Research Article

Mathematical Modelling of a Friction Stir Welding Process to Predict the Joint Strength of Two Dissimilar Aluminium Alloys Using Experimental Data and Genetic Programming

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Friction stir welding (FSW) is the most popular and efficient method of solid-state joining for similar as well as dissimilar metals and alloys. It is mostly used in applications for aerospace, rail, automotive, and marine industries. Many researchers are currently working with different perspectives on this FSW process for various combinations of materials. The general input process parameters are the thickness of the plate, axial load, rotational speed, welding speed, and tilt angle. The output parameters are joint hardness, % of elongation, and impact and yield strengths. Genetic programming (GP) is a relatively new method of evolutionary computing with the principal advantage of this approach being to evaluate efficacious predictive mathematical models or equations without any prior assumption regarding the possible form of the functional relationship. This paper both defines and illustrates how GP can be applied to the FSW process to derive precise relationships between the output and input parameters in order to obtain a generalized prediction model. A GP model will assist engineers in quantifying the performance of FSW, and the results from this study can then be utilized to estimate future requirements based on the historical data to provide a robust solution. The obtained results from the GP models showed good agreement with experimental and target data at an average prediction error of 0.72%.

1. Introduction

Some metals such as aluminium and its alloys are known as nonweldable materials using traditional methods of welding and are unable to provide enough strength due to porosity in the fusion zone. However, recent improvements in welding methodology and researchers' studies have led to the development of a new welding technique known as friction stir welding (FSW) [1, 2]. In 1991, the Welding Institute, UK, invented a solid-state joining technique that was initially applied to aluminium alloys. The FSW basic concept is exceptionally plain in which a nondevourable solid-state heat-treated hard metal tool (with a pin and shoulder) is introduced into the butting ends of sheets or plates to be joined and moved along the line of joint at specific rotational speed, traverse speed, axial force, and tilt angle. This process of welding produces good-quality welding [3]. As the rotating tool is in contact with joining materials, it heats up the joint,

which further leads to plastic deformation of the joint. This process comes under the solid-state welding category as there is no weld pool formation at the joint; rather a rotary motion of the tool transfers the material to produce the joint. The different tool geometries lead to the development of various crystallization structures of grains, which finally results in a different strength of weld joint according to the type of geometry [4, 5].

1.1. Literature Review. The joining of heat-treated aluminium with non-heat-treated aluminium alloys requires using rotational tool speed, traverse speed, and tilt angle as input and hardness, tensile strength, and yield strength as output parameters. The output parameters for the dissimilar metals are difficult to achieve due to distinctive heat coefficients, the base metal chemical composition, and the properties of heat-treated aluminium and non-heat-treated aluminium alloy [6]. The study of the optimized effect of the welding

parameters on 5 mm thick AA6082 aluminium plates using ANOVA technique is based on L8 orthogonal array showing that the tool's rotational, welding, and plunge speed are the significant parameters in deciding the strengths and percentage elongation [7, 8].

FSW is a solid-state joining process, which is suitable for joining aluminium-copper alloy compared to fusion welding processes. The mathematical model with process parameters and tool geometry to predict the responses such as yield strength, tensile strength, and ductility of friction stir welds of the AA2014-T6 aluminium alloy are formulated [6] with empirical relations. Optimization of the process parameters to achieve high tensile strength to find the effect of the process parameters of the FSW joint for similar aluminium alloys H30 helped in developing a practical approach of determining the optimum conditions leading to higher tensile strength [9].

The significant optimal transverse feed is achieved with the help of a square tool while finding the effect of welding parameters on mechanical properties such as the hardness and tensile strengths of the axial type of weld zone [10]. ANOVA and Taguchi method were found to be very helpful in the case of the AA6063 alloy for the submerged status of FSW to obtain the optimal welding conditions for maximum hardness strength with welding process parameters such as rotational speed, welding speed, and tool pin profiles (cylindrical, threaded, and tapered) [4, 11–14].

The tool geometry parameters (shoulder and pin diameter, pin and shoulder shape, and length) played a crucial role in heat generation and material flow in finding the influence of welding parameters on mechanical strengths of similar or dissimilar aluminium alloys [15, 16]. Tool rotational speed was the most influential factor during the optimal process parameters of FSW of dissimilar Al alloys (AA6262 and AA7075) using grey relational analysis of multiple response characteristics such as tensile strength (UTS) and Vickers hardness (VHN) [17].

A response surface methodology (RSM) model was developed to investigate the effects of tool shoulder and probe geometries on the Al FSW with respect to weld strength, cross-sectional area, and grain size to define what was appropriate for the FSW characteristics [5]. Data variance analysis showed that the rotational speed and diameter of a tool are the major and the minor significant factors, respectively. Similarly, this is seen in studying the effect of welding factors on the microstructure and mechanical strength of heterogeneous tailored welded blank sheets (5083-H12 and 6061-T6 Al alloys) [18]. Optimization of FSW parameters was established in different conditions of base material and the microstructures of the welded condition compared with the postweld heat-treated microstructures welded in annealed and T6 condition [19]. Work was also extended on the FSW using aluminium alloys and the influence of tool geometry on microstructure, defect type, and mechanical properties of a joint. For a higher shoulder and pin diameter, the resultant defects were least compared to smaller dimensions of them [20]. The proper adjustment of welding parameters is presented in such a way that the welding interface is heated to a plastic state at the place of welding. The functional

behavior of the weldments is determined by the tensile strength, metallurgical behavior, surface roughness, weld hardness, and microhardness. Various works on the welding parameters and tool pin profile in defining weld quality under the influence of rotational and travel speed on friction stir processed zone formation in AA 5083 aluminium alloy plates are carried out. The welded samples were examined by using optical microscopy to define the different joined zones and to identify possible defects [21].

1.2. Genetic Programming. Genetic programming (GP) is a computerized process of building programs closely based on the Darwinian principle of natural selection to solve specific problems carefully and is considered as an expansion of genetic/evolutionary algorithms which uses them effectively. GP evolves a program that forecasts the actual output from an experimental data file of inputs and outputs [22, 23]. The GP Discipulus software uses Java, C/C++, and assembly interpreter [24] to write a program that maps inputs onto output data. In general, GP primarily generates considerable numbers of random computer programs, where each program is executed and rated according to a fitness metric defined by the developer. The best problem-solver program is selected in each generation and breeds it [25]. Spontaneously, if two computer programs are even slightly useful in solving a problem, then some of their parts probably have some merit. By combining temporary chosen merit parts of effective programs, we may produce new computer programs that may be even more well fitted to solving the problem. After the application of genetic methods to the developed current population (the group of programs), the population of the new generation programs supersedes the old ones. Each in the population of computer programs is then measured for fitness, and the process is repeated over many generations. This process will produce populations of computer programs which, over many generations, tend to exhibit increasing average competence in dealing with their environment.

