Visual Abstract

Optimization of the tensile strength of friction stir welded heat treatable aluminum alloy by using bio-inspired artificial intelligence algorithms

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ABSTRACT. The concepts and inspiration of biological evolution in nature are used to create new and effective competing tactics in the burgeoning field of bio-inspired computing optimization algorithms. In the present work, nine specimens of similar alloys i.e., AA6262 were Friction Stir Welded. Tool Rotational Speed (RPM), Traverse Speed (mm/min), and Plunge Depth (mm) were the input parameters while the Ultimate Tensile Strength (MPa) was an output parameter. The main objective of the work is to obtain the maximum optimized Ultimate Tensile Strength (MPa) by using Bio-Inspired Artificial Intelligence Algorithms i.e., Differential Evolution and Max Lipschitz optimization (Max LIPO) Algorithm. The results showed that the Differential Evolution algorithm resulted in a slightly higher value of the Ultimate Tensile Strength of 184.87 MPa in comparison to the Max LIPO algorithm which resulted in the Ultimate Tensile Strength value of 183.94 MPa.

KEYWORDS. Artificial Intelligence; Bio-Inspired Algorithms; Friction Stir Welding; Ultimate Tensile Strength; Optimization

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INTRODUCTION

A revolving tool generates frictional heat during friction stir welding (FSW), a solid-state joining technique that is used to fuse materials. The non-consumable tool is turned and inserted into the joint between two work parts. It has a contoured probe and shoulder [1-3]. The substance then heats up and softens as it moves along the joint line. This plasticized substance, which is mechanically combined to form a solid phase weld, is likewise contained by the shoulder. Whether cast, rolled, or extruded, aluminum alloys of all types are joined via this technique most frequently in industry [4-

9]. According to the alloy grade and machine capacity, FSW has been demonstrated to weld aluminum alloy butt joints with a thickness somewhere between 0.3mm and 75mm in a single cycle.

Industrial optimization is a comprehensive discipline that enables producers to move as rapidly and waste-free as feasible from prototyping through mass production and beyond. It's a data-driven acceptance of a superior method that makes use of cutting-edge technology and is supported by mathematics [10-13]. The goal of optimization is to arrive at the "optimal" design in relation to a list of prioritized requirements or restrictions. Maximizing elements like productivity, strength, dependability, lifespan, efficiency, and usage is one of these. In general, all machine learning algorithms (such as classification, clustering, and regression) are introduced in order to address a class of optimization issues known as data fitting. Minimizing the amount of error between the expected and actual results is one of the main objectives of training a machine learning system. [14-20] A loss or cost function, typically defines the difference between the expected and actual value of data, can be used to measure optimization.

Du et al. [21] looked through 114 sets of test data for three commonly used alloys to determine the hierarchy of causative causes for tool failure. Using three decision tree-based methodologies, the relative influence of six key friction stir welding factors on tool failure was ranked. The maximal shear stress is discovered to be the main cause of tool failure. Du et al. [22] examined the conditions that result in void development using a decision tree and a Bayesian neural network. Three different types of input data sets, including raw welding parameters and computational variables, were used to examine friction stir welding. Three different aluminum alloys, AA2024, AA2219, and AA6061, were friction stir welded, and 108 different sets of experimental findings on void formation were assessed. The neural network-based approach used the welding parameters, specimen and tool combinations, and material parameters as input to forecast the void production with an accuracy of 83.3%. Polyphenylene sulfide (PPS) and aluminum alloy 7475 sheets were attached together using friction stir welding (FSW) in a lap joint configuration. The response surface methods-created design matrix has been used in a number of FSW studies. The tensile lap shear strength (TLS) for each experimental run is calculated. Investigated was how well machine learning methods might predict the joint's TLS. The most effective method for predicting the TLS was found to be the support vector machine (SVM) framework with RBF kernel [23]. Guan et al. [24] provided a method for creating machine learning models driven by force data that accurately anticipate faults and their categories in friction stir welding (FSW). The machine learning algorithms created using the input of 15 force variables were 98.0% accurate at classifying defects as tunnels and porosities and 95.8% accurate at detecting flaws. Nadeau et al. [25] examined the effectiveness of various machine learning techniques on a friction stir welding cell environment, including principal component analysis, K-nearest neighbor, multilayer perceptron, single vector machine, and random forest techniques. The input variables from this cell environment are specifically separated into two groups: the application variables and the friction stir welding process variables. The application factors focus on the chemical composition, joint configuration, sheet thicknesses, initial mechanical qualities, and aluminum alloys.

From literature survey, it is observed that there are limited number of papers which have employed Bio-Inspired Artificial Intelligence Algorithms for the optimization of mechanical property of Friction Stir Welded AA6262 joints. The most common applications for AA6262 are in the details of car brake systems, structural elements for civil constructions, railways, and street heavy vehicles. In the present study, two Bio-Inspired Algorithms i.e., Differential Evolution and Max Lipschitz optimization (Max LIPO) Algorithm are deployed for the maximization of the Ultimate Tensile Strength (MPa) of the similar Friction Stir Welded AA6262 joints.

The two operations that make up differential evolution are the recombination and difference vector-based mutation operators. Each solution in this stochastic population-based method is referred to as a genome or chromosome. Each chromosome goes through mutation and recombination, which are essentially the two operators, during the process as shown in Fig. 1.

Several terminologies are important to remember. The solution that is going through evolution and is then used in mutation to produce a donor vector is called a target vector. Trial Vector is created by further mutating the Donor Vector. In order to determine which over solution is superior between Trial Vector and Target Vector, greedy solution is used. It should be remembered that choosing superior solutions only happens after creating the test vectors. A mutation operation is a pretty straightforward procedure. Eqn. 1 represents a chromosome's (X_i) donor vector (V). We must choose one of three distinct random solutions, r_1, r_2, or r_3, for this process. Scaling factor F is a fixed value between 0 and 2.

$$V = X_{r_1} + F\left(X_{r_2} - X_{r_3}\right) \tag{1}$$

From Eqn. 1, it can be shown that the Target Vector is not a part of the mutation process. Applying the recombination process comes next after the mutation process is finished. The recombination process is used to broaden the population's diversity. Eqn. 2 provides the nomenclature for the recombination process.

$$u^j = \begin{cases} v^j, \; if \; r \le p_c \; OR \; j = \delta \\ x^j, \; if \; r > p_c \; AND \; j \ne \delta \end{cases} \tag{2}$$

where r is a random number between 0 and 1, p_c is the crossover probability, and δ is the randomly chosen variable position. Where u_j is the j[th] variable of the trial vector, v_j is the j[th] variable of the donor vector, and x_j is the j[th] variable of the target vector. The equation shows that the Target Vector takes part in the recombination process. It should be noticed that a large value of p_c yields more variables from the donor vector and assures that at least one variable is retrieved from the donor vector. After receiving the trial vector, we must determine whether or not it falls within the decision variable's boundaries.

