SUPPORT VECTOR MACHINE AND DECISION TREE ALGORITHM FOR SURFACE CHARACTERIZATION OF FRICTION STIR WELDING OF ALUMINIUM ALLOY 2024 PIPES

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Abstract:

For many engineering applications, the finish on a surface can have a big effect on the performance and durability of parts. Rough surfaces generally wear more rapidly and have greater friction coefficients than smooth surfaces. Typically, roughness is a dependable predictor of mechanical part performance, as irregularities tend to form nucleation sites for breaks or corrosion. Roughness is a measure of the fine irregularities on a surface. The surface roughness is a function of both raw material properties and manufacturing variables. Weld surface characteristics such as corrosion resistance, oxidation, and wear resistance toughness are affected by the cutting tool geometry, tool rotational speed and weld speed of Friction stir welding process.The objective of this study is to evaluate the weld surface roughness using support vector machine learning algorithm and decision tree algorithm for classification of weld by FSW process parameters and to build a mathematical model for prediction using artificial neural network in R studio software. Currently, there is very little information about classification of weld surface roughness using machine learning algorithms for friction stir welded aluminium alloy 2024 pipe joint available.

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Introduction:

Several factors affect FS welded surface roughness, such as tool geometry, tool wear, coolant and cutting parameters. The influence of FSW tool pin diameter, length, shape has been previously investigated by few on flat surfaces. FS welding with a worn FSW tool also resulted in worse surface roughness .Few pipe joints were FS welded to analyze the effect of coolant that higher surface roughness was observed on welded joints which were produced without coolant, as compared to those with a supply of coolant. Results from these studies indicated that a higher feed rate and depth of cut increase the surface finish values while cutting speed had the opposite effect on aluminum, brass alloys, carbon alloy steels, EN-31 steel and stainless steels. The microstructure of any material comprises the phase structure and the grain structure. The phase structure indicates the type of phases, the relative amount of the various phases which are present and their distribution where they are present like whether they are within the grain or at the grain boundary or to the kind of whether they are at the surface or in the core or there is a continuous variation. So, it is about the size shape of the grains and the distribution. The both phase as well as grain structure are important from the mechanical properties point of view which in turn affect the tribological behaviour of the surfaces determining the life of the component. So, it is important to look into the microstructure related aspects of the surfaces. The surface roughness is an indirect index of tool condition; the tool wear, tool breakage, tool breakdowns, etc. are reflected in the surface roughness profile of work piece during machining.

The measurement of surface roughness of work piece to investigate the tool wear was reported by Haruki Kino et al [1]. They have employed a new fractal analysis where the fractal characteristics of machined surfaces were utilized to monitor in-process tool wear. From their investigation, the fractal dimension and the surface roughness (R_a) showed similar tendencies depending on various cutting conditions. The increase in the fractal dimensions with cutting length (tool wear) showed a similar tendency associated with the increase in surface roughness. From the images obtained using light scattering method, the fractal dimension was found to increase regularly as with the increase of tool wear. A qualitative investigation of tool wear was conducted by measuring surface roughness and fractal dimensions; no quantitative assessment could obtain from the experiment results. Manikant Kumar et al.[2] have reviewed a number of methods that have been employed to monitor the surface roughness of work piece and therefore, discussed the relationship of tool geometry/tool wear with the surface roughness, tool vibration, and cutting force in machining. Benardos and Vosniakos [3]studied neural network modeling approach for the prediction of surface roughness (Ra) in CNC face milling using the principles of Taguchi design of experiments (DoE) method. The factors considered in the experiment were the depth of cut, the feed rate per tooth, the cutting speed, the engagement and wear of the cutting tool, the use of cutting fluid and the three components of the cutting force. Using feed forward artificial neural networks (ANNs) trained with the Levenberg-Marquardt algorithm, the most influential of the factors were determined, to predict the surface roughness with a mean squared error equal to 1.86% and to be consistent throughout the entire range of values. A noncontact displacement sensor was used to assess the surface topography of the work piece to relate the tool wear. The investigation showed the predicted R_a values were better correlated with measurements in flank milling than in end milling. However, a considerable amount of error of 12 and 23% were calculated for the flank and end milling tests, respectively. Azman Ismailet al.[4] investigated the external surface hardness of friction stir welded aluminum alloy 6063 pipe joint. Several welded samples were produced on varying process parameters which were successfully joined by using a non-consumable tool with a flat shoulder and a cylindrical pin. Khaled Boulahem et al. [5] focused on the development of amathematical model of arithmetic mean heights of surface (Sa)in friction stir welded AA2017 aluminium alloy using Taguchi L_8orthogonal design of experiments and response surface methodology. Machining variables such as rotation speed, traverse speed and tool shoulder diameter were considered in building the model. 3D surface topographies were used to characterize the surface roughness. The analysis of variance results showed that all the welding parameters are statistically significant at 95 % confidence level. According to Main Factor Plots, an increase in the rotation speed decreases the surface roughness while any increase in the traverse speed or the tool diameter shoulder increases it. Kassim et al [6] investigated the tool condition by measuring the surface roughness of work piece in end milling and face milling, and both for roughing and semi finishing operations. A CCD camera with appropriate focusing has been used to capture the image of surface roughness, and the images of machined surfaces were analyzed using structural and statistical-based approaches. From their observation, the run-length statistics-based method was fast and reliable in differentiating tool conditions, while the structure-based Hough transform method was computationally intensive. Though a considerable accuracy was obtained, some fitting error was still in the results. For instance, some total fitting error of 61 and 189 were counted for the sharp and dull tool, respectively, from the Hough transformation method.