The best individual that appeared in any generation of a run (the best-so-far individual) is designated as the result produced by genetic programming. The grading level of the computer programs that are produced is the essential feature of GP. The results of GP are thus inherently hierarchical.

The Discipulus software uses Automatic Induction of Machine Code technology to deal with the speed problem of machine learning, which allows the user to conduct a greater number of runs to investigate relationships between inputs and output and to uncover bad data or outliers, assess time, and so on [26]. The generated models are intended to develop process prediction mathematical models. Hence, the GP method is selected for the present work. GP solutions are computer-based programs that are easy to inspect, document, evaluate, and test. The GP solutions help in understanding the type of the derived correlation between input and output data, which was previously unknown. GP evolves both the structure and the constants of the solution simultaneously [27].

Discipulus GP actively discriminates between relevant input data and inputs that have no bearing on a solution [28]. In other words, Discipulus performs input variable selection as a by-product of its learning algorithm. GP is successfully

used to solve problems in a vast number of fields such as systems, data, time series prediction and economic modelling, curve fitting, symbolic regression, industrial process control, financial trading, optimization and scheduling, and bioinformatics [29].

There are numerous techniques available, such as linear regression, statistical and artificial neural network, fuzzy logic ANFIS, and response surface methodology, to derive correlations but they have shown limited accuracy. This study aims at deriving a mathematical model showing empirical correlations between inputs and output for predicting the mechanical properties of joint strength of FSW using a genetic programming approach that can be used in forecasting to an accuracy level of 99.2 to 99.6%. This new model would be more straightforward by eliminating the large computations involved in any conventional equation of state applications. It would likewise be very helpful in developing and examining the developed correlations without conducting experiments for the validation of data in the future [30].

2. Materials and Methods

In this study, two dissimilar aluminium alloys AA7075 and AA6061 having different thicknesses of 3, 4, and 5 mm whose chemical compositions are listed in Table 1 were examined. Butt joint welding configuration using a vertical milling machine with a special purpose tool (cylindrical taper profile with pin diameter of 6 mm, 10° taper, pin length of 1.8 mm, and shoulder diameter of 20 mm) is carried out. To derive a mathematical model, we require an enormous amount of data from experimentation for which various process parameters at different levels having more influence on the mechanical properties of the joint formed by FSW are derived from the literature. They are axial load, the rotational speed of the tool, welding speed, tilt angle, and plate thickness and their levels are shown in Table 2. Butt welded samples are prepared with a rig consisting of MS backing plate to support base metal along the rolling direction. The various mechanical properties of AA6061 and AA7075, namely, hardness, elongation, and tensile and impact strengths, are noted in Table 3. Welding is carried out by placing plates on the advancing side and retreating side alternately and clamping these firmly to prevent the butt faces from being forced apart from proper stirring and mixing of material and finishing by rotation and translation movement of the tool. The tilt of the tool towards a trailing direction ensured that the shoulder of the tool held the stirred material by a threaded pin and moved material efficiently from the front to the back of the pin. The amount of penetration of a pin depth and tool shoulder radius contacting the workpiece is decided by the pin length. Pin length criteria are helpful in producing welds with the inner channel, surface groove, excessive flash, or local thinning of the weld plates and so on.

Each butt joint was cut to the pieces of specimens for yield and impact strength tests based on the ASTM standard. A universal testing machine was used to conduct the tensile tests and their loading and elongation record of specimens was also taken to calculate tensile strength and elongation rate on the bases of their fracture loading of specimens. The

Charpy type of impact test is used to evaluate the impact energy of FSW joint as per ASTM standards.

3. Genetic Models

GP is the most common approach among evolutionary computation methods in which the programs adapt hierarchically classified programs obtained dynamically by changing the size and form evolved during simulation. The random program was developed using available function and terminal genes of symbolic regression from set F (arithmetic operators $\{+, -, *, \text{ and } /\}$) and set T , respectively, producing an initial population to adapt to the environment of the solution. The program structures keep being modified subject to adaptability based on guidelines using fitness measurement function. Fitness measurement shows how far the predicted data by the GP coincides with the experimental data. Genetic modification of program contents starts, and it follows that when the calculation of fitness measurement is applied to an initial population and becomes repetitive, it is called evolution. Once termination criteria are met, the evolution process stops to get the number of generations of the solution. Data sets collected from the various measurements of mechanical properties of FSW joint strength were taken for this analysis. The tensile strength, impact strength, and elongation are our targeted output. Axial load, welding speed, tool rotational speed, tilt angle, and thickness of plate are taken as inputs. The data samples were randomized manually using Notitia software. Feeding the randomized data set into the software is initially done by splitting them into three categories, namely, training, validation, and applied testing [2, 24]. Discipulus always accepts the last column as the proposed output. Many experimental runs help generate the optimal solution in finding the best parameters within the least time using arbitrary settings as shown in Table 3. Another term called the correlation coefficient (r/R) plays an important role, where the term r represents the linear relationship coefficient between two variables using strength and the path. r varies in $-1 < r < +1$, where (+) and (−) signs indicate positive and negative linear relationships, respectively. When $r = +1$, the inputs and output have a perfect positive correlation; it can be seen that as input values increase, the output values also increase and vice versa when $r = -1$ (a perfect negative fit). If $r = 0$, this indicates no linear relationship and if r approaches zero, it represents a random, nonlinear relation between the two variables. r^2 gives the coefficient of determination to predict from a particular model. $0 < r^2 < 1$ denotes the strength of the linear correlation inputs and outputs or represents the percent of the data closest to the line of best fit. In the crossover rate, homologous crossover acts as a modification to imitate natural evolution more precisely than the conventional crossover where the two new emerging programs are set to form a subsequent and most suitable program by switching groups of neighbouring instruction. Blocks between the two emerging programs to deliver the upcoming group are such that they are of the same length and above the position from both emerging programs. Nonhomologous crossover occurs when instruction blocks are swapped between two evolving programs with no reference to the size and location of the two

TABLE 1: Chemical composition of AA6061 and AA7075.

Elements	Mg	Mn	Fe	Si	Cu	Cr	Zn	Ti	Al
Base metal (AA6061)	0.8-1.2	0.0-0.15	0.0-0.70	0.4-0.8	0.15-0.40	0.05-0.35	0.0-0.25	0.15	Remaining
Base metal (AA7075)	2.9	0.3	0.5	0.4	2	0.28	6.1	0.2	Remaining

TABLE 2: Important input factors and their levels.

Process parameters	Symbol	Unit	Level 1	Level 2	Level 3
Tilt angle	ν_0	(°)	3	4	--
Axial load	ν_1	(KN)	2	2.5	3
Tool rotational speed	ν_2	(rpm)	600	900	1200
Welding speed	ν_3	(mm/sec)	70	90	115
Thickness of plate	ν_4	(mm)	3	4	5

TABLE 3: Parameter setting for genetic programming.