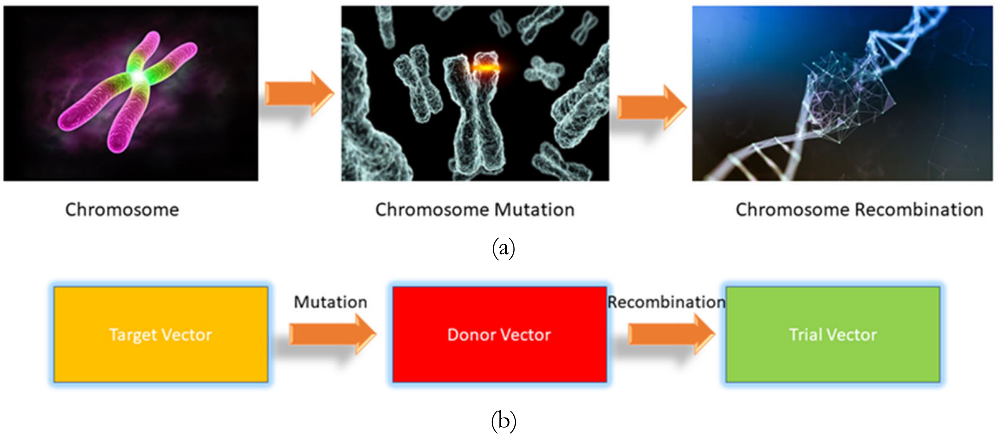


Figure 1: a) Differential Evolution process b) Obtaining Trial Vector from Target Vector

After the generation of Trial Vector, we need to evaluate the fitness function of all offspring (f_U). Population is updated by using Greedy Solution as shown in Eqn. 3.

$$if \; f_{U_i} < f_i \quad \begin{cases} X_i = U_i \\ f_i = f_{U_i} \end{cases} \tag{3}$$

It is observed that the X and f remains the same if $f_{U_i} > f_i$.

Now let's discuss about LIPO Algorithm. Let $A \subseteq \mathbb{R}$ *and* $f: A \to \mathbb{R}$ and f *is Lipschitz on* A *if there exists* $K \in \mathbb{R}$ such that for each $x, y \in A$ the Eqn. 4 is satisfied.

$$\left| f(x) - f(y) \right| \le K \left| x - y \right| \tag{4}$$

Eqn. 4 can be rearranged and can be written as Eqn. 5.

$$\left| \frac{f(x) - f(y)}{x - y} \right| \le K \tag{5}$$

It is deduced from the Eqn. 5 that slope of any secant line to f lies between -K and +K.

The notion of Lipschitz function can be generalized to higher dimensions. Let's say $A \subseteq \mathbb{R}^n$ *and* $f: A \to \mathbb{R}^n$. f is Lipschitz on A if K>0 and Eqn. 6 is satisfied.

$$\left[\sum_{i=1}^{n} \left[f_i(\vec{x}) - f_i(\vec{y}) \right]^2 \right]^{\frac{1}{2}} \le K \left[\sum_{j=1}^{n} \left(x_j - y_j \right)^2 \right]^{\frac{1}{2}} \tag{6}$$

It is observed that the Lipschitz functions are suitable to incorporate as a Machine Learning algorithm because the predicted values $f(\vec{x})$ *and* $f(\vec{y})$ are as close as K times how close $\vec{x}$ *and* $\vec{y}$ are as observed from Eqn. 6.

MATERIALS AND METHODS

Friction Stir Welding is a solid-state joining process that is used to fuse those alloy components mainly of aluminium alloys which are difficult to weld by another conventional welding process. In the Friction Stir Welding process, a tool is used whose material is harder than the base alloy to be joined. Fig. 2 shows the process set of the vertical milling machine where the AA6262 alloy plates of dimensions 100 mm X 50 mm X 6mm are clamped on the vertical milling machine where Friction Stir Welding is carried out.

Tool Traverse Speed (mm/min), Tool Rotational Speed (RPM), and Plunge Depth (mm) were the three process parameters considered in this investigation. The FSW machine from RV Machine Tool was used to produce a variety of joints with settings that were continuously updated. Aluminum alloy 6262 plates measuring 100 mm long, 50 mm broad, and 6 mm thick are used to create the test specimens both before and after welding. The tool configuration used in the research investigation is shown in Fig. 3. Tab. 1 lists the ingredients that make up AA 6262 based on Matweb database. The physical and mechanical properties of AA6262 alloy is shown in Tab. 2. The input and output parameters for the current investigation are shown in Tab. 3. For the preparation of tensile test specimens, the ASTM E8 guidelines have been followed. A universal testing machine controlled from electromechanical means (Make: FIE, Model: UTN 40) was used for assessing the specimen's tensile properties.

Figure 2: Friction Stir Welding process setup

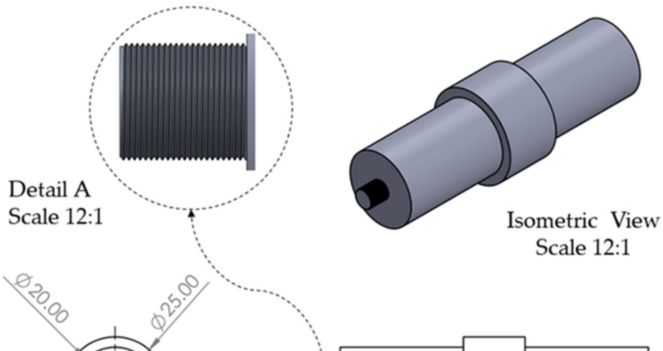


Figure 3: FrictionStir Welding Tool Design used in the present work

Si	Fe	Cu	Cr	Mn	Mg	Zn
0.4-0.8	0.0-0.7	0.4-1.4	0.0-0.2	0.0-0.15	0.8-1.2	0.0-0.25

Table 1: Chemical Composition of Aluminium alloy 6262 (wt%).

Density	Young's Modulus	Ultimate Tensile Strength	Yield Strength
2.72 g/cm^3	69 GPa	280 MPa	260 MPa

Table 2: Physical and Mechanical properties of Aluminium alloy 6262.