The prediction of surface roughness and flank wear was performed by Özel and Karpat [7] for variety of cutting conditions during turning. They have developed and utilized a NN model to investigate tool wear and surface roughness where the regression model was used to capture process parameters. A comparison has been carried out between results from NN model and regression model analyses. The developed prediction system is found to be capable of accurate surface roughness and tool wear prediction for the range it has been trained. The results have shown that a decrease in the feed rate resulted in better surface roughness but slightly faster tool wear development, and increasing cutting speed resulted in a significant increase in tool wear development but resulted in better surface roughness. Increase in the work piece hardness resulted in better surface roughness but higher tool wear. Despite a significant rate of success, the result was obtaining some minimal error of 10 and 9% for flank wear and surface roughness identification, respectively. It is reported from Siddhpura and Paurobally [8] that the regenerative vibration or chatter accelerates tool wear resulting in poor surface finish and in turn reduces tool life. Kotaiah et al [9] employed the surface roughness of work piece with other parameters to estimate the tool condition in inward turning operation. They used NN model to relate surface roughness with tool wear and cutting conditions. The crossover probability was considered as 98%, and the probability of mutation was taken as 1%. Chae et al [10] have monitored the tool condition by measuring the surface roughness in a micromilling process and thus investigated the difference between the theoretical and experimental results. Their developed model was based on single variable method, which would be more potential if all three variables, i.e., cutting speed, feed rate, and depth of cut, are considered changing simultaneously. Kirby and Chen [11] have measured vibration of cutting to predict the surface roughness of work piece which was then processed using a fuzzy-net model to correlate with the tool life. An accuracy of 95% was obtained from their proposed model in predicting the surface roughness and thus the tool life. However, the five steps fuzzy networking method and dealing with a wide range of data have made the monitoring and predicting process considerably complex. Although the surface roughness measurement is carried out for the long-term perspective, there is no unified methodology to measure, evaluate, and represent the surface roughness in relation to metal-cutting tools. Above research has shown that surface roughness measurement have been used to investigate the tool condition indirectly. Fractal analysis, light scattered method, and statistical and structural analyses are used to analyze captured surface roughness images to correlate with the tool wear. Regression model, NN, and fuzzy logic techniques are utilized to predict the tool wear from surface roughness values. A decrease in weld speed results in better surface roughness, which causes slightly faster tool wear; an increase in tool rotational speed produces better surface roughness and higher tool wear. Regenerative vibration accelerates FSW tool wear resulting in poor weld surface roughness and tool life [12-16].There are a number of different measurement techniques that can be used to measure surface roughness. Different classes of measurement techniques include direct measurement methods, comparison methods, non-contact methods, and in-process methods. Direct methods evaluate surface finish through the use of a stylus, which is drawn along the surface while perpendicular to the surface. The registered profile created by this process is then used to determine roughness parameters. This technique calls for disruption of the machining process. A sharp stylus may also make micro-scratches on tested surfaces [17-18]. Comparison techniques use samples of surface roughness generated by the same equipment, process and material as the surface to be examined. Visual and tactile senses are used to contrast a sample with a surface of known surface roughness. Due to the subjective nature of the process, this technique is useful for non-critical applications. Non-contact methods use sound or light in place of the stylus. Optical instruments come in several types, like con focal and white light interference, and differ based on the principle behind them. Some non-contact equipment is made from contact-type detectors that have been repurposed by switching out the physical probe with optical sensors and microscopes. Some non-contact techniques can also be on-process techniques [19-21]. To determine surface finish with sound, an ultrasonic pulse is first sent to the surface, where the ultrasonic sound waves are altered and reflected back at the testing device. The reflected waves are then assessed to determine surface roughness parameter. Inductance is another on-process technique used to evaluate surface roughness on magnetic materials. In this approach, an inductance pickup gauges the distances to the test surface using electromagnetic energy. This test provides a parametric value that can then be used to determine comparative roughness.