Parameters	Value assigned
Population size (P)	600
Number of generations	1000
Maximum depth of tree	6
Maximum generation	60
Functional set	Multiply ($\times$), plus ($+$), minus ($-$), divide ($/$)
Terminal set	Tilt angle, axial load, tool rotational speed, welding speed, thickness of plate, tensile strength, elongation, and impact strength.
Number of runs	100
Mutation rate	15%
Crossover rate	(i) 0.80 for nonhomologous (ii) 0.20 for homologous
Reproduction rate	0.05
Fitness r^2	$\sqrt{\sum_{k=1}^n (\text{error} = \text{Program data} - \text{observed data})^2_n}$
Termination	Individual program emerges when the sum of absolute errors is zero (is less than specified) (a) the required number of runs is accomplished (10000) or (b) the required correlation coefficient (r^2) is obtained (when r^2 is less than 0.1)
Terminal set	$T = \{P, \text{random-constants}\}$

sets of instruction blocks. The homologous crossover parameter sets the percentage of crossover events that are “homologous” as opposed to the percentage that is “nonhomologous.”

4. Results and Discussion

The evolutionary method using precise instructions and terminal genes from a set of function library and termination

library types builds an organism (known as a mathematical model) fit for the estimation of results behaving similarly to the nature of computer programs that differ in form and size [24, 26]. Various models for outputs are developed by GP using the training data [29]. The best mathematical models obtained from GP simulation are given from (1) to (5).

$$\text{Tensile strength} = \sqrt{[381.45(I^2 - 1)] - G + \cos(\nu_2)}, \quad (1)$$

$$A = -1.51 - 2\sqrt{\frac{0.011}{\nu_2} + 2.116\nu_0} - \left\{ \left[1.51 + \sqrt{\frac{0.011}{\nu_2} + 2.116\nu_0} \right] \left[\frac{1.51}{\nu_2} - 1.641 \right] \right\}^2,$$

$$B = \left\{ \left[1.51 + \sqrt{\frac{0.011}{\nu_2} + 2.116\nu_0} \right] \left[\frac{1.51}{\nu_2} - 1.641 \right] \right\}^2 [1.51\nu_2 - 1.641],$$

$$C = 2 \left\{ \left[\frac{1.51}{\nu_2} - 1.641 \right] + 7.6(\nu_2(\sqrt{B} + AB))^2 \right\},$$

$$D = -[15.2(\nu_2(\sqrt{B} + AB))]^2 + \left[\frac{1.51}{\nu_2} - 1.641 \right],$$

$$\begin{aligned}
E &= \frac{(D + \sqrt{C} - \nu_1 / [1.51/\nu_2 - 1.641])}{\{1.253 + 3\nu_1 / [1.51/\nu_2 - 1.641] - 2D - 2\sqrt{C}\}}, \\
F &= \left[\frac{1.51}{\nu_2} - 1.641 \right] - \left\{ 1.253 + 3 * \frac{\nu_1}{[1.51/\nu_2 - 1.641]} - 2 * D - 2\sqrt{C} \right\}^2, \\
G &= \frac{\{1.253 + 3\nu_1 / [1.51/\nu_2 - 1.641] - 2D - 2\sqrt{C}\}^2}{[1.51/\nu_2 - 1.641]} - \left\{ 1.253 + \frac{3\nu_1}{[1.51/\nu_2 - 1.641]} - 2D - 2\sqrt{C} \right\}^2, \\
H &= \frac{FG + G^2 - 25.04 + 2\nu_0}{[25.04 + 2\nu_0 - \nu_3]^2}, \\
I &= \left(\frac{H}{[\nu_0 - 3.153]} \right) \left(\sqrt{\left[\frac{((H / [\nu_0 - 3.153]) - [\nu_0 - 3.153]) / \nu_2}{\nu_1 \nu_2} [\nu_0 - 3.153]} \right]} \right), \\
J &= \left(\sqrt{\left[\frac{(H / [\nu_0 - 3.153]) - [\nu_0 - 3.153]}{\nu_2} \frac{[\nu_0 - 3.153]}{\nu_1 \nu_2} \right]} \right) E - 2I^2 + \nu_1, \\
K &= \frac{1.383 (I - J)^2}{\nu_3} \left\{ 2.5085 J^4 \nu_3 - \frac{1.54997}{(I - J)} + \frac{G - 1 + [0.8077/GH^6 + 0.8077/GH]}{J} \right\},
\end{aligned} \tag{2}$$

$$\text{elongation} = 0.1 - \frac{\left\{ (K ((G - 1 + [0.8077/GH^6 + 0.8077/GH]) / J)) 2 [2 (-1.953K + \nu_2) / (I - J) + (I - J)]^2 \right\}}{(\{2.2 [2 ((\nu_2 - 1.953K) / (I - J)) + (I - J)]\} + 1.54\nu_0 + 2.4)}, \tag{3}$$

$$\begin{aligned}
A &= 2 * \left\{ \sqrt{\left\{ \frac{-1.1 + \nu_0}{\nu_1} \right\}} - 0.964 \right\} + 1.1, \\
B &= \sqrt{-\frac{(\nu_2 + 1.1)}{\nu_3} * \sqrt{\left\{ \frac{-1.1 + \nu_0}{\nu_1} \right\}}}, \\
C &= \sqrt{-\frac{(\nu_2 + 1.1)}{\nu_3} * \sqrt{\left\{ \frac{-1.1 + \nu_0}{\nu_1} \right\}}} - \sqrt{\left\{ \frac{-1.1 + \nu_0}{\nu_1} \right\}}, \\
D &= -(1.1 + B) + 0.26 * \frac{B}{1.1 + B} - 1.38 * \left[\left\{ -0.26 * \nu_1^2 * \frac{B}{1.1 + B} \right\} * C^4 \right]^2, \\
E &= \left\{ 5.52 * \left[\left\{ -0.26 * \nu_1^2 * \frac{B}{1.1 + B} \right\} * C^4 \right]^2 \right\}^2, \\
F &= C - \left[\left\{ -0.26 * \nu_1^2 * \frac{B}{1.1 + B} \right\} * C^4 \right]^2 - 5 * E, \\
G &= 2 * \sqrt{\frac{\left\{ 1.1 + [-0.1 * [2.64 - \nu_1 + F - \nu_2] * F^2 + (D - E)] / F \right\} \nu_3}{F}} \frac{\nu_3}{1}, \\
H &= D - E + 2 * \left\{ -6.6 * \nu_3 * \frac{\{G * (D - E)\}^2}{[F * (D - E)]} \right\}^2, \\
I &= H + \left[\nu_4 * \left\{ -9.33 * \nu_3^2 * \frac{\{G * (D - E)\}^2 F}{[F * (D - E)] \ 1} \right\}^{0.5} \right] \frac{1}{(F * \nu_3)}, \\
J &= 1.26 - 0.04 * \frac{(\{[1.43 * I/F - H] * \nu_2 / F + \nu_3\} / \nu_1)}{\nu_3},
\end{aligned} \tag{4}$$