S.No	Sample ID	Tool rotational speed (rpm)	Tool traverse speed (mm/min)	Plunge depth (mm)	Ultimate Tensile Strength (MPa)
1.	Sample 1	800	40	0.1	167.47
2.	Sample 2	800	50	0.2	188.51
3.	Sample 3	800	60	0.3	164.80
4.	Sample 4	1000	40	0.2	165.4
5.	Sample 5	1000	50	0.3	186.32
6.	Sample 6	1000	60	0.1	171.66
7.	Sample 7	1200	40	0.3	188.90
8.	Sample 8	1200	50	0.2	179.94
9.	Sample 9	1200	60	0.1	176.75

Table 3: Experimental Parameters for preparation of specimens and obtained UTS value.

Now, the next step is to implement the Bio-inspired algorithms on the obtained data. Firstly, data from the research investigation is gathered. The dataset is set up in a CSV (comma-separated values) file format. The Google Colab platform is then imported using the CSV file. For carrying out the necessary activities, Python libraries including pandas, NumPy, seaborn, and matplotlib.pyplot were imported. The work's process procedure is depicted in Fig. 4.

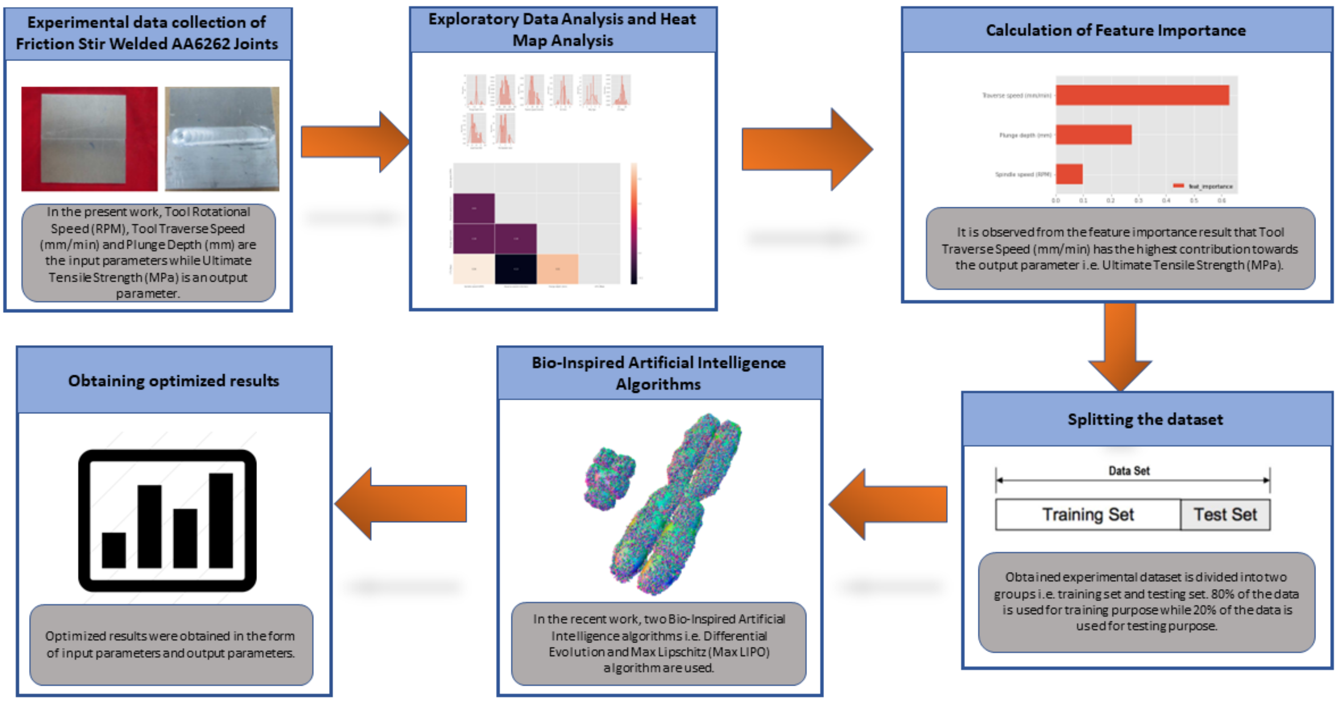


Figure 4: Implementation of the Bio-Inspired Algorithms on the experimental dataset

Exploratory data analysis (EDA), which is frequently used to discover what data might reveal more than the standard modeling or hypothesis assignment, aids in a complete understanding of the variables in the data collection and their interactions. As seen in Fig. 5, it can also help you decide whether the statistical techniques you're thinking about applying for data analysis are appropriate. The resultant plot of the Heat Map is displayed in Fig. 6. To illustrate the level of correlation between multiple factors, statistical coefficients are presented as a heat map. It helps to find characteristics that are best for developing machine learning models. The heat map transforms the correlation matrix into a color designation.

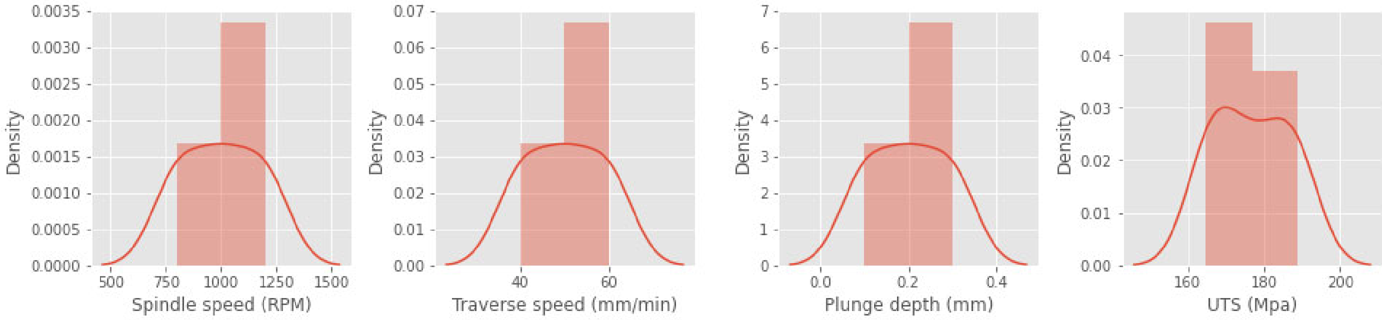


Figure 5: Results obtained from Exploratory Data Analysis.

The next stage is to determine whether input parameters have a strong correlation with the output parameter, or the Ultimate Tensile Strength, by determining the feature importance. The 80/20 rule is then used to divide the dataset into two portions, with 20% of the data being used for testing and 80% being used for training.

