	1	257.26
9	1	1	1	243.33
10	-1	-1	-1	224.4
11	1	-1	-1	260
12	-1	-1	1	225
13	1	-1	-1	238
14	1	-1	-1	243
15	-1	-1	1	225
16	-1	1	-1	248
17	1	1	1	229
18	0	0	0	236.9
19	1	-1	1	230
20	1	1	-1	251
21	-1	1	-1	230
22	-1	-1	-1	230
23	-1	1	1	246.39
24	0	0	0	241.7

25	1	-1	1	261
26	1	1	-1	266
27	-1	1	1	262

The used tool is shown in Fig. 1(b). A vertical milling machine (VMM) was originally selected to conduct the pipes FSW. Through using a chuck connected to the dividing head of the VMM and a tailing head, the revolving motion of the pipes – which reflect the traverse speed(s) – was permitted. The dividing head is controlled by an inverter motor instead of by manual hands. To carry the two pipes, a sturdy fixture is needed which can be rotated with them. You will find our past concepts and projects at [3] [12]. Our final configuration, used in this article, has been a fixture with complete longitudinal support to the pipes. After the welding, the question of disassembling the two pipes was overcome by breaking the device into two parts. By locking spinning motion, each component is firmly bound to the other. The specification of the fixture is seen in Fig.1(a). The entire device is wrapped in a sealed shell, while the ends with hydraulic seals protruded through openings. This package includes an inlet and outlet holes for water entering and escape. A tensile examination for each specimen was performed to assess the deemed responses. Specimens were designed for the tensile examination, as in Fig.1(c) by standard ASTM D3039.

B. *ANN-GA method to preparation and optimization of process parameters*

ANN-GA is the hybrid approach to mathematical handling of data with sequential data preparation and data optimization [19] [20]. The artificial neural network (ANN) is a computer system designed to simulate the way information is analyzed and interpreted by the human brain. It is the basis of artificial intelligence (AI) and solves problems which, would prove impossible or challenging, by human or mathematical standards. ANNs have self-learning capabilities that allow them, to deliver better results, as more data becomes available. The theme of the biological neural system is inspired by the functional relations between parallel operating elements of ANN. To approximate some non-linear function, the variety of connections between these components gives different structures. Therefore, these networks are often renowned as global function approximations. These architectures produce functions with distinct sophistication and power to achieve a particular Goal from a data set given &, consequently, the values of relations between components, i.e., weights, are changed to adjust/train the network. the optimised values of weight obtained by learning are then run by ANN accordingly. The qualified neural network, modified Ought to be of optimal weights, able to generate an analogous response to an input pattern with expected accuracy. Using investigation of mean square error and regression, the implementation of neural fitting can be helpful in selecting data, creating, and training a network, and assessing its execution[21,19]. Where the value of the mean square error is close to zero and the regression values are close to one, it means that the network's data training output is decent enough. The GA is a tool that drives biological evolution based on natural selection optimization to solve problems of both restricted and unrestricted types. It essentially acts as a cumulative population generation from the preceding one until the optimized pattern is not accomplished [19,23].

III. Result and discussion

A. *Experimental learning and preparation of data by building the ANN model*

The command "nntool" is initially used to start an input-output curve alignment, in neural network wizard MATLAB 7.11.0 (R2017b) and fitting app. In fact, because of their great fitting capacities, neural networks can fit any real specific function to deliberately perform fitting function. A 3 x 27 matrix , containing a set of 27 values corresponding to 3 factors, which loads rotation speed (rpm), shoulder diameter (mm) traveling speed (mm / min) as input data, to clearly present the network problem. To define the desired network output, target data was loaded as a 1x27 matrix, with a set of 27 values corresponding to 1 tensile strength factor (MPa). After data assortment the next stage is validation and test results, the collection of 27 values is randomly allocated for this reason in a classic way as 6 for validation and testing and 27 for training. Test examples are introduced to it during network testing, and network modification is made according to the errors. Validation tests are used to gage network uncertainty, and end testing until uncertainty ceases going forward. Therefore, because test samples have little influence on data processing, checking samples before and after processing offer an individual network output measurement. Let the number of neurons in the neurons after that, secret layer of the network to imply a specific neural network, which is 10 in the current.

To create the relation between outputs and goals, different regression values are evaluated, as illustrated in Fig. 4(a). The R-value of regression above 1 indicates a strong association and a value close to 0 reflects a random relation. Table 5 reports the primary findings for distinct regression values with training algorithms. The data training against produced the decisive result across the different test runs, which is obvious by the mean value 1.28 square error and 0.93749 regression value. In addition, the findings obtained from ANN were further exploited in the GA to refine the underwater friction stir welding input parameters and UTS of parts.