$$\text{impact strength} = F * \sqrt{\left(H * \frac{J}{\nu_1} \right)}, \tag{5}$$

$$\begin{aligned}
A &= -\cos(v3) + \cos\{381.45[\cos(v3) + v3] + v3\}, \\
B &= -\cos\{381.45[\cos(v3) + v3] + v3\} \frac{v2}{A^2}, \\
C &= \sqrt{\left\{381.45 \left[4 * \frac{-1.175 + v1}{v0}\right] + v3\right\}}, \\
D &= \{A - \cos(B - 1.365) - \cos(2 - v2)\} \cos\{381.45(C - v3)\}, \\
E &= \cos\left(\left[-\frac{2.02[D + 0.74]\{2D + 0.74\}^3}{v3}\right] - [383.45(v3 - C)] + 0.74 - v2\right), \\
F &= \sin\left\{\sin\frac{[\cos(E - v2) + v2 + 1]}{[383.45(v3 - C)]} + 1.175 + v1\right\}, \\
G &= [\{2D + 0.74\} - \cos(E - v2)] \cos\{381.45[381.45(4F + v3)]^{0.25}\}, \\
H &= 2\left[(1 - G + v0)^2 - G\right] - \frac{v4}{\left[\frac{383.45(v3 - C)}{[381.45(4F + v3)]}\right]}, \\
I &= \sqrt{\left\{381.45\left[8\left([\cos(v2)]^2 - 1\right)^2 + 0.7 + v1 - \{G - \cos(v2)\}\right] + v3\right\}} + G - \cos(v2) - v3.
\end{aligned} \tag{6}$$

Comparison between the experimental and predicted outputs using a mathematical model from GP is shown in Tables 4, 5, and 6 for elongation and tensile and impact strengths of a FSW joint, respectively. Errors in determining predicted outputs are negligible, and the percentage of error is less than ± 0.6 , which shows that results obtained from a GP mathematical model are highly acceptable.

Figures 1(a), 2(a), and 3(a) show the percentage deviation between the best model regarding individual generation and experimental results during regression fit using the set of function genes with a normal distribution behavior. It is evident that in early generations the best models are not as precise as the models generated subsequently. The GP model analysis suggests specific outputs of mechanical properties of FSW joint for the experimental scheme under various input factors that can be associated with the performance. The GP models generated allow representation of the experimental data without thorough awareness of the occurrence. Besides, their study allows us to obtain a deeper insight into the relevant input conditions in describing the output phenomenon by showing changes in any of the inputs observed in properties of the FSW joint produced which are linked to the changes in the performance.

Figures 1(b), 2(b), and 3(b) show the normal Q-Q plot for tensile strength, elongation, and impact strength with a 95% level of confidence. The blue circles in this Q-Q plot start out on one side of the line and then are almost entirely on the other side for a long stretch and then move to the other side of the reference line again. This behavior indicates some degree of skewing. In Figure 1(a), the mean and standard deviation of the normal Q-Q distribution plot of tensile strength for the error variation between the experimental and predicted values was -0 ± 0.4 MPa. In Figure 2(b), the mean and standard deviation of the normal Q-Q distribution plot of elongation for the error variation

between the experimental and predicted values was $-0 \pm 0.2\%$. However, in Figure 3(b), the mean and standard deviation of the normal Q-Q distribution plot of impact strength for the error variation between the experimental and predicted values was $-0.8E - 4 \pm 0$ J/m².

4.1. Linear Regression Analysis. In order to compare the GP results with the other types of regression analysis, an attempt has been made to perform the linear regression analysis of experimental results. The linear regression analysis of elongation and tensile and impact strengths of a FSW joint involving $v0$ to $v4$ input variables has been carried out using Minitab® V18 statistical software with the experimental data of Tables 4, 5, and 6. The corresponding linear regression models are presented in (7), (8), and (9) and error obtained in comparison with experimental data is also tabulated in Tables 4, 5, and 6. Various residual plots of outputs are shown in Figures 4, 5, and 6.

$$\begin{aligned}
\text{Tensile strength} &= 174.2 - 1.03V0 + 9.09V1 \\
&\quad + 0.01463V2 + 0.1243V3 \\
&\quad + 0.12V4,
\end{aligned} \tag{7}$$

$$\begin{aligned}
\text{elongation} &= 1.76 + 1.832V0 + 0.615V1 \\
&\quad - 0.000659V2 + 0.00247V3 \\
&\quad + 0.201V4,
\end{aligned} \tag{8}$$

$$\begin{aligned}
\text{impact strength} &= 0.915 + 0.0031V0 - 0.0376V1 \\
&\quad + 0.000118V2 + 0.000119V3 \\
&\quad - 0.0422V4.
\end{aligned} \tag{9}$$