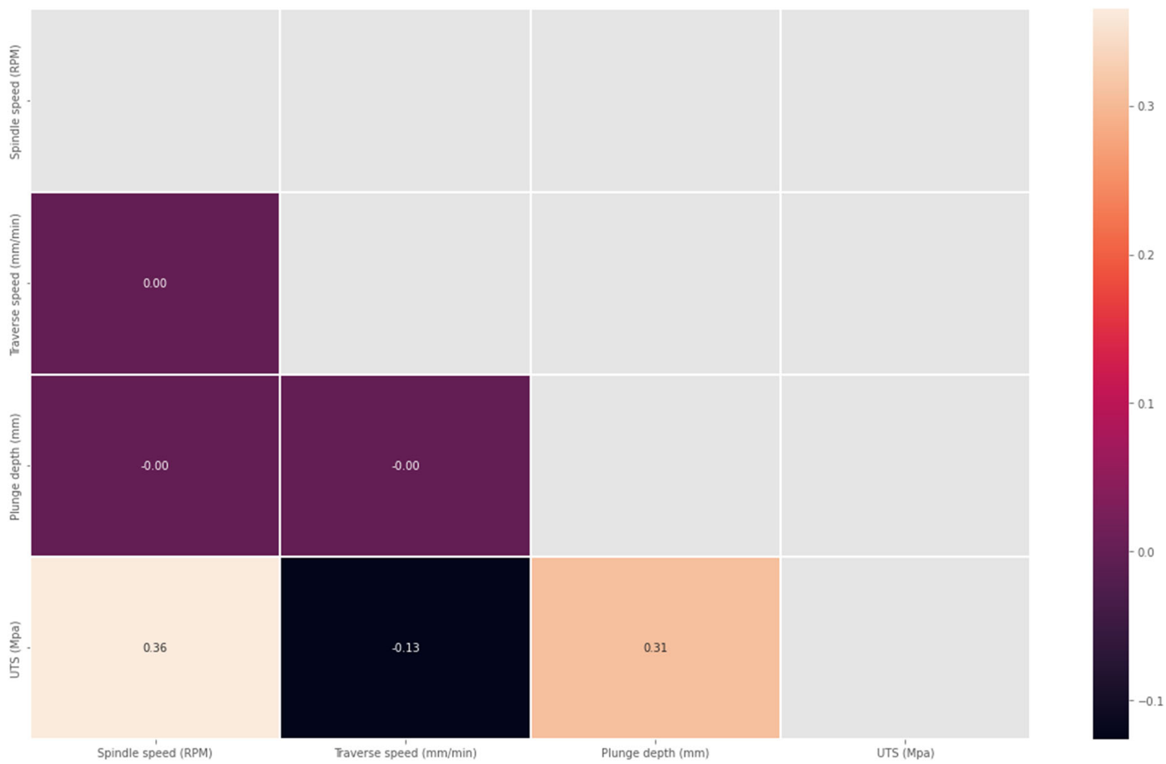
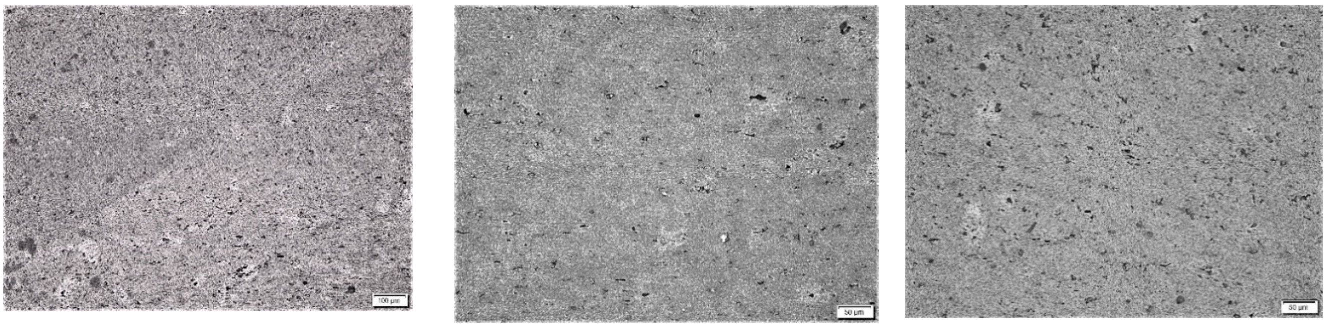


Figure 6: Heat Map Plot.

RESULTS AND DISCUSSION

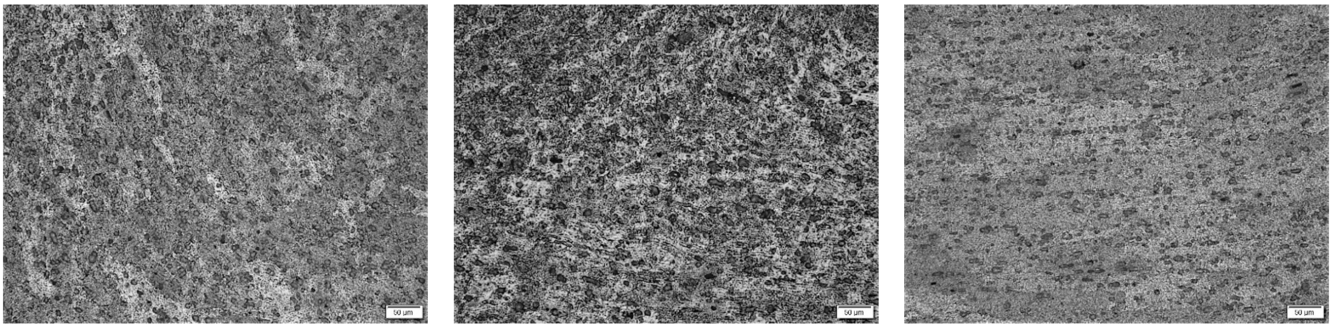
Microstructure analysis

For microstructure analysis, Olympus (BX41M) equipment was used. The microstructure of AA6062 shows $AlMg_2Si$ precipitates with in the base material and in HAZ and showing TMAZ, HAZ at higher magnifications. Fig. 7 shows the Thermo Mechanically Affected Zone (TMAZ) microstructure obtained for the nine samples. The elongated and bigger grains, which are thermally impacted by heat and rotating pin, are seen in the TMAZ. Fig. 8 shows the microstructure images in the Stir Zone (SZ). Due to dynamic recrystallization caused by friction stir welding, the stir zone is characterized by extremely small, equi-axed grains that are far smaller than those seen in the Heat Affected Zone (HAZ) and TMAZ. It has been noted that the particle size in HAZ is significantly larger than the grain size of the base substrate and is about twice as coarse as the grain size of the base metal as observed from Fig. 9.