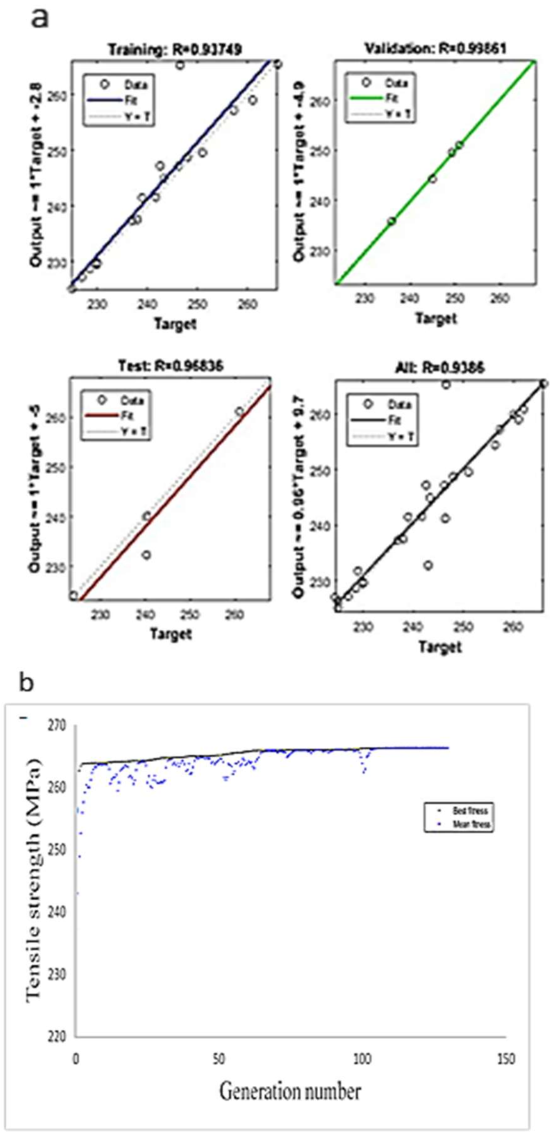

Fig.2 (a) Turning5 regression plot algorithm, (b) ANN-GAassimilation effects for optimization of UTS

TABLE IV.
ANN ALGORITHMS WITH REGRESSION VALUES.

Algorithm on Data Training	Codified As	Work of training : R	Effectiveness : R	Trial: R	Each: R
Marquardt - Levenberg	turning5	0.93749	0.99861	0.9683	0.9386

B. *Configuring the ANN-GA for UTS optimization model*

The evolutionary ANN-GA technique was used to optimize UTS and to set optimum value parameter combinations by adjusting upper and lower limit variables in GA. The desired goal fitness function is loaded with the net file (.mat format) supplied by the 'turning5' best integral ANN model. The @UTS, the fitness function type, is then stacked and the file is used to execute the task in the form of UTS. As per the concept, constraints such as linear continuity, limits, and integer variable indices, etc. were defined following the definition of number of variables (3 in the current case) and fitness function. In addition, mutation rate as 0.05, elite count as 1, a rank scaling feature aimed at fitness scaling, 100 generations as stop criterion, double vector population with size 50, crossover fraction as 0.5, development function based on restriction and other default trace illustration variables in favor of best fitness are included in the selected results. To obtain optimized performance in terms of the best and mean tensile strength values enlisted by

GA in Table 6, equivalent practice is then extended to the best fit ANN model that is 'turning5'. In this analysis, the Levenberg-Marquardt (turning5) algorithm used in the opposite training algorithm concludes from the evaluation of GA-ANN results.

The confirmation experiment was conducted with the validation experiment and their results are tabulated in Table5.The estimated ANN-GA optimal solution of the input parameters and their related calculated output responses are shown in Table 5. The feasible solution for the ease of carrying out the validation test was drawn from the closest round of value of the optimal solution. The UWFSW joint was subjected to the UTS test after validation of UWFSW's experimenting with the feasible solution and the findings were tabulated in Table 3. It is observed from the results that the best results of the UTS were like the joint outcomes of the FSW conformation.

GA-assisted ANN provides the highest UT value 266 MPa, as shown in Fig. 4b, following different input parameters such as rotation speed 1800 rpm, travel speed 10 mm / s, shoulder diameter 3 mm. The percentage of error was also determined between the calculated ANN-GA and the experimental effects of the validation. The error percentage was small and well within the acceptance limit.

TABLE V.
ANN RESULTS ASSISTED WITH GA.

Algorithm of training	GA-optimized parameters			UTS (MPa) [Preferable Value]	UTS (MPa) [Median Value]
	N	S	D		
turning	1800	10	3	267.036	267.033

IV. CONCLUSION

The ANN modelling with GA optimization was carried out for UTS, of UWFSW 6063 alloy, in the existing investigations. The ANN was used to create the correlation by providing the experimental input of the L27orthogonal array and their output responses. Then, with GA, the findings were more refined. The following observations from the optimization of ANN-GA modelling and the effects of UWFSW joint characterization made with feasible solutions were observed.

1- The ANN modelling projected performance responses with high precision (98.19%) and the least RMSE value was identified. If there are more training data sets, the precision of the outcomes of the ANN will increase. The GA was also successfully performed to figure out UWFW's optimized method parameters.
2- The ANN modelling algorithms are provided by the MATLAB program to find the least RMSE value from the least number of output response inputs to provide the optimum solution.
3- This technique provides reliability and verifies the precision of the optimum solution obtained. The GA provides the feasible input parameters for the conformity test and they are a rotational speed of 1800 rpm, a tool travel speed of 10 mm/min and a shoulder diameter of 3 mm. The UWFSW joint made with the feasible solution (experiment of confirmation) exhibits UTS of 199.0212 MPa.

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