TABLE 4: Comparison between experimental and predicted values of tensile strength at $R^2 = 99.5\%$.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Tensile strength (MPa)		Error	Linear regression	Error
					Experimental	GP			
3	2	600	75	4	201.4173	201.4149	0.002396	199.4963	1.92105
3	2	600	90	4	207.5238	206.971	0.552811	199.6827	7.8411
3	2	900	115	4	200.4701	200.8218	-0.35167	204.3825	-3.91235
3	2	1200	115	4	210.9491	211.2845	-0.33536	208.7715	2.17765
3	2.5	600	75	4	212.8087	212.9875	-0.17885	204.0413	8.76745
3	2.5	600	90	4	214.7545	214.4605	0.294006	204.2277	10.5268
3	2.5	900	90	4	226.1082	226.7305	-0.62225	208.6167	17.4915
3	2.5	1200	115	4	221.0869	221.4523	-0.36539	213.3165	7.77045
3	3	600	75	4	208.9469	208.806	0.140945	208.5863	0.36065
3	3	600	115	4	217.343	217.9036	-0.56067	209.0835	8.25955
3	3	900	75	4	229.8519	229.2028	0.649048	212.9753	16.87665
3	3	900	90	4	233.5722	233.628	-0.0558	213.1617	20.4105
3	3	900	90	5	233.9161	233.6219	0.29422	213.2857	20.6304
3	3	900	115	4	242.6929	242.4103	0.282562	213.4725	29.22045
3	3	1200	75	3	227.4726	227.1649	0.307632	217.2403	10.23235
3	3	1200	75	4	227.1322	227.1745	-0.04233	217.3643	9.76795
3	3	1200	75	5	226.8476	227.184	-0.33641	217.4883	9.35935
3	3	1200	115	3	227.9172	227.7119	0.205277	217.7375	10.17975
3	3	1200	115	4	228.1085	227.7122	0.396347	217.8615	10.24705
3	3	1200	115	5	228.2549	227.7125	0.54248	217.9855	10.26945
4	2	600	75	4	197.3443	196.8444	0.499908	198.4663	-1.12195
4	2	600	75	5	197.1878	196.8481	0.339767	198.5903	-1.40245
4	2	600	90	3	212.6613	212.6237	0.037552	198.5287	14.1326
4	2	600	90	4	213.2592	212.7725	0.486725	198.6527	14.6065
4	2	900	75	3	213.7823	213.4791	0.303131	202.7313	11.05105
4	2	900	75	4	213.8493	214.1454	-0.29617	202.8553	10.99405
4	2	900	75	5	214.0453	214.1446	-0.09932	202.9793	11.06605
4	2	900	90	4	227.3222	227.8775	-0.55531	203.0417	24.2805
4	2	900	90	5	227.7843	227.8655	-0.08118	203.1657	24.6186
4	2	900	115	3	226.5605	227.1803	-0.61986	203.2285	23.33205
4	2	900	115	4	226.9803	227.1879	-0.20764	203.3525	23.62785
4	2	900	115	5	227.3916	227.191	0.200684	203.4765	23.91515
4	2	1200	90	3	216.5077	217.1303	-0.62257	207.3067	9.201
4	2	1200	90	4	217.0157	217.0639	-0.04823	207.4307	9.585
4	2	1200	90	5	217.5187	217.2333	0.2854	207.5547	9.964
4	2	1200	115	3	215.5096	215.5605	-0.05092	207.6175	7.89215
4	2	1200	115	4	215.2814	215.5672	-0.28584	207.7415	7.53995
4	2	1200	115	5	215.202	215.5741	-0.37207	207.8655	7.33655
4	2.5	600	75	3	210.9097	211.1155	-0.20586	202.8873	8.02245
4	2.5	600	75	4	210.9576	210.9654	-0.00786	203.0113	7.94635
4	2.5	600	75	5	210.8665	210.847	0.019516	203.1353	7.73125
4	2.5	600	90	4	205.5315	205.905	-0.37355	203.1977	2.3338
4	2.5	600	90	5	206.0258	206.0515	-0.02574	203.3217	2.7041
4	2.5	600	115	3	209.6681	209.8436	-0.17548	203.3845	6.28365
4	2.5	900	75	4	225.0363	224.4874	0.548965	207.4003	17.63605
4	2.5	900	90	4	220.4077	220.5082	-0.10057	207.5867	12.821
4	2.5	900	115	4	227.377	227.1711	0.205856	207.8975	19.47955

TABLE 4: Continued.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Tensile strength (MPa)		Error	Linear regression	Error
					Experimental	GP			
4	2.5	1200	75	4	216.1377	216.0029	0.134796	211.7893	4.34845
4	2.5	1200	90	4	215.9696	215.655	0.314621	211.9757	3.9939
4	2.5	1200	115	4	220.2623	219.8801	0.382263	212.2865	7.97585
4	3	600	75	4	204.118	204.1865	-0.06847	207.5563	-3.43825
4	3	600	115	4	217.8454	218.1242	-0.27884	208.0535	9.79195
4	3	900	115	4	238.2042	238.2691	-0.06488	212.4425	25.76175
4	3	1200	75	4	218.2925	218.8536	-0.56111	216.3343	1.95825
3	2	1200	115	5	211.2005	211.2984	-0.09787	208.8955	2.30505
3	2.5	600	75	5	213.5635	213.1032	0.460327	204.1653	9.39825
3	2.5	900	75	5	224.5181	225.1232	-0.60516	208.5543	15.96385
3	2.5	1200	115	5	220.9586	221.4597	-0.50114	213.4405	7.51815
3	3	600	75	5	209.4358	208.8087	0.627182	208.7103	0.72555
3	3	900	75	5	230.5879	230.988	-0.4001	213.0993	17.48865
3	3	900	90	5	233.9161	233.6219	0.29422	213.2857	20.6304
3	3	1200	75	5	226.8476	227.184	-0.33641	217.4883	9.35935
3	3	1200	115	5	228.2549	227.7125	0.54248	217.9855	10.26945
4	2	600	75	5	197.1878	196.8481	0.339767	198.5903	-1.40245
4	2	900	75	5	214.0453	214.1446	-0.09932	202.9793	11.06605
4	2	900	90	5	227.7843	227.8655	-0.08118	203.1657	24.6186
4	2	900	115	5	227.3916	227.191	0.200684	203.4765	23.91515
4	2	1200	90	5	217.5187	217.2333	0.2854	207.5547	9.964
4	2	1200	115	5	215.202	215.5741	-0.37207	207.8655	7.33655
4	2.5	600	75	5	210.8665	210.847	0.019516	203.1353	7.73125
4	2.5	600	90	5	206.0258	206.0515	-0.02574	203.3217	2.7041
4	2.5	900	75	5	225.7942	225.9323	-0.13811	207.5243	18.26995
4	2.5	900	90	5	220.4536	220.4198	0.033768	207.7107	12.7429
4	2.5	900	115	5	228.0017	228.3694	-0.36765	208.0215	19.98025
4	2.5	1200	75	5	216.5734	216.9923	-0.41885	211.9133	4.66015
4	2.5	1200	90	5	216.3825	215.9084	0.474014	212.0997	4.2828
4	2.5	1200	115	5	220.4091	219.8816	0.527542	212.4105	7.99865
4	3	600	75	5	204.4071	204.1895	0.217575	207.6803	-3.27315
4	3	600	115	5	217.7037	218.1192	-0.4155	208.1775	9.52625
4	3	900	90	5	226.0705	226.6372	-0.56667	212.2557	13.8148
4	3	1200	75	5	219.0428	219.1528	-0.11002	216.4583	2.58455
4	3	1200	90	5	219.528	219.6197	-0.09166	216.6447	2.8833

The amount of error is very high during building up of empirical relation with elongation and impact strength compared to tensile strength as tensile strength has higher experimental values to 3 digit numbers. Linear regression requires higher digit number for output values in comparison with input parameters (v_0-v_4) to achieve higher level of accuracy. It is more suitable for two inputs and more number of inputs leads to erroneous empirical relation derived.

Figure 7 shows that the boxplots of various outputs of FSW joint give a clear indication of no error or error at a fourth decimal place, which is negligible. There are two boxes representing statistical data on a plot consisting of a rectangle

with a vertical line inside to indicate the median value. The quartile is defined as the middle number between the smallest number, highest value, and the median of the data set and median of data. The higher and lower quartiles are shown by horizontal lines on either side of the rectangle with the box on the left for experimental and the box on the right for GP. From the boxplots, it is seen that there is absolutely no variation between both boxes of experimental and GP results. Therefore, GP results are capable of producing results without experimentation at a higher accuracy level. Thus, boxplots are very effective in comparing two or more results of different methods.