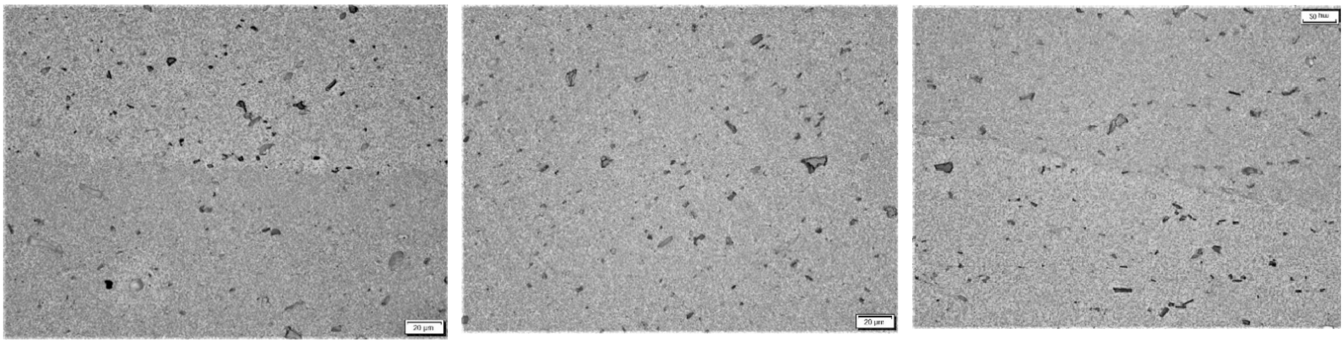
Sample 1 Sample 2 Sample 3

Sample 4 Sample 5 Sample 6



Sample 7 Sample 8 Sample 9

Figure 7: TMAZ Microstructures.



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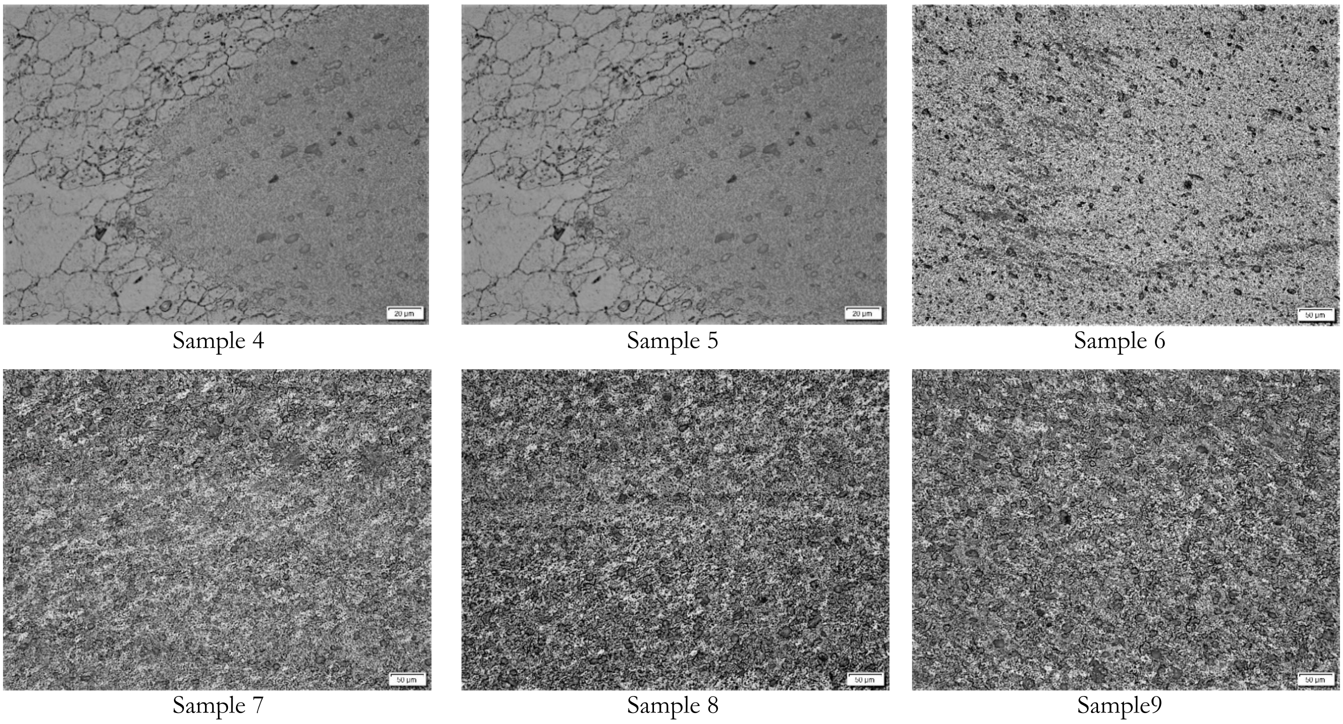
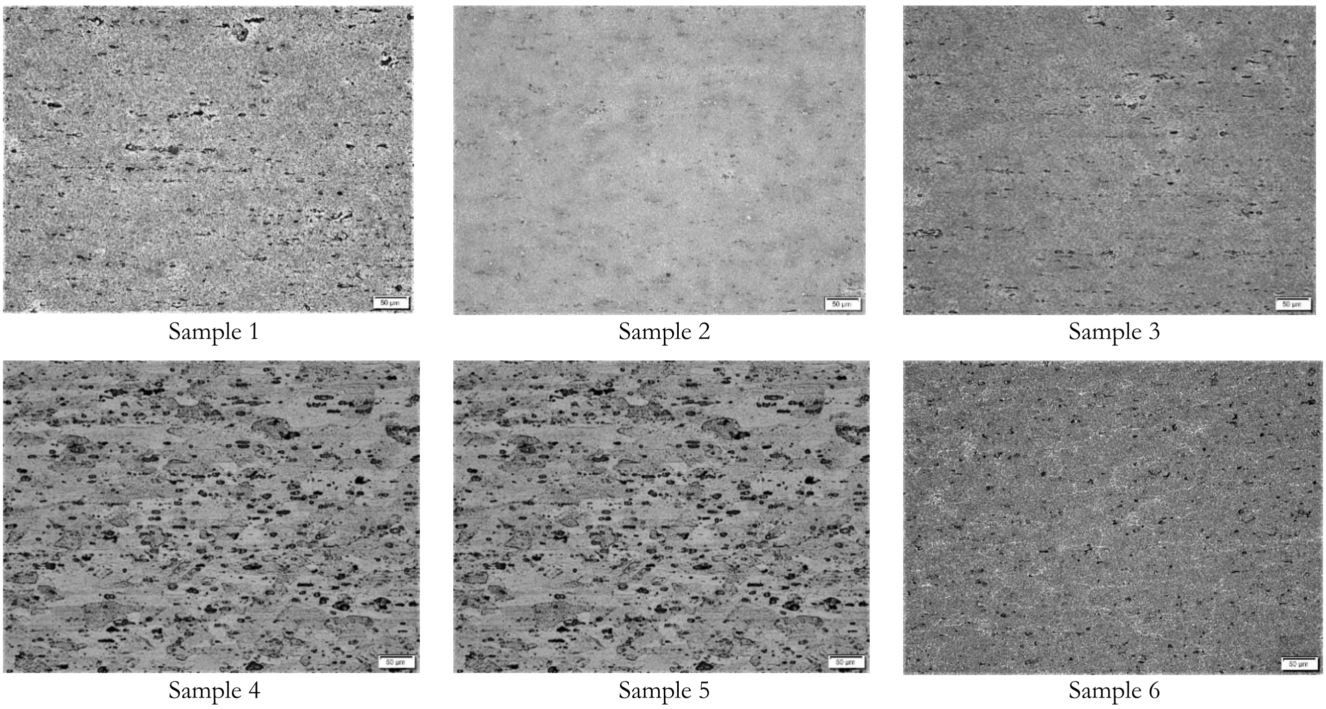
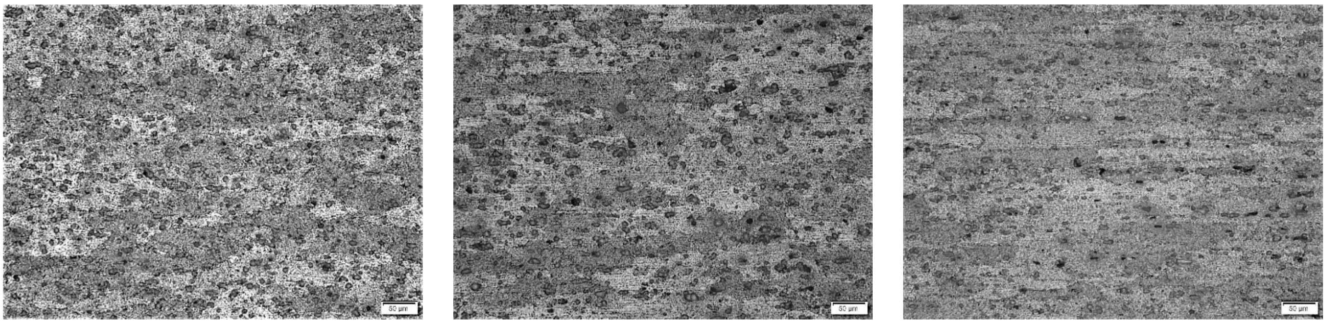


