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Research Article

A Novel Approach to Improve Tensile Strength of Al/Mg Hybrid Friction Stir welding Joint by Stochastic Optimization

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Abstract

Ultrasonic-stationary shoulder-assisted friction stir welding is a novel hybrid welding technique that reveals promising prospects in joining Al/Mg dissimilar alloys. This study aims to develop a design procedure for optimizing the mechanical property of the Al/Mg hybrid friction stir welding joint. For this purpose, firstly, different nonlinear neuro-regression analysis has been performed in order to overcome insufficient approaches for modeling, designing, and optimizing mechanical property in Friction stir welding joint. Then, stochastic optimization methods were performed to model the friction stir welding process. Ultrasonic Power, Welding Speed, and Rotational Velocity are the three most essential criteria that have been used as indicators of process performance. The response characteristic can be predicted as ultimate tensile strength. After calculating the $R^2_{training}, R^2_{testing}, and\ R^2_{validation}$ values, the limits of the nonlinear models are examined to see whether the model is acceptable for optimization. The best approach model was the second-order trigonometric multiple nonlinear (SOTN) model. In the optimization step, four different Modified Stochastic Optimization Algorithms, including Random Search (MRS), Simulated Annealing (MSA), Nelder Mead (MNM), and differential equations (MDE) methods, were used. It has been observed that the different scenario types and the constraints chosen for the design variables are effective in the optimization results obtained using three different scenarios. Results showed that the maximum tensile strength was 182.301 MPa when ultrasonic power was selected as 186.938 W, 40.6854 mm/min for welding speed, and 1075.34 rpm for rotation speed.
Keywords: Friction stir welding; tensile strength; neuro-regression analysis; stochastic optimization.

1. Introduction

In the current production technology, the demand for high-strength and low-weight structures has increased the need for lightweight hybrid materials. Aluminum (Al) and Magnesium (Mg) alloys, known as commercial metals, play a critical role in the automotive, aerospace, and shipbuilding industries because these materials have high specific strength and formability [1,2]. The widespread use of Al / Mg alloys has increased the importance of the reliable coupling of these alloys. However, due to the formation of intermetallic compounds (IMCs) caused by mental melting and re-solidification during the welding process, it is problematic to combine Al / Mg alloys with standard fusion welding [3-6]. Intermetallic compounds (IMCs) are ordered phases with distinct crystal structures and characteristics than elemental metals. They can be binary, ternary, or polymetallic. Because dissimilar alloys usually have differing atom diameters, crystal structures, and electronegativities, IMCs quickly develop in joints when they are joined. In addition, the ductility and brittleness of IMC are generally poor. When a joint is subjected to external stresses, a fracture can quickly form and spread within the IMC, causing the joint's mechanical qualities to weaken [7]. As a result, when combining different alloys, IMC formation must be avoided. Friction stir welding has been extensively researched as a solid-state welding technology for joining dissimilar materials, such as Ti/Al, Al/St, Al/thermoplastic, and different polymer matrix composites [8-11]. Because of the low peak welding temperature, since it can prevent the development of Al-Mg IMCs, Friction Stir Welding (FSW) is proven to be superior in connecting Al/Mg alloys.

Nonetheless, FSW cannot entirely remove IMCs, limiting the amount of joint tensile strength that may be increased. Therefore, FSW weldability, which is improved by using an additional tool or extra energy, has recently been a growing trend. Stationary Shoulder Friction Stir Welding (SSFSW) is a novel branch of FSW that uses external stationery [12]. By reducing flash and shoulder markings, the outer stationary shoulder optimizes joint formation, increases material flow, and reduces heat input through its heat sink effect. As mechanical energy, the composition and size of Al-Mg IMCs are influenced by ultrasonic vibration. Lv et al. [13] investigated the intermetallic compound layers of friction stir welded Al-Mg joints without and with ultrasonic vibrations. Results showed that during welding Al/Mg dissimilar alloys, ultrasonic may also enhance material flow and reduce material adherence [14]. A novel hybrid welding process of ultrasonic aided SSFSW (U-SSFSW) is created based on the previous two approaches to accomplish the combined benefits of the ultrasonic and stationary shoulder

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[15]. Thus, in ultrasonic welding of Al/Mg dissimilar alloys, it can improve material flow while reducing material adhesion.

