Some Trends in Friction Stir Welding

Sandeep P. Nevagi
Assistant Professor
Department of Mechanical Engineering
Walchand College of Engineering, Sangli, Maharashtra, India

Abstract — Friction stir welding (FSW), is a relatively new solid state joining process patented in 1991[1]. It uses friction to generate heat and weld the plates in solid state. FSW was initially used to weld aluminium alloys, and is well suited for joining aluminum alloys[2]. It has an advantage over fusion welding when joining highly alloyed aluminium. High quality joints may even be made in aluminum alloys. FSW is environment friendly and energy efficient as compared to most of the welding processes.

Keywords: Friction Stir Welding (FSW), Weld Aluminium Alloys

I. Introduction

Aluminium alloys are replacing steels in industrial applications. Some aluminium alloys have strength comparable with structural steels and low weight thus allowing for a reduction of weight. Joining of these materials can sometimes cause undesirable results. Due to lack of structural transformations in solid state, excellent thermal and electrical conductivity, fusion and resistance welding of aluminium alloys cause problems in. That led to the development of Friction Stir Welding, a solid state joining technique in which the material is heated by friction between the material in form of plates and the tool. The tool is made of two main parts, shoulder and a pin. Shoulder generates the heat, contains the plasticized material in the weld zone and the pin mixes the material to be welded, creating a joint. This results in defect-free welds having good mechanical properties.

II. Principle of FSW

Fig. 1 shows the schematic of Friction stir welding, it consists of inserting a rotating tool into the joint of two plates and moving the tool along the joint line.

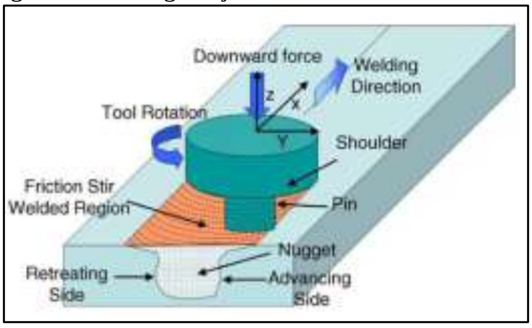

Fig. 1: FSW schematic drawing [3]

Heat is generated due to the friction between the tool and the plates to be welded. Due to heating and tool motion, localised softening and plastic deformation and stirring of material takes place. Due to this a joint is produced in solid state.

III. Process parameters of FSW

The process parameters of FSW are as follows:

A. *Tool Shape*

It is one of the main parameters of FSW. The shape size of the pin and shoulder are responsible for friction, stirring, entry as well as forces during the weld.

B. *Tool RPM*

Rotation of the tool in clockwise or anticlockwise direction along. Rotation causes stirring of the materials to be welded. High rpm of the tool results in high temperature along the joint line.

C. *Linear speed of tool*

Linear motion of the tool moves the stirred material around the pin. This speed also completes the weld along the line.

D. *Angle of tool wrt workpiece surface, depth of pin insertion, preheating, precooling, Tool down force*

These parameters affect the holding of stirred material, flash, concavity along weld line, defect reduction, etc.

E. *Tool Material*

Tool life, cost, reaction with the workpiece material ease of machining tool to required geometry.

IV. CURRENT RESEARCH IN FSW

Prabhuraj et.al. [4] studied the influence of retrogression and re-aging post weld heat treatment on potentiodynamic corrosion and stress corrosion cracking resistance of the stir zone of AA7075-T651 alloy plates under the butt configuration joined using friction stir welding. They used a 3.56 wt% NaCl solution to perform a potentiodynamic corrosion test on the stir zone of the joint. Stress corrosion cracking test were done on the circumferential notch tensile specimens at various conditions of axial stress level in 3.56 wt% NaCl solution. The threshold stress level failure of circumferential notch tensile specimens of retrogression and re-aging post weld heat treatment joints and as-welded joints is 81.81% and 72.31% respectively as compared to the parent metal threshold stress level. They also studied microstructural features of butt joint using optical, scanning electron and transmission electron microscope. They concluded that retrogression and re-aging post weld heat treatment joints resulted in higher resistance to potentiodynamic corrosion and stress corrosion cracking.

Luesak et.al.[5] evaluated the optimal objective and parameter values of friction stir welding process of dissimilar materials: AA5083 and AA606 by using a modified differential evolution approach. They studied the effect of shoulder diameter, rotation speed, welding speed, tilt angle, pin type, reinforcement particle type, and tool pin movement direction on ultimate tensile strength, hardness, and minimum heat input of the FSW weld zone. The experiments were created using the D-optimal experimental design method and to obtain the mathematical model for optimizing the parameters. They found that the results of the modified differential evolution approach were better than results given by particle swarm optimization (PSO), the original differential evolution algorithm (DE), and the D-optimal design (experiment).

Wang et. al. [6] studied the effect of heat treatment on the microstructure and corrosion of FSW joints of 7050-T76 Al alloy. They kept two pieces of 7050-T76 Al alloy plates in a salt bath at 470 ± 2 °C for 2 hours and water quenched. These two pieces of plates were joined using FSW and this was then aged under conditions of 120 °C × 6h + 163 °C × 12h. They concluded that heat treatment decreased the macro-galvanic corrosion effects between zones of FSW.

Kumar et. al. [7] compared the performance of three machine learning (ML) classification