TABLE 5: Comparison between experimental and predicted values of % elongation at $R^2 = 99.3$.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Elongation (%)		Error	Linear regression	Error
					Experimental	GP			
3	2	600	75	4	10.6	10.58972	-0.01028	13.42925	-2.82925
3	2	600	90	4	9.8	9.935991	0.135991	13.4663	-3.6663
3	2	600	115	4	12.3	12.31535	0.015351	13.52805	-1.22805
3	2	900	90	4	8.2	8.212519	0.012519	15.4433	-7.2433
3	2	900	115	4	13	12.61499	-0.38501	15.50505	-2.50505
3	2	1200	90	4	7.2	7.499517	0.299517	17.4203	-10.2203
3	2.5	600	75	4	7.99	7.825613	-0.16439	13.73675	-5.74675
3	2.5	600	90	4	8.8	8.686644	-0.11336	13.7738	-4.9738
3	2.5	600	115	4	8.4	8.531275	0.131275	13.83555	-5.43555
3	2.5	900	75	4	6.8	6.794509	-0.00549	15.71375	-8.91375
3	2.5	900	90	4	7.9	7.832968	-0.06703	15.7508	-7.8508
3	2.5	900	115	4	8.1	7.955772	-0.14423	15.81255	-7.71255
3	2.5	1200	75	4	7.6	7.602399	0.002399	17.69075	-10.0908
3	2.5	1200	90	4	7.5	7.640862	0.140862	17.7278	-10.2278
3	2.5	1200	115	4	8.1	8.265376	0.165376	17.78955	-9.68955
3	3	600	75	4	9	9.003488	0.003488	14.04425	-5.04425
3	3	600	90	4	9.3	9.507143	0.207143	14.0813	-4.7813
3	3	600	115	4	9.1	9.102601	0.002601	14.14305	-5.04305
3	3	900	90	4	11	10.72836	-0.27164	16.0583	-5.0583
3	3	900	90	5	11.6	11.36213	-0.23787	16.2593	-4.6593
3	3	900	115	3	10.8	11.06383	0.263827	15.91905	-5.11905
3	3	900	115	4	11.1	11.01522	-0.08478	16.12005	-5.02005
3	3	900	115	5	11.8	11.60359	-0.19641	16.32105	-4.52105
3	3	1200	75	4	9.5	9.406263	-0.09374	17.99825	-8.49825
3	3	1200	90	3	9.6	9.381887	-0.21811	17.8343	-8.2343
3	3	1200	90	4	9.7	9.373203	-0.3268	18.0353	-8.3353
3	3	1200	115	3	8.9	8.98249	0.08249	17.89605	-8.99605
3	3	1200	115	4	9	8.98249	-0.01751	18.09705	-9.09705
3	3	1200	115	5	9.2	9.224294	0.024294	18.29805	-9.09805
4	2	600	75	3	12.6	12.564	-0.036	15.06025	-2.46025
4	2	600	75	4	12.3	12.50683	0.206832	15.26125	-2.96125
4	2	600	75	5	12.9	12.62934	-0.27066	15.46225	-2.56225
4	2	600	90	3	10.3	10.46052	0.160518	15.0973	-4.7973
4	2	600	90	4	10.8	10.66317	-0.13683	15.2983	-4.4983
4	2	600	90	5	11	10.83043	-0.16957	15.4993	-4.4993
4	2	600	115	3	8.2	8.279408	0.079408	15.15905	-6.95905
4	2	600	115	4	8.4	8.279408	-0.12059	15.36005	-6.96005
4	2	600	115	5	8.7	8.663003	-0.037	15.56105	-6.86105
4	2	900	75	3	8.3	8.192486	-0.10751	17.03725	-8.73725
4	2	900	75	4	8.1	8.220214	0.120214	17.23825	-9.13825
4	2	900	75	5	8.5	8.29337	-0.20663	17.43925	-8.93925
4	2	900	90	3	7.8	8.055097	0.255097	17.0743	-9.2743
4	2	900	90	5	8.5	8.278371	-0.22163	17.4763	-8.9763
4	2	900	115	3	9.6	10.02004	0.420042	17.13605	-7.53605
4	2	900	115	4	9.8	10.03759	0.237595	17.33705	-7.53705
4	2	1200	75	3	13.1	12.78323	-0.31677	19.01425	-5.91425
4	2	1200	75	4	12.7	12.71508	0.015078	19.21525	-6.51525

TABLE 5: Continued.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Elongation (%)		Error	Linear regression	Error
					Experimental	GP			
4	2	1200	90	3	11.2	11.36919	0.16919	19.0513	-7.8513
4	2	1200	90	5	11.3	11.42188	0.121882	19.4533	-8.1533
4	2	1200	115	3	12.2	12.17725	-0.02275	19.11305	-6.91305
4	2	1200	115	4	12	12.14144	0.141442	19.31405	-7.31405
4	2	1200	115	5	12.6	12.38238	-0.21762	19.51505	-6.91505
4	2.5	600	75	3	12.7	12.72953	0.029527	15.36775	-2.66775
4	2.5	600	75	4	12.25	12.60696	0.356962	15.56875	-3.31875
4	2.5	600	75	5	13	12.73714	-0.26286	15.76975	-2.76975
4	2.5	600	90	3	12.4	12.3729	-0.0271	15.4048	-3.0048
4	2.5	600	90	4	11.8	12.19971	0.399713	15.6058	-3.8058
4	2.5	600	90	5	12.6	12.23691	-0.36309	15.8068	-3.2068
4	2.5	900	90	4	9.25	9.1138	-0.1362	17.5828	-8.3328
4	2.5	900	115	4	10.1	10.11175	0.011749	17.64455	-7.54455
4	2.5	1200	75	4	11	11.33745	0.337448	19.52275	-8.52275
4	2.5	1200	90	4	11.4	11.42875	0.028755	19.5598	-8.1598
4	2.5	1200	115	4	12.2	11.88495	-0.31505	19.62155	-7.42155
4	3	600	75	4	12.7	12.6509	-0.0491	15.87625	-3.17625
4	3	600	90	4	12.3	12.44309	0.143089	15.9133	-3.6133
4	3	600	115	4	11.8	11.48007	-0.31993	15.97505	-4.17505
4	3	900	75	4	10.1	9.74895	-0.35105	17.85325	-7.75325
4	3	900	90	4	9.3	9.357395	0.057395	17.8903	-8.5903
4	3	900	115	4	9.35	9.391239	0.041239	17.95205	-8.60205
4	3	1200	75	4	12	12.40683	0.406835	19.83025	-7.83025
4	3	1200	90	4	12.2	12.08855	-0.11145	19.8673	-7.6673
3	2	600	75	3	10.5	10.54728	0.047283	13.22825	-2.72825
3	2	600	90	3	10.1	10.04854	-0.05146	13.2653	-3.1653
3	2	600	115	3	11.8	11.50068	-0.29932	13.32705	-1.52705
3	2	900	90	3	7.9	8.212519	0.312519	15.2423	-7.3423
3	2	900	115	3	11.6	11.83127	0.231271	15.30405	-3.70405
3	2	1200	90	3	7.8	7.551078	-0.24892	17.2193	-9.4193
3	2.5	600	75	3	8	7.825613	-0.17439	13.53575	-5.53575
3	2.5	600	90	3	8.4	8.406551	0.006551	13.5728	-5.1728
3	2.5	600	115	3	8.9	8.74754	-0.15246	13.63455	-4.73455
3	2.5	900	75	3	7.1	7.337808	0.237808	15.51275	-8.41275
3	2.5	900	90	3	7.6	7.651297	0.051297	15.5498	-7.9498
3	2.5	1200	75	3	7.2	7.602399	0.402399	17.48975	-10.2898
3	2.5	1200	90	3	7.1	6.999386	-0.10061	17.5268	-10.4268
3	2.5	1200	115	3	7.9	7.564971	-0.33503	17.58855	-9.68855
3	3	600	75	3	9.1	9.036617	-0.06338	13.84325	-4.74325
3	3	600	90	3	9.3	9.520501	0.220501	13.8803	-4.5803
3	3	600	115	3	8.7	9.102601	0.402601	13.94205	-5.24205
3	3	900	90	3	11	10.80059	-0.19941	15.8573	-4.8573
3	3	900	115	3	11.1	11.06383	-0.03617	15.91905	-4.81905
3	3	1200	115	3	8.9	8.98249	0.08249	17.89605	-8.99605
4	2	600	75	3	12.7	12.564	-0.136	15.06025	-2.36025
4	2	600	90	3	10.7	10.68751	-0.01249	15.0973	-4.3973
4	2	600	115	3	8.3	8.279408	-0.02059	15.15905	-6.85905