Figure 8: Microstructure images of Stir Zone.



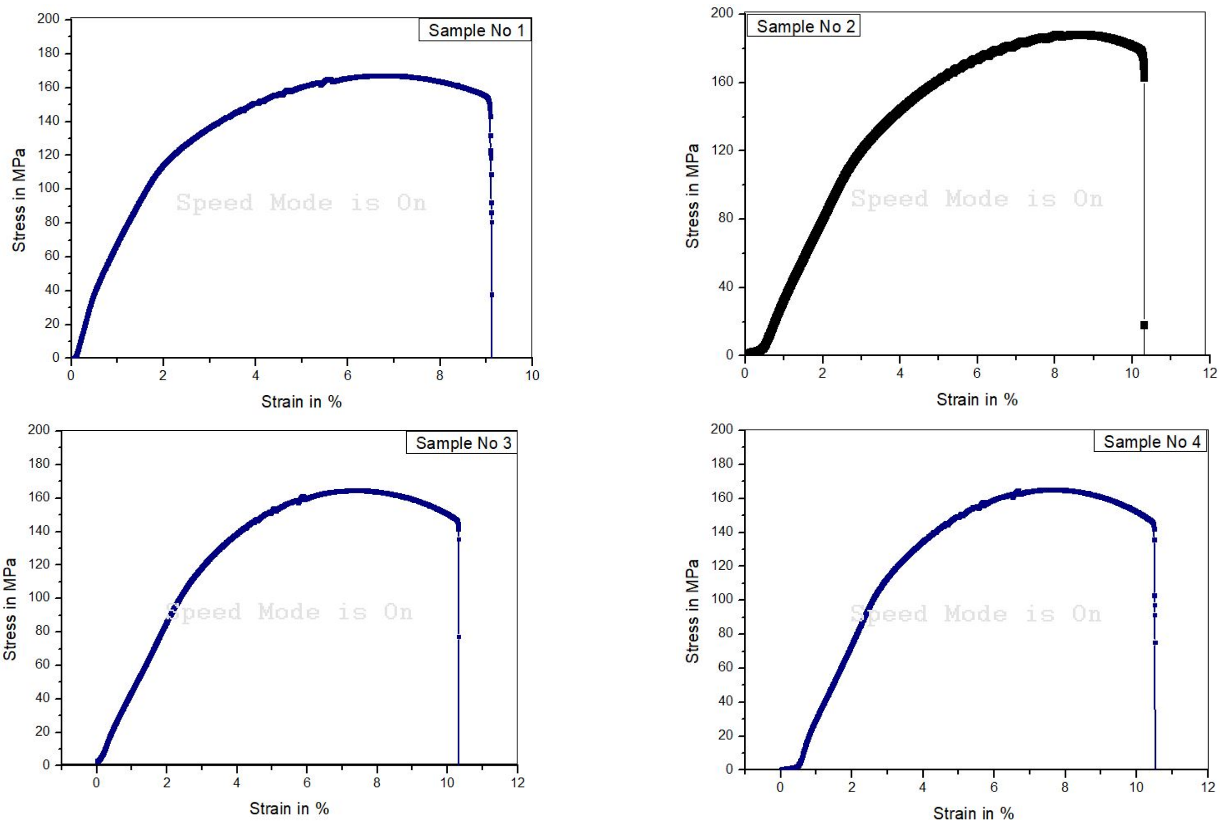


Sample 7 Sample 8 Sample 9

Figure 9: Microstructure images of Heat Affected Zone.

Structural Stress Analysis

The welds' resistance to structural stress was evaluated. This required taking tensile samples out of the welded joints. Since the attributes associated with the various weld locations vary most in the transverse plane of the FSWs, this direction was chosen for research. The degree of softening and recrystallization within the weld nugget will be partially revealed by the tensile test. Fig. 10 shows the obtained stress strain curves for the weld specimens. According to ASTM requirements, the load was applied at a steady rate of 1.5 KN/min, causing the tensile specimen to deform. After necking and recording the load versus displacement, the specimen ultimately fails.