Methodology

Surface Roughness Measurement of Welded Pipes

The roughness testing machine Mitutoyo SJ – 201as shown in Figure1 is used for measuring weld surface roughness. The Surftest SJ-201P is a shop-floor type surface-roughness measuring instrument, that traced the weld surfaces of friction stir welded aluminium alloy 2024 pipe, calculated their surface roughness based on roughness standards, and result is displayed in Table2. The specification of the aluminium alloy 2024 pipe is given in Figure2.

Figure 1FSW in milling machine

Figure 2 FSW samples

Figure3.Surftest SJ-201P

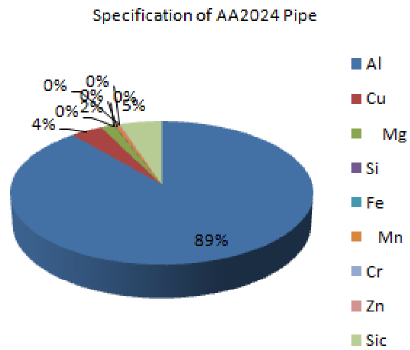


Figure 4 Specification of AA 2024 pipe

Table2 shows that the effects of welding parameters on the weld surface quality of the FS Welded pipe joints is statistically significant. There was a large-scale difference between the surface roughnesses values of the joints welded under different process parameter conditions. Increasing tool rotational speed showed a positive effect on the surface roughness. This may be due to more heat developed during the stirring process. As shown in table 2,pipe joints welded at 1460 rpm and weld speed of 26 mm/min and tool pin diameter of 3.5 mm had smoother surfaces than the joints welded at 550 rpm, 22mm/min, and 4.5 mm diameter. It may be due to application of force by maintaining contact gap between tool and pipe, the particles pressed for alonger time, in vertical position may return to horizontal position and surface layers were densified. Joints showed a definitive relationship between the tool rotational speed and surface roughness. With increasing the tool rotational speed from 550 rpm to 1460 rpm improved the weld surface quality significantly. Average surface roughness (Ra) and mean peak-to-valley height(Rz) are two most important parameters for evaluation of surface roughness.

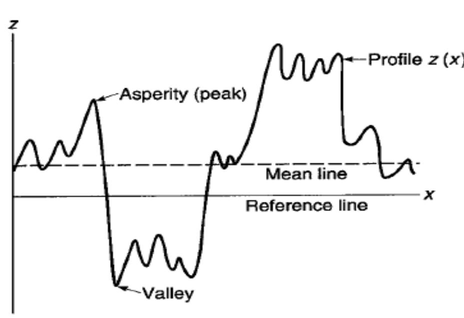


Figure5.Schematic of a surface profile

Ra, CLA, or AA is the arithmetic mean of the absolute values of vertical deviation from the mean line through the profile as shown in Figure3. The standard deviation **σ** is the square root of the arithmetic mean of the square of the vertical deviation from the mean line.

In mathematical form, we write

$$R_a = CLA = AA = \frac{1}{L}\int_0^L |Z - M|\,dx \qquad (1)$$

And

$$m = \frac{1}{L}\int_0^L z\,dx \qquad (2)$$

Where L is the sampling length of the profile (profile length).The variance is given as

$$\boldsymbol{\sigma}^2 = \frac{1}{L}\int_0^L (z - m)^2\,dx \qquad (3)$$

$$= R_q^2 - m^2 \qquad (4)$$

Where,
σ is the standard deviation and Rq is the square root of the arithmetic mean of the square of the Vertical deviation from a reference line, or

$$R_q^2 = RMS^2 = \frac{1}{L}\int_0^L (z^2)\,dx \qquad (5)$$

Table 1Center-Line Average and Roughness Grades

R_a Values up to a Value in μm	Roughness Grade Number
0.025	N1
0.05	N2
0.1	N3
0.2	N4
0.4	N5
0.8	N6
1.6	N7
3.2	N8
6.3	N9
12.5	N10
25.0	N11

FS Welded Samples Ra range

In many cases, the R_a and
σ are interchangeable, and for Gaussian surfaces,

$$\sigma \sim \sqrt{\frac{\pi}{2}}\, R_a \sim 1.25\, R_a \qquad (6)$$

The value of R_a is an official standard in most industrialized countries. Table 1gives internationally adopted R_a values together with the alternative roughness grade number. The **σ** is most commonly used in statistical analyses.