Many experiment methodologies, such as response surface methodology [16] and the Taguchi method [17], have been included in the modeling and parameter optimization of the FSW process in recent years. Because of its self-learning and prediction skills, artificial neural networks (ANN) are frequently used in mathematical modeling for monitoring and assessment applications. ANN is more suited to constructing nonlinear mathematical techniques to simulate and determine outputs by inputs than the response surface approach and Taguchi method [18]. A training step is required to complete self-learning and ANN predicting. Backpropagation (BP) is now the most common training algorithm utilized in ANN, according to published research, based on accuracy and quick response [19]. However, this algorithm's gradient approach for weight correcting may result in a local optimum, where the searching space cannot leap off during the training step [20]. This problem is solved through algorithm optimization. Therefore, several society intelligence algorithms have been developed to ensure the suitability of existing optimization techniques and to provide practical simulation in complex multi-parameter optimizations, such as Particle Swarm optimization [21], Artificial Bee Colony algorithm [22], Imperial Competitive Algorithm [23] and Brainstorm optimization [24]. Verma et al. [25] used an Artificial Neural Network to investigate the influence of FSW parameters which are rotational speed and travel speed, and artificial aging of the characteristics of AA7004 alloy for the first time. The results show that a 320 rpm and 1 mm/s travel speed gives 341 MPa maximum strength and joint efficiency of 80 percent. Also, they have caused re-precipitation of precipitates in the weld zone, which has improved joint efficiency by 59 to 80 percent when as-welded samples are aged under 150 °C for 24 hours. Medhi et al. [26] tried to find the best welding inputs for combining two different materials using the FSW method to produce high-quality joints. They worked on a theory that combines the exploration and exploitation capabilities of the non-dominated sorting genetic algorithm-II (NSGA-II) with the Technique for Order of Preference by Similarity to Ideal Solution (TOPSIS) technique. They observed the increase in ultimate tensile strength, hardness, and impact energy. Liu et al. [27] used ultrasonic-assisted friction stir welding (UaFSW) based on a fixed shoulder system to join 6061-T6 aluminum alloy with AZ31B magnesium alloy to reduce or eliminate the disadvantages caused by continuous IMCs. Their studies determined the maximum tensile strength and elongation of the UaFSW joint were 152.4 MPa and 1.9 percent, respectively. These values were 17 MPa and 0.8 percent higher than the conventional joints. Song et al. [28] worked to combine the dissimilar alloys of AZ31B Mg and 6061-T6 Al, and U-SSFSW was utilized. The correlations between the design parameters of welding and rotating speeds and ultrasonic power and the objectives of ultimate tensile strength of US-SSFSW joints were modeled using a Radial Basis Function Neural Network (RBFNN). The results showed that the RBFNN-GWO system's enhanced design inputs provide the highest ult. tensile strength of 158 MPa.

This study aims to obtain the optimal process parameters that give the maximum ultimate tensile strength in the friction stir welding joints with a novel optimization approach. The design variables were selected as Ultrasonic Power, Welding Speed, and Rotational Velocity; the objective function of the introduced mathematical optimization problems was also ultimate tensile strength. We used the experimental data from the study [30] to carry out this approach. First, ten different regression models were performed, and the validity of the models was evaluated using $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$ values. Then optimization process was applied using modified Random Search (MRS), Simulated Annealing (MSA), Nelder Mead (MNM), and Differential Equations (MDE) Algorithms for three different optimization scenarios.

2. Materials and Method

2.1 Modelling

In the current research approach, neuro-regression approach has been applied to obtain the most efficient values for the parameters and the best mathematical model [29]. In this method, all data is divided into three sections, each containing 80%, 15%, and 5% of the total data, respectively—the first section is used for training, the second for testing, and the third for validation. The training process minimizes experimental and predicted value errors, modifying the regression models and their coefficients, as given in Table 1. First, this procedure provides information about the predictive capacity of the candidate models. Second, the adherence of candidate models to predicted values should be checked to determine whether the model is exact. In this section, the maximum and minimum values of models in the given range for each design variable are calculated after obtaining appropriate models from $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$. Furthermore, this technique examines if the chosen models satisfy various realistic requirements.