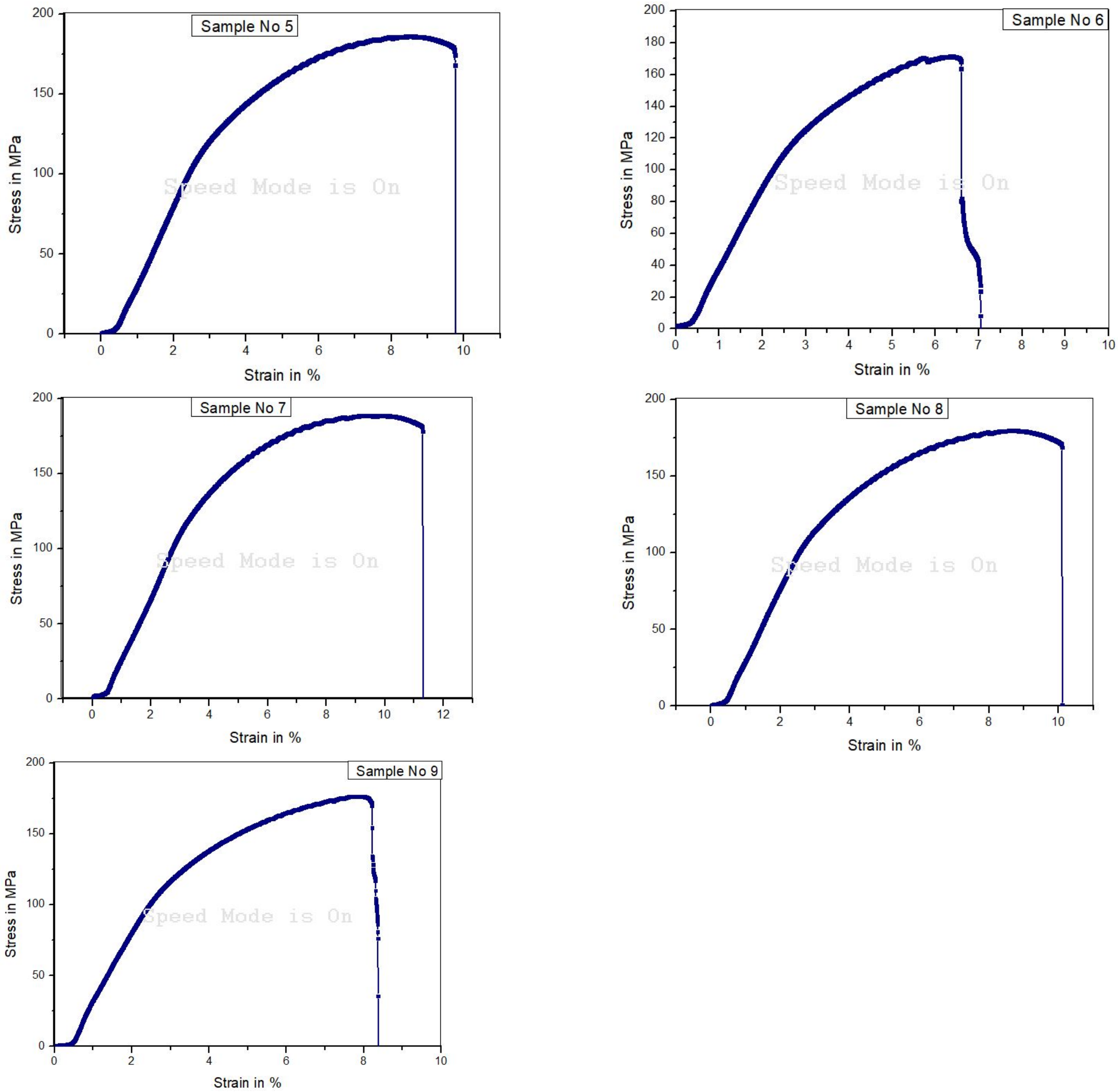


Figure 10: Structural Stress-Strain Properties.

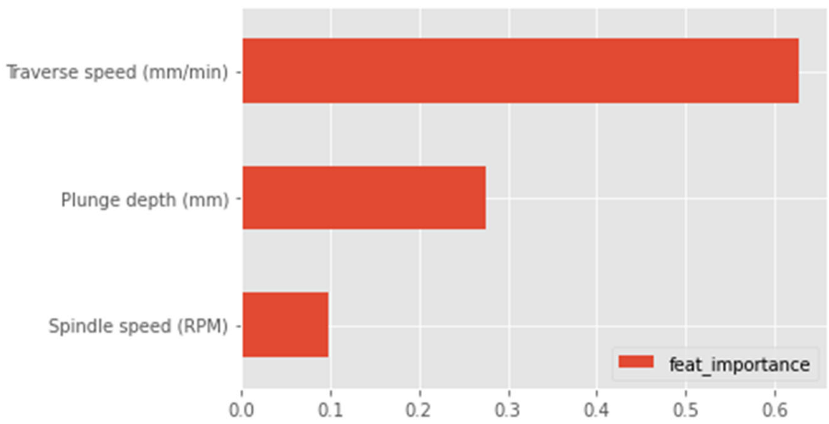


Figure 11: Feature Importance Results.

Optimization analysis

The results of the acquired feature importance analysis are shown in Fig. 11, and it can be seen that the output parameter is highly dependent on the tool traverse speed (mm/min) which is followed by the Plunge depth.
The high dependence of Ultimate tensile strength of the friction stir welded joints on the tool traverse speed can be verified from the Ramachandran et al. [26] study work.
The obtained optimized results are indicated in Tab. 4.

Algorithms	Tool Traverse Speed (mm/min)	Tool Spindle Speed (RPM)	Plunge Depth (mm)	Ultimate Tensile Strength (MPa)
Differential Evolution	52.75	1124.21	0.29	184.87
Max LIPO	54.25	1175.30	0.29	183.94

Table 4: Obtained optimized results

Differential evolution (DE), a population-based metaheuristic search method, optimizes a problem by repeatedly developing a potential solution based on an evolutionary process, it is observed. Such algorithms can swiftly explore very large design spaces and make few, if any, assumptions about the underlying optimization problem. DE employs a heuristic, just like all evolutionary algorithms, hence my explanation will be a little flimsy. Like any evolutionary algorithms, DE aims to conduct a random search that isn't too arbitrary. The mutation operator in DE first evaluates the vector between two randomly chosen population members, after which it adds that vector to a third randomly chosen population member. This works well since it makes use of the current population to determine the size and direction of the step to be taken. It is fair to take large steps when the population is spread; nevertheless, it is reasonable to take tiny steps when the population is densely populated.