TABLE 5: Continued.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Elongation (%)		Error	Linear regression	Error
					Experimental	GP			
4	2	900	75	3	8.5	8.192486	-0.30751	17.03725	-8.53725
4	2	900	90	3	7.8	8.055097	0.255097	17.0743	-9.2743
4	2	1200	75	3	13	12.78323	-0.21677	19.01425	-6.01425
4	2	1200	90	3	11.2	11.36919	0.16919	19.0513	-7.8513
4	2	1200	115	3	12.2	12.17725	-0.02275	19.11305	-6.91305
4	2.5	600	75	3	12.7	12.72953	0.029527	15.36775	-2.66775
4	2.5	600	90	3	12.4	12.3729	-0.0271	15.4048	-3.0048
4	2.5	900	75	3	9	9.157757	0.157757	17.34475	-8.34475
4	2.5	900	90	3	8.7	9.142856	0.442856	17.3818	-8.6818
4	2.5	1200	75	3	11.2	11.39373	0.193726	19.32175	-8.12175
4	2.5	1200	90	3	11.6	11.58502	-0.01498	19.3588	-7.7588
4	3	600	75	3	12.9	12.57058	-0.32942	15.67525	-2.77525
4	3	600	90	3	12.7	12.49178	-0.20822	15.7123	-3.0123
4	3	600	115	3	11.5	11.57182	0.071815	15.77405	-4.27405
4	3	900	75	3	10.3	9.788599	-0.5114	17.65225	-7.35225
4	3	900	90	3	9.5	9.395347	-0.10465	17.6893	-8.1893
4	3	900	115	3	9.3	9.485898	0.185898	17.75105	-8.45105
4	3	1200	75	3	12.5	12.42801	-0.07199	19.62925	-7.12925
4	3	1200	115	3	11.8	12.07808	0.278084	19.72805	-7.92805

FIGURE 1: (a) Comparison between experimental and predicted values of tensile strength and (b) normal Q-Q plot of error between experimental and GP data.

TABLE 6: Comparison between experimental and predicted values of impact strength at $R^2 = 99.4$.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Impact strength (J/m ²)		Error	Linear regression	Error
					Experimental	GP			
3	2	600	115	3	0.62	0.627465	-0.007465129	0.130185	0.489815
3	2.5	600	115	3	0.56	0.56651	-0.006510201	-0.05781	0.617815
3	3	900	75	3	0.89	0.888732	0.001268461	-0.21518	1.105175
3	3	900	90	3	0.95	0.956007	-0.006007421	-0.21339	1.16339
3	3	1200	75	3	0.9	0.90866	-0.008660352	-0.17978	1.079775
3	3	1200	90	3	0.89	0.890057	-5.67889E-05	-0.17799	1.06799
4	2	600	115	3	0.89	0.890585	-0.000584826	0.133285	0.756715
4	2	900	75	3	0.88	0.876978	0.003022139	0.163925	0.716075
4	2	900	115	3	0.9	0.898867	0.001133347	0.168685	0.731315
4	2	1200	90	3	0.81	0.810876	-0.000875952	0.20111	0.60889
4	2.5	900	75	3	0.95	0.956236	-0.006236064	-0.02408	0.974075
4	2.5	900	115	3	0.89	0.880833	0.009166732	-0.01932	0.909315
4	2.5	1200	90	3	0.91	0.912273	-0.002273049	0.01311	0.89689
4	3	600	90	3	0.718	0.716218	0.001782065	-0.24569	0.96369
4	3	900	75	3	0.73	0.724777	0.005222838	-0.21208	0.942075
4	3	900	90	3	0.745	0.739808	0.005191798	-0.21029	0.95529
4	3	1200	75	3	0.72	0.715923	0.004076512	-0.17668	0.896675
4	3	1200	90	3	0.71	0.713943	-0.003943005	-0.17489	0.88489
4	3	1200	115	3	0.72	0.727521	-0.007521241	-0.17192	0.891915
3	2	600	90	4	0.8	0.799481	0.000518906	0.08501	0.71499
3	2.5	600	90	4	0.63	0.630611	-0.00061142	-0.10299	0.73299
3	2.5	600	115	4	0.58	0.575422	0.00457819	-0.10002	0.680015
3	3	900	90	4	0.91	0.918671	-0.008671191	-0.25559	1.16559
3	3	1200	75	3	0.9	0.90866	-0.008660352	-0.17978	1.079775
3	3	1200	90	3	0.89	0.890057	-5.67889E-05	-0.17799	1.06799
4	2	600	75	4	0.65	0.651921	-0.001920617	0.086325	0.563675
4	2	600	115	3	0.89	0.890585	-0.000584826	0.133285	0.756715
4	2	600	115	5	0.82	0.813068	0.006931789	0.048885	0.771115
4	2	900	75	3	0.88	0.876978	0.003022139	0.163925	0.716075
4	2	900	115	3	0.9	0.898867	0.001133347	0.168685	0.731315
4	2	900	115	5	0.865	0.865083	-8.29792E-05	0.084285	0.780715
4	2	1200	75	5	0.71	0.712427	-0.002426603	0.114925	0.595075
4	2	1200	90	3	0.81	0.810876	-0.000875952	0.20111	0.60889
4	2	1200	90	5	0.77	0.777844	-0.007843952	0.11671	0.65329
4	2	1200	115	4	0.78	0.78315	-0.003149838	0.161885	0.618115
4	2.5	600	90	4	0.86	0.860959	-0.000958576	-0.09989	0.95989
4	2.5	1200	75	4	0.8	0.808779	-0.008778763	-0.03088	0.830875
4	2.5	1200	90	4	0.93	0.931005	-0.001005299	-0.02909	0.95909
4	3	600	75	4	0.72	0.717328	0.002671809	-0.28968	1.009675
4	3	900	75	4	0.74	0.737732	0.002268126	-0.25428	0.994275
4	3	1200	75	4	0.725	0.715911	0.009089208	-0.21888	0.943875
4	3	1200	90	4	0.718	0.713928	0.004072254	-0.21709	0.93509
3	2	600	90	4	0.8	0.799481	0.000518906	0.08501	0.71499
3	2.5	600	90	4	0.63	0.630611	-0.00061142	-0.10299	0.73299
3	2.5	600	115	4	0.58	0.575422	0.00457819	-0.10002	0.680015
3	3	900	90	4	0.91	0.918671	-0.008671191	-0.25559	1.16559
3	3	1200	75	3	0.9	0.90866	-0.008660352	-0.17978	1.079775