Table 1. *Multiple Regression Model Types[29]*

Model Name	***Nomenclature***	***Formula***
Multiple Linear	L	Y = a[1] + a[2] x1 + a[3] x2 + a[4] x3
Multiple Linear Rational	LR	Y = (a[1] + a[2] x1 + a[3] x2 + a[4] x3)/(b[1] + b[2] x1 + b[3] x2 + b[4] x3)
Second Order Multiple Linear	SON	Y = a[1] + a[2] x1 + a[3] x2 + a[4] x3 + a[5] x1^2 + a[6] x1 x2 + a[7] x2^2 + a[8] x1 x3 + a[9] x2 x3 + a[10] x3^2
Second-Order Multiple Nonlinear Rational	SONR	Y = (a[1] + a[2] x1 + a[3] x2 + a[4] x3 + a[5] x1^2 + a[6] x2^2 + a[7] x3^2 + a[8] x1 x2 + a[9] x1 x3 + a[10] x2 x3)/(b[1] + b[2] x1 + b[3] x2 + b[4] x3 + b[5] x1^2 + b[6] x2^2 + b[7] x3^2 + b[8] x1 x2 + b[9] x1 x3 + b[10] x2 x3)
Third Order Multiple Nonlinear	TON	Y = a[1] + a[2] x1 + a[3] x2 + a[4] x3 + a[5] x1^2 + a[6] x2^2 + a[7] x3^2 + a[8] x1 x2 + a[9] x1 x3 + a[10] x2 x3 + a[11] x1^3 + a[12] x2^3 + a[13] x3^3 + a[14] x1^2 x2 + a[15] x2^2 x3 + a[16] x3^2 x1 + a[17] x3^2 x2 + a[18] x1 x2 x3
First Order Trigonometric Multiple Nonlinear	FOTN	Y = a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Cos[x1] + a[6] Cos[x2] + a[7] Cos[x3]
First Order Trigonometric Multiple Nonlinear Rational	FOTNR	Y = (a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Cos[x1] + a[6] Cos[x2] + a[7] Cos[x3])/(b[1] + b[2] Sin[x1] + b[3] Sin[x2] + b[4] Sin[x3] + b[5] Cos[x1] + b[6] Cos[x2] + b[7] Cos[x3])
Second Order Trigonometric Multiple Non-linear	SOTN	Y = a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Cos[x1] + a[6] Cos[x2] + a[7] Cos[x3] + a[8] Sin[x1]^2 + a[9] Sin[x2]^2 + a[10] Sin[x3]^2 + a[11] Cos[x1]^2 + a[12] Cos[x2]^2 + a[13] Cos[x3]^2
Second Order Trigonometric Multiple Nonlinear Rational	SOTNR	Y = (a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Cos[x1] + a[6] Cos[x2] + a[7] Cos[x3] + a[8] Sin[x1]^2 + a[9] Sin[x2]^2 + a[10] Sin[x3]^2 + a[11] Cos[x1]^2 + a[12] Cos[x2]^2 + a[13] Cos[x3]^2)/(b[1] + b[2] Sin[x1] + b[3] Sin[x2] + b[4] Sin[x3] + b[5] Cos[x1] + b[6] Cos[x2] + b[7] Cos[x3] + b[8] Sin[x1]^2 + b[9] Sin[x2]^2 + b[10] Sin[x3]^2 + b[11] Cos[x1]^2 + b[12] Cos[x2]^2 + b[13] Cos[x3]^2)
Third Order Multiple Nonlinear Trigonometric	TOTN	Y = a[1] + a[2] Sin[x1] + a[3] Sin[x2] + a[4] Sin[x3] + a[5] Sin[x1]^2 + a[6] Sin[x2]^2 + a[7] Sin[x3]^2 + a[8] Sin[x1 x2] + a[9] Sin[x1 x3] + a[10] Sin[x2 x3] + a[11] Sin[x1]^3 + a[12] Sin[x2]^3 + a[13] Sin[x3]^3 + a[14] Sin[x1^2 x2] + a[15] Sin[x2^2 x3] + a[16] Sin[x3^2 x1] + a[17] Sin[x3^2 x2] + a[18] Sin[x1 x2 x3]

2.2 Optimization

Optimization is obtaining the most appropriate design by minimizing or maximizing the specified single or multi-objective that corresponds to all constraints.