CONCLUSION

In the present work, similar joints of AA6262 alloys were joined by Friction Stir Welding process. The present work carried out the implementation of the Bio-Inspired Artificial Intelligence Algorithm on the experimental dataset successfully. Following conclusions are made:

- From Feature importance results it is observed that the Tool Traverse Speed (mm/min) has highest impact on the output parameter i.e., Ultimate Tensile Strength (MPa).
- The elongated and bigger grains, which are thermally impacted by heat and rotating pin, are seen in the TMAZ microstructure images.
- Due to dynamic recrystallization caused by friction stir welding, the stir zone is characterized by extremely small, equi-axed grains that are far smaller than those seen in the Heat Affected Zone (HAZ) and TMAZ.
- It has been noted that the particle size in HAZ is significantly larger than the grain size of the base substrate and is about twice as coarse as the grain size of the base metal.
- The future scope of the work is to compare the results with the results of other Bio-Inspired Algorithms and to conclude which of the algorithm is best for the investigation.

REFERENCES

[1] Heidarzadeh, A., Mironov, S., Kaibyshev, R., Çam, G., Simar, A., Gerlich, A., Khodabakhshi, F., Mostafaei, A., Field, D.P., Robson, J.D. and Deschamps, A., (2021). Friction stir welding/processing of metals and alloys: a comprehensive review on microstructural evolution. Progress in Materials Science, 117, p.100752.
[2] Kumar Rajak, D., Pagar, D.D., Menezes, P.L. and Eyvazian, A., (2020). Friction-based welding processes: friction welding and friction stir welding. Journal of Adhesion Science and Technology, 34(24), pp. 2613-2637.
[3] Singh, V.P., Patel, S.K., Ranjan, A. and Kuriachen, B., (2020). Recent research progress in solid state friction-stir welding of aluminium–magnesium alloys: a critical review. Journal of Materials Research and Technology, 9(3), pp. 6217-6256.

[4] Isa, M.S.M., Moghadasi, K., Ariffin, M.A., Raja, S., bin Muhamad, M.R., Yusof, F., Jamaludin, M.F., bin Yusoff, N. and bin Ab Karim, M.S., (2021). Recent research progress in friction stir welding of aluminium and copper dissimilar joint: a review. Journal of Materials Research and Technology, 15, pp. 2735-2780.
[5] Jesus, J.S., Costa, J.M., Loureiro, A. and Ferreira, J.M., (2018). Assessment of friction stir welding aluminium T-joints. Journal of Materials Processing Technology, 255, pp. 387-399.
[6] Ramamurthy, M., Balasubramanian, P., Senthilkumar, N. and Anbuchezhiyan, G., (2022). Influence of process parameters on the microstructure and mechanical properties of friction stir welds of AA2014 and AA6063 aluminium alloys using response surface methodology. Materials Research Express, 9(2), p.026528.
[7] Iqbal, M.P., Tripathi, A., Jain, R., Mahto, R.P., Pal, S.K. and Mandal, P., (2020). Numerical modelling of microstructure in friction stir welding of aluminium alloys. International Journal of Mechanical Sciences, 185, p.105882.
[8] Sinhmar, S. and Dwivedi, D.K., (2019). Effect of weld thermal cycle on metallurgical and corrosion behavior of friction stir weld joint of AA2014 aluminium alloy. Journal of Manufacturing Processes, 37, pp. 305-320.
[9] Leon, J.S., Bharathiraja, G. and Jayakumar, V., (2020). A review on friction stir welding in aluminium alloys. In IOP Conference Series: Materials Science and Engineering 954(1), p. 012007. IOP Publishing.
[10] Kochenderfer, M.J. and Wheeler, T.A., (2019). Algorithms for optimization. Mit Press.
[11] Yang, T., Yi, X., Wu, J., Yuan, Y., Wu, D., Meng, Z., Hong, Y., Wang, H., Lin, Z. and Johansson, K.H., (2019). A survey of distributed optimization. Annual Reviews in Control, 47, pp. 278-305.
[12] Sun, S., Cao, Z., Zhu, H. and Zhao, J., (2019). A survey of optimization methods from a machine learning perspective. IEEE transactions on cybernetics, 50(8), pp. 3668-3681.
[13] Zhan, Z.H., Shi, L., Tan, K.C. and Zhang, J., (2022). A survey on evolutionary computation for complex continuous optimization. Artificial Intelligence Review, 55(1), pp. 59-110.
[14] Martins, J.R. and Ning, A., (2021). Engineering design optimization. Cambridge University Press.
[15] Jin, Y., Wang, H., Chugh, T., Guo, D. and Miettinen, K., (2018). Data-driven evolutionary optimization: An overview and case studies. IEEE Transactions on Evolutionary Computation, 23(3), pp. 442-458.
[16] Lan, G., (2020). First-order and stochastic optimization methods for machine learning (p. 123). New York: Springer.
[17] Feurer, M. and Hutter, F., (2019). Hyperparameter optimization. In Automated machine learning (pp. 3-33). Springer, Cham.
[18] Soydaner, D., (2020). A comparison of optimization algorithms for deep learning. International Journal of Pattern Recognition and Artificial Intelligence, 34(13), p.2052013.
[19] Vasant, P., Zelinka, I. and Weber, G.W., (2018). Intelligent computing & optimization. In Conference proceedings ICO p. 804.
[20] Fouad, M.M., El-Desouky, A.I., Al-Hajj, R. and El-Kenawy, E.S.M., (2020). Dynamic group-based cooperative optimization algorithm. IEEE Access, 8, pp.148378-148403.
[21] Du, Y., Mukherjee, T., Mitra, P. and DebRoy, T., (2020). Machine learning based hierarchy of causative variables for tool failure in friction stir welding. Acta Materialia, 192, pp. 67-77.
[22] Du, Y., Mukherjee, T. and DebRoy, T., (2019). Conditions for void formation in friction stir welding from machine learning. npj Computational Materials, 5(1), pp. 1-8.
[23] Sandeep, R. and Natarajan, A., (2022). Application of machine learning approaches to predict joint strength of friction stir welded aluminium alloy 7475 and PPS polymer hybrid joint. Proceedings of the Institution of Mechanical Engineers, Part C: Journal of Mechanical Engineering Science, p.09544062221090082.
[24] Guan, W., Zhao, Y., Liu, Y., Kang, S., Wang, D. and Cui, L., (2022). Force data-driven machine learning for defects in friction stir welding. Scripta Materialia, 217, p.114765.
[25] Nadeau, F., Thériault, B. and Gagné, M.O., (2020). Machine learning models applied to friction stir welding defect index using multiple joint configurations and alloys. Proceedings of the Institution of Mechanical Engineers, Part L: Journal of Materials: Design and Applications, 234(5), pp. 752-765.
[26] Ramachandran, K.K., Murugan, N. and Shashi Kumar, S., (2015). Influence of tool traverse speed on the characteristics of dissimilar friction stir welded aluminium alloy, AA5052 and HSLA steel joints. Archives of civil and mechanical Engineering, 15(4), pp. 822-830.