Table2. Measured surface roughness values

SL.NO	SAMPLES	N	W	D	Ra value(μm)
1	FSW#1	550	22	3.5	12.54
2	FSW#2	1460	22	3.5	12.30
3	FSW#3	550	26	3.5	13.76
4	FSW#4	1460	26	3.5	8.67
5	FSW#5	550	22	4.5	13.35
6	FSW#6	1460	22	4.5	11.52
7	FSW#7	550	26	4.5	10.85
8	FSW#8	1460	26	4.5	7.03

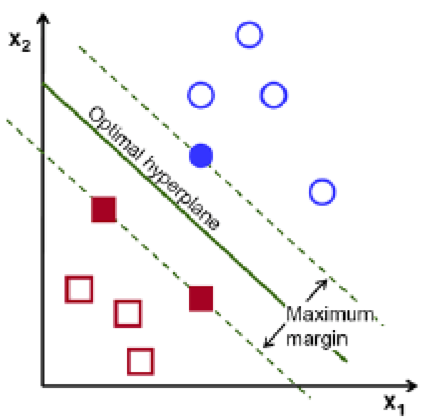
Table 3. Predicted surface roughness values

N	W	D	R
550	22	4	14.385
550	16	5	17.342
550	26	4	12.037
550	22	6	13.255
550	26	6	10.907
650	16	3.5	17.889
750	16	3.5	17.589
850	16	3.5	17.289
950	18	4.5	15.251
1050	18	4.5	14.951
1150	18	4.5	14.651
1250	18	5.5	13.785
1350	20	5.5	12.311
1460	20	5	12.264
1460	26	6	8.177
1460	22	4	11.655

1460	26	4	9.307
1460	22	6	10.525
1450	20	5.5	12.011
1450	20	5	12.294

Machine learning algorithm for classification of welds

Machine learning (ML) is a branch of artificial intelligence that systematically applies algorithms to synthesize the underlying relationships among data and information. Artificial intelligence is used for classifying the welds as good quality and bad quality weld by various machine learning algorithms [22]. Support Vector Machines SVM is a go-to for high performance with little tuning. In SVM, a hyperplane is selected to separate the points in the input variable space by their class, with the largest margin. The closest datapoints (defining the margin) are called the support vectors. But real data cannot be perfectly separated, that is why a*C* defines the amount of violation of the margin allowed. The lower C, the more sensitive SVM is to training data.



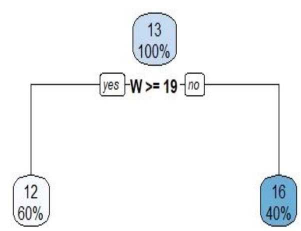


Figure 6 Schematic diagram of SVM classification

Figure 7 classification by weld speed using Decision tree algorithm

From the experimental data closest data points having surface roughness value between 6.3 micron and 12.5 micron are finalized as hyper plane points. From experiment all the surface roughness values Except FSW#3 and FSW #5 are falling as close to the hyperplane that is acceptable weld surface quality range as per the ASME manuals. Only two points are falling beyond hyper plane that is not within the range of accepted surface roughness values. Number of Support Vectors is 6.This validates the experiment conducted in this research work.

Decision tree algorithm used for classifying the weld surface quality based on process parameters. From the Figure 7 it is understood that when weld speed is >=19 mm per minute 60 % chances that the welded joint will have good surface finish. If the weld speed is less than 19 mm per minute 40 % chances are there that the welded joint will have poor surface finish.

Horizontal axis represents Spindle speed and hence cutting tool rotational speed in rpm. Vertical axis represents surface roughness value. The figure shows relationship between tool rotational speed and surface roughness values. From the figure it is understood that when the tool rotational speed is lower surface roughness value increases that is not desirable. When the tool rotational speed is increased surface roughness value decreases that is desirable. From this it is concluded that tool rotational speed has positive impact in getting good quality weld surface that leads to high fatique strength and crack free stress free surfaces. The life of the welded joint is increased.