There are two types of optimization techniques: traditional and non-traditional. Only continuous and differentiable functions are suitable for traditional optimization approaches. Traditional optimization techniques cannot be used in their specificity in engineering designs because they work on continuous and differentiable functions. Therefore, stochastic optimization methods such as genetic algorithms (GA), simulated annealing (SA), and particle swarm (PS) are more convenient for engineering applications. However, due to the characteristics of stochastic methods, correct solutions cannot be reached. Using more than one method with different principles for the same optimization problem enhances the dependableness of the solution. In this study, different optimization scenarios, including some problems of optimization problems, were used. Four different stochastic optimization algorithms were used to determine optimal process parameters. These algorithms are the Modified Nelder-Mead (MNM), Modified Differential Evolution (MDE), Modified Simulated Annealing (MSA), and Modified Random Search (MRS) [29].

2.2.1. Nelder-Mead Algorithm

The Nelder-Mead optimization technique is a fundamental direct search approach. As a result, no derivative information is required, and the function's reduction begins with simplex. The iteration continues until the simplex is reached, which becomes flat. It signifies that the function's outcome is almost identical at all vertices. The Nelder-Mead algorithm's iteration phases include ordering, centroid, and transformation [29].

2.2.2. Differential Evolution Algorithm

The differential evolution optimization method is one of the appropriate stochastic optimizations. It may determine the best solution in complex structured composite design challenges. Instead of iterating over solutions, it deals with a population of them. As a result, even if the differential evolution technique does not attain globally optimal points with all optimization problems, it is considered resilient and efficient [29].

2.2.3. Simulated Annealing

The simulated annealing optimization technique is another common search technique based on the actual annealing of metals. During the melting process, the material transfers to a lower energy level and becomes stiff. The algorithm is superior at finding the global optimum because of its inherent structure. In addition, it can handle optimization problems that are continuous, mixed-integer, or discrete [29].

2.2.4. Random Search Algorithm

The random search optimization technique is a standard random reach algorithm to generate a population of unpredictably placed starting spots. It utilizes a local optimization strategy to reach a local extremum point from each starting position. As a solution, the best local minimum is chosen. Specific booster subroutines, like the conjugate gradient, main axis, Levenberg-Marquardt, Newton, Quasi-Newton, and nonlinear interior-point approach, are utilized in the recommended version of the algorithm to optimize the values of all parameters for the objective function. In this stage, the fitness function is evaluated with symbolic variables, and then the method is repeated [29].

2.3 Problem Definition

The optimal design of ultrasonic power (W), welding speed (mm/min), and rotational speed (rpm) giving the maximum tensile strength value in a friction stir welding joint, is realized as follows. Experimental data from the reference work [30] to be used in modeling are shown in Table 2. The optimization procedure is conducted by Mathematica [49] program.

- Ten different mathematical models are implemented to provide friction stir source data and the limitations and suitability of the functions are checked for the values of $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$.
- Optimization was performed using four different modified stochastic optimization algorithms, namely, Differential Evolution (DE), Simulated Annealing (SA), Random Search (RS), and Nelder-Mead (NM), for three different optimization scenarios using appropriate models.

2.4 Optimization Scenarios

Three different design-optimization scenarios have been introduced to define the process. The following logic was used while creating the optimization scenarios:

Scenario 1

In this scenario, the objective function defines the ultimate tensile strength, the ranges of the design variables are chosen considering the experimental data, and it was possible for each variable to take any real number. For example, 0 < ultrasonic power (W) < 1800, 30 < welding speed (mm/min) <80 and 900 < rotational speed (rpm) < 1200. The aim is to maximize the tensile strength of the weld material. In addition, the limits of the objective function can be calculated with this approach.

Scenario 2

Relying on the proposed experimental setup, the more specific optimization problem can also be identified as involving the optimization of objective functions, all design constraints are assumed to be real numbers at the intervals: 0 < ultrasonic power (W) < 1800, 30 < welding speed (mm/min) < 80, and 900 < rotational velocity (rpm) < 1200. Design variables are forced to be integers, provided they comply with engineering requirements.

Scenario 3

The more detailed optimization issue may alternatively be stated as maximum tensile strength; design variables some values are chosen from experimental data and constraints are ultrasonic power ∈ {0, 600, 1000, 1400, 1800}; welding speed ∈ {30, 40, 50, 60, 70, 80}; rotational speed ∈ {900, 1000, 1100, 1200}. This scenario will allow seeing the optimum results that the proposed model produces only under certain conditions.