TABLE 6: Continued.

V0 (°)	V1 (KN)	V2 (rpm)	V3 (mm/s)	V4 (mm)	Impact strength (J/m^2)		Error	Linear regression	Error
					Experimental	GP			
3	3	1200	90	3	0.89	0.890057	$-5.67889E-05$	-0.17799	1.06799
4	2	600	75	4	0.65	0.651921	-0.001920617	0.086325	0.563675
4	2	600	115	3	0.89	0.890585	-0.000584826	0.133285	0.756715
4	2	600	115	5	0.82	0.813068	0.006931789	0.048885	0.771115
4	2	900	75	3	0.88	0.876978	0.003022139	0.163925	0.716075
4	2	900	115	3	0.9	0.898867	0.001133347	0.168685	0.731315
4	2	900	115	5	0.865	0.865083	$-8.29792E-05$	0.084285	0.780715
4	2	1200	75	5	0.71	0.712427	-0.002426603	0.114925	0.595075
4	2	1200	90	3	0.81	0.810876	-0.000875952	0.20111	0.60889
4	2	1200	90	5	0.77	0.777844	-0.007843952	0.11671	0.65329
4	2	1200	115	4	0.78	0.78315	-0.003149838	0.161885	0.618115
4	2.5	600	90	4	0.86	0.860959	-0.000958576	-0.09989	0.95989
4	2.5	1200	75	4	0.8	0.808779	-0.008778763	-0.03088	0.830875
4	2.5	1200	90	4	0.93	0.931005	-0.001005299	-0.02909	0.95909
4	3	600	75	4	0.72	0.717328	0.002671809	-0.28968	1.009675
4	3	900	75	4	0.74	0.737732	0.002268126	-0.25428	0.994275
4	3	1200	90	4	0.718	0.713928	0.004072254	-0.21709	0.93509

(a)

(b)

FIGURE 2: (a) Comparison between experimental and predicted values of elongation and (b) normal Q-Q plot of error between experimental and GP data.

By comparing the errors of experimental data with GP and linear regression, it is seen that the equations derived by GP gave higher accuracy as regards results with least or no error, whereas the linear regression models generate output with higher error value, which may lead to an erroneous or wrong prediction of outputs. Linear regression also increases the uncertainty in the models, where the precision has to be maintained but GP outputs are very helpful.

5. Conclusion

Mechanical properties are the critical measurements of technological quality of a FSW joint. They exert considerable influence over both production costs and productivity. The proposed work adopts a potential and novel approach using GP for such significant measurements in deriving empirical modelling of mechanical properties. The proposed GP

FIGURE 3: (a) Comparison between experimental and predicted values of impact strength and (b) normal Q-Q plot of error between experimental and GP data.

FIGURE 4: Residual plots of tensile strength using linear regression method.

FIGURE 5: Residual plots of elongation using linear regression method.

FIGURE 6: Residual plots of impact strength using linear regression method.

approach does not depend on any standard mathematical decree or any past awareness of the type of solution. GP employs evolving theories to develop automatically mathematical models that fit the given experimental historical data

without making any assumptions about the shape, size, and complexity of the problem under any number of input parameters. In this study, new models of the elongation and tensile and impact strength at different input conditions

FIGURE 7: The quality distribution of GP models and experimental work of different outputs of FSW joint.

are formulated using Discipulus GP software and C programming. Without further conducting any experimental runs, joint properties are determined quickly by substitution of input conditions. The accuracy of new GP models in comparison to the test results is greater by about ± 0.06 to 0.001. New GP models are used as an alternative method to estimate the joint properties where the experimental results or correlations are not available. However, the precision of solutions achieved by GP depends on allied evolutionary inputs, the amount of test data, and their level of accuracy.

GP are time-consuming processes since they involve a reasonably large number of iterations but remain worth adopting as a method by considering the prediction accuracy of the model developed. The capability of the genetic models for predicting the responses of a process is advantageous as they have a higher degree of accuracy compared to the performance of other analytical methods such as ANN, DFA, ANFIS, and RSM. The proposed mathematical model verifies the test results to the reliability of about 99.4 to 99.6%. The GP approach, therefore, proved itself to be a highly expert and valuable means for recognizing correlations in data.

Future Scope of the Work

The work can be extended further by applying the GP on FSW employing other aluminium alloys such as 5XXX and 7XXX used in the automotive industry to increase its use in the automotive industry. Further implementation of GP on the forces generated during single as well as multiple passes for different alloys, working conditions, and process parameters would possibly be very beneficial. GP could also be implemented in fine-grained FSW aluminium alloys that exhibit improved strength and ductility.

Also, further GP studies may be conducted, considering most of the welding parameters, on a wider range of values. Fatigue analysis and shear tests can be handled. Higher

thickness aluminium plates can be welded by employing double-sided FSW. Finally, GP application of FSW is extended by employing on other materials such as copper, titanium, and magnesium for future studies.

Conflicts of Interest

The authors have no conflicts of interest.

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