The figure shows relationship between weld speed in millimeter per minute and surface roughness value in microns. From the figure it is understood that increase in weld speed reduces the surface roughness values that is favorable condition for getting efficient welded pipe joint of aluminium alloy 2024.

Analysis of results

At tool rotational speed of 550 rpm the weld surface roughness resulted as 12.54µm, 13.76µm.13.35µm, and 10.85µm. At tool rotational speed 1460 rpm the weld surface roughness observed as 12.30µm, 8.67µm, 11.52µm,7.03µm. The weld surface roughness 8.67 and 7.03 resulted at tool rotational speed of 1460 rpm. From the figure 8 (a), 9(a) & 9(b) it is evident that higher TRS provides good quality surface with lesser roughness values. The weld samples FSW#4, FSW#8 are best samples at tool rotational speed 1460 rpm and weld speed of 26 mm/min. When the tool pin diameter is at 4.5 mm very smooth weld surface with roughness value of 7.03 is observed. These observations are noted from Figure 8(a),8(b),&8(c).

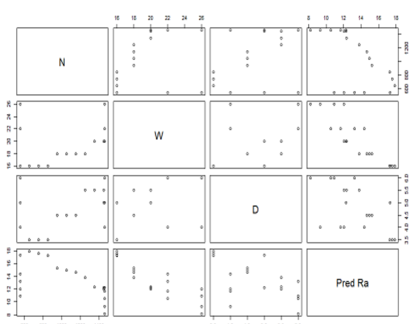


Figure 8(a)direct effect of N, W, and D on R_a

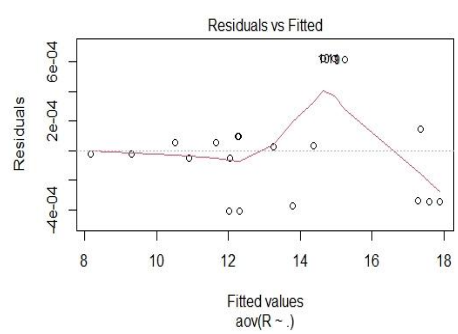


Figure 8(b) Residual vs. fitted values

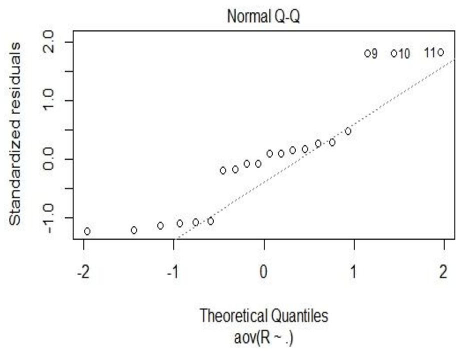


Figure 8(c) Normal Q-Q plot

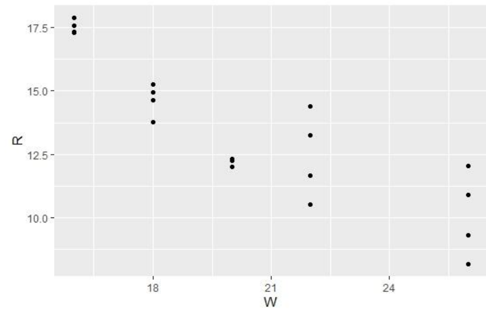


Figure 9(a) Effect of weld speed on roughness

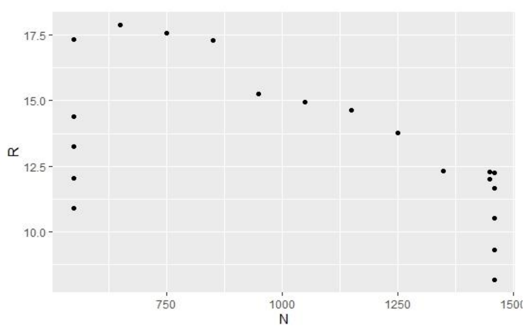


Figure 9 (b) Effect of spindle speed on roughness

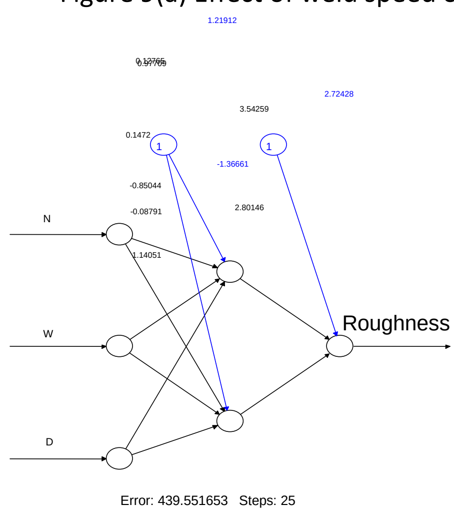


Figure 10NN Architecture for prediction of R_a

Anova Result

Residuals:

Min 1Q Median 3Q Max
-4.101e-04 -3.419e-04 2.430e-06 9.404e-05 6.258e-04

Coefficients:

	Estimate	Std. Error	t value	Pr(>|t|)	
(Intercept)	3.121e+01	5.659e-04	55148	<2e-16	***
N	-3.000e-03	2.204e-07	-13614	<2e-16	***
W	-5.870e-01	2.497e-05	-23505	<2e-16	***
D	-5.650e-01	1.012e-04	-5583	<2e-16	***

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Signif. codes:  0 ‘***’ 0.001 ‘**’ 0.01 ‘*’ 0.05 ‘.’ 0.1 ‘ ’ 1

Residual standard error: 0.0003576 on 16 degrees of freedom
Multiple R-squared:      1,          Adjusted R-squared:      1
F-statistic: 3.804e+08 on 3 and 16 DF,  p-value: < 2.2e-1
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R studio neural network programme is used for predicting the weld surface roughness value with the input parameters as tool rotational speed weld speed and tool pin diameter and the feed forward network architecture is considered as shown in Figure 5.The anova result indicates that tool rotational speed is major contributor for good surface finish weld pipes. Higher the tool rotational speeds lower the weld surface roughness. The effect of weld speed and tool pin diameter on weld surface roughness are given in Figure 6(a) and Figure 6(b)

It is clear that friction stir welding parameters has an impact on the surface roughness of the pipe joints. During FS welding, the cutting force required to cause the tearing of the chips as the tool advances induces a severe plastic deformation at surface and subsurface layers. This deformation results in cold working that affects the metal ductility, hardness, and strength. Meanwhile, a subsurface material fracture occurs due to the violent deformation of the chip, which generates worse surface roughness. The weld strength increases as the surface roughness and weld deformation of the joined pipes increase. The length of bond zones increases with increasing deformation. Therefore, the weld strength of parts depends on the length of bond zones. Then, there is an effect of surface roughness on the welding strength, Joined pipes show resistance to little fluctuating tensile stress. It is observed that the parts rupture from the welding-interface hardness values are about the same at interfaces of pipes having different surface roughness and equal deformation. In the manufacturing industry, the surface must be within certain limits of roughness to improve corrosion resistance and to reduce life cycle cost.

CONCLUSION

Surface roughness in FS welding operation is responsible of many cases of fatigue crack initiation due to generated stress concentrations. Therefore, in the case of improving quality of surface roughness joints, this study is devoted to define the welding parameters and tool geometry leading to welded joints with optimum surface roughness. The rotation speed tool and traverse speed tool are very important parameters in controlling the surface morphology of the joint. The surface roughness is a result of the geometry of the tool and feed rate. The results indicated that an increase in the ratio (transverse speed/rotational speed) improves the surface state. Within the limitations of this experimental study on the relationship between surface roughness and welding process parameters of aluminiumalloy2024 pipe, the following conclusions can be drawn:

- Surface vector machine and deep learning algorithm can be applied to predict quality of weld based on the process parameters TRS, WS, D. These two techniques can be applied to prevent machine failure and maintenance activities.

- The surface roughness values except FSW#3 and FSW #5 are falling as close to the hyper plane that is acceptable weld surface quality range as per the ASME manuals. Only two points are falling beyond hyper plane that is not within the range of accepted surface roughness values. This validates use of support vector machine algorithm and decision tree algorithm the experiment conducted in this research work.
- Low quality of weld was observed when surface roughness increased, as a consequence of the changes induced after welding.
- The tensile strength is surface roughness dependent; as increasing the surface hardness and roughness have the effect of increasing the strength, which can be attributed to the strengthening of the material and the rise of stress concentrators.
- This study proves that the greater the tool rotational speed & weld speed, lesser will be surface roughness which is highly recommended. Also difference between shoulder diameter and pin diameter must be selected carefully. More difference creates more pressure on weld area hence smooth surface is obtained.

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