Table 2. *Friction Stir Welding Process Parameters[30]*

Run	***Ultrasonic Power (W)***	***Welding Speed (mm/min)***	***Rotational velocity (rpm)***	***Ultimate Tensile Strength (MPa)***
1	0	30	900	71
2	0	30	1000	77
3	0	30	1100	53
4	0	40	900	109
5	0	40	100	126
6	0	40	1200	66
7	0	50	900	122
8	0	50	100	134
9	0	50	1100	119
10	0	60	900	147
11	0	60	1000	137
12	0	60	1100	117
13	0	70	1000	118
14	0	70	1100	110
15	0	80	1100	79
16	600	30	1000	94
17	600	60	1000	131
18	600	80	1000	58
19	1000	30	1000	115
20	1000	60	1000	133
21	1000	80	1000	87
22	1400	30	1000	13
23	1400	60	1000	152
24	1400	80	1000	134
25	1800	30	1000	92
26	1800	60	1000	120
27	1800	80	1000	80

3. Results and Discussion

In this study, ten different regression models for ultrasonic power, welding speed, and rotational speed in friction stir welding joints were tested with three different 'goodness of the fit' measures, , $R^2_{training}$, $R^2_{testing}$, $R^2_{validation}$. Table 3 shows the mathematical models used in the neuro-regression analysis for the related process parameters in friction stir welding connections. Optimum parameters x1, x2, and x3 correspond to ultrasonic power, welding speed, and rotational speed. Models with the highest R^2 values define the relationship between response and reality better than other models. When the table is examined, it is seen that $R^2_{testing}$, and $R^2_{validation}$ values in some models are not close to 1 or have negative values. This situation also showed that high

$R^2_{training}$ values alone could not describe the phenomenon. In addition, negative coefficients indicate that the model cannot be described as statistically significant. Accordingly, the results show that the most reliable model is Quadratic Trigonometric Multiple Nonlinear (SOTN), as the values of $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$are 0.995, 0.806, and 0.846, respectively. When the SOTN model is examined in terms of tensile strength, the negative minimum tensile strength value may not be considered appropriate. However, considering the models where the minimum or maximum ultimate tensile strength values are asymptotically infinite, this can be considered positive for the stability of the model. As a result, tensile strength values are acceptable and within reasonable limits.

Optimization results of the process parameters in ultimate tensile strength according to three different scenarios with different constraints are presented in Table 4. Using the SOTN model, design parameters that maximize tensile strength were determined for each scenario using four different algorithms: MRS, MDE, MSA, and MNM. The intervals of scenario 1 were chosen considering the limits of the experimental study, and each variable took a real value. It obtained more successful results in terms of tensile strength in this scenario.

While the maximum tensile strength was the same in MRS, MNM, and MDE algorithms, MSA was different. In addition, it is seen that the design parameters that provide the maximum tensile strength are given within limits and as real numbers. In Scenario 2, some design variables were forced to be integers while getting the optimization results, provided they comply with the engineering requirements. The results showed that the MDE algorithm for scenario 2 gives better results than the other three algorithms. In scenario 3, the optimum results produced by the model were values that will be seen only under certain conditions, and the final tensile strength values for all algorithms are the same. The optimization results of the ultimate tensile strength parameter show that the maximum tensile strength in the three algorithms of scenario 1 (MRS, MNM, MDE) is 182.301 MPa, and in the MDE algorithm of the second scenario, 182.237MPa. However, it can be said that the insufficient solutions in the 2nd and 3rd scenarios are due to the restrictions made compared to the Scenario 1. In general, it can be said that all algorithms have acceptable results within limitations, although it is clear that MDE produces more successful outcomes in scenarios 1 and 2. Finally, the results reveal that the Ultimate Tensile Strength can be maximized to 182.301MPa for the following optimal conditions; Ultrasonic Power: 186.938 W, Welding Speed: 40.6854 mm/m inch, Rotation Speed: 1075.3.

Table 3. *Results of the Neuro-regression models in terms of fitting performance and boundedness.*

Models	$R^2_{training}$	$R^2_{testing}$	$R^2_{validation}$	Max. Ultimate Tensile Strength	Min. Ultimate Tensile Strength
Y = 231.84 + 0.000495499 x1 + 0.328724 x2 - 0.133415 x3	0.977	-0.246	0.352	138.956	65.587
Y = (2.1144*10^-8 + 3227.18 x1 + 2.46248*10^-9 x2 - 9.74408*10^-11 x3)/(1.90369*10^-11 + 27.7249 x1 + 2.06805*10^-11 x2 - 6.7093*10^-13 x3)	0.990	-1.753	-0.552	116.4	116.4
Y = -1140.89 - 0.0163631 x1 + 0.0000410955 x1^2 + 6.47544 x2 + 3.00384*10^-6 x1 x2 - 0.0729875 x2^2 + 2.20297 x3 - 0.0000163631 x1 x3 + 0.00154806 x2 x3 -0.00114843 x3^2	0.995	-1.2903	0.884	209.015	40.685
Y = (2.01217 + 12.7823 x1 - 8352.59 x1^2 + 30.4753 x2 - 50552.6 x1 x2 + 769.567 x2^2 + 760.715 x3 + 11783.3 x1 x3 + 20432.3 x2 x3 - 198.539 x3^2)/(46.4385 + 1.09301 x1 - 69.1329 x1^2 + 2368.52 x2 - 371.918 x1 x2 + 4523.71 x2^2 - 3777.59 x3 + 94.0089 x1 x3 - 319.732 x2 x3 + 14.8251 x3^2)	0.995	0.004	0.975	2.289*10^12	-6.644*10^15
Y = -451.465 + 0.042831 x1 - 0.0000123597 x1^2 - 4.05251*10^-8 x1^3 - 53.6399 x2 - 0.00196325 x1 x2 + 2.66068*10^-6 x1^2 x2 - 0.577702 x2^2 + 0.00234579 x2^3 + 2.77865 x3 + 0.000042831 x1 x3 + 0.163982 x2 x3 - 1.96325*10^-6 x1 x2 x3 + 0.0001186 x2^2 x3 - 0.0051376 x3^2 + 4.2831*10^-8 x1 x3^2 - 0.0000818925 x2 x3^2 + 2.38379*10^-6 x3^3	0.999	-1.302	0.983	199.449	-14.859

Y = 46.9925 - 10.1483 Cos[x1] - 4.58153 Cos[x2] + 37.2763 Cos[x3] - 8.31784 Sin[x1] + 11.8687 Sin[x2] + 77.3452 Sin[x3]	0.982	-0.415	0.436	158.696	-64.711
Y = (-5372.22 + 102.542 Cos[x1] - 189.613 Cos[x2] + 5924.52 Cos[x3] + 1.28016 Sin[x1] - 604.597 Sin[x2] + 1654.09 Sin[x3])/(-42.3369 + 0.884183 Cos[x1] - 1.73952 Cos[x2] + 47.6956 Cos[x3] + 0.017317 Sin[x1] - 4.97124 Sin[x2] + 12.0455 Sin[x3])	0.999	-0.137	-0.400	1.962*10^13	-4.396*10^11
Y = 5.11515 + 1.02361 Cos[x1] - 1.76996 Cos[x1]^2 - 1.41558 Cos[x2] + 27.9902 Cos[x2]^2 + 11.9876 Cos[x3] + 43.7613 Cos[x3]^2 - 12.4817 Sin[x1] + 31.5856 Sin[x1]^2 + 12.1898 Sin[x2] - 10.7053 Sin[x2]^2 + 114.622 Sin[x3] - 18.5691 Sin[x3]^2	0.995	0.806	0.846	182.301	-155.226

Y = (20.8944 + 7.67565 Cos[x1] + 0.826635 Cos[x1]^2 + 77.4142 Cos[x2] + 41.7063 Cos[x2]^2 + 23.7181 Cos[x3] + 25.2186 Cos[x3]^2 + 12.9568 Sin[x1] + 21.0678 Sin[x1]^2 + 35.4982 Sin[x2] -19.8119 Sin[x2]^2 + 2.71789 Sin[x3] - 3.32416 Sin[x3]^2)/(-0.204871 + 0.118014 Cos[x1] + 0.312046 Cos[x1]^2 + 0.637254 Cos[x2] + 0.632187 Cos[x2]^2 + 0.416064 Cos[x3] + 0.0173435 Cos[x3]^2 + 0.112826 Sin[x1] + 0.483083 Sin[x1]^2 + 0.274419 Sin[x2] + 0.162942 Sin[x2]^2 - 1.06296 Sin[x3] + 0.777785 Sin[x3]^2)	0.999	-19.814	0.273	2.002*10^13	-2.322*10^15
Y = 116.852 - 8.06062 Sin[x1] + 13.2376 Sin[x1]^2 - 12.1903 Sin[x1]^3 + 101.768 Sin[x2] - 127.618 Sin[x2]^2 - 129.696 Sin[x2]^3 - 6.4981 Sin[x1 x2] + 24.6749 Sin[x1^2 x2] + 60.2451 Sin[x3] + 204.718 Sin[x3]^2 - 232.073 Sin[x3]^3 - 25.3439 Sin[x1 x3] - 21.149 Sin[x2 x3] - 3.96789 Sin[x1 x2 x3] - 16.2345 Sin[x2^2 x3] + 15.4914 Sin[x1 x3^2] - 10.6171 Sin[x2 x3^2]	1.	-0,405	0.868	577.338	-67.726

Table 4. *Results of optimization problems for the selected models.*

Objective Functions	*Scenario Number*	*Constraints*	*Optimization Algorithm*	*Ultimate Tensile Strength*	*Suggested Design*
SOTN	1	0 < x1 < 1800, 30 < x2 < 80, 900 < x3 < 1200	MSA	173.611	x1 = 1299.06, x2 = 75.559, x3 = 900.
			MRS	182.301	x1 = 186.938, x2 = 40.685, x3 = 1075.34
			MNM	182.301	x1 = 557.646, x2 = 65.818, x3 = 1100.47
			MDE	182.301	x1 = 903.221, x2 = 59.535, x3 = 1031.36
	2	0 < x1 < 1800, 30 < x2 < 80, 900 < x3 < 1200, {x1, x2, x3} \[Element] Integers	MSA	177.183	x1 = 300, x2 = 47, x3 = 1075
			MRS	143.972	x1 = 590, x2 = 66, x3 = 1100
			MNM	169.919	x1 = 614, x2 = 72, x3 = 1100
			MDE	182.237	x1 = 1054, x2 = 47, x3 = 912
	3	x1 == 0 || x1 == 600 || x1 == 1000 || x1 == 1400 || x1 == 1800, x2 == 30 || x2 == 40 || x2 == 50 || x2 == 60 || x2 == 70 || x2 == 80, x3 == 900 || x3 == 1000 || x3 == 1100 || x3 == 1200	MSA	167.648	1 = 1400., x2 = 50., x3 = 1000.
			MRS	167.648	x1 = 1400, x2 = 60, x3 = 1000
			MNM	167.648	x1 = 1400, x2 = 60, x3 = 1000
			MDE	167.648	x1 = 1400, x2 = 60, x3 = 1000

4. Conclusions

This paper aimed to design optimization based on nonlinear multiple neuro regression analysis to maximize ultimate tensile strength in friction stir welding joints using Mathematica software.

After modeling the ultimate tensile strength using process variables, the following conclusions may be drawn:

- This is the first study on the optimal design of the operating parameters of the friction stir welding joint with a comprehensive neuro-regression analysis.
- 10 different regression models were evaluated, and the most suitable one (SOTN) for the output was selected. The $R^2_{training}$, $R^2_{testing}$, and $R^2_{validation}$ values of the models have acceptable levels.
- It has been shown that neuro-regression models with only high $R^2_{training}$, values are unsuitable and reliable in engineering, even if they give reasonable results. For this reason, it is suggested that $R^2_{testing}$, and $R^2_{validation}$should be close to 1 for real-life applications.
- The optimization results were influenced by the different scenario types and the selection of constraints for design variables.
- Although it is clear that MDE produces more successful results in scenarios 1 and 2, it can be said that all algorithms have acceptable results. Ultrasonic power: 186.938 W, Welding Speed: 40.685 mm/min, and Rotational Velocity: 1075.3 were found for ultimate tensile strength of 182. 301Mpa.
- It has also been shown that trigonometric models (SOTN) can be used to determine the input parameters of friction stir welding joints. Maximizing the ultimate tensile strength with the collaboration of stochastic optimization methods (MDE, MNM, MRS, MSA) is appropriate.

Declaration of Interest

The authors declare that there is no conflict of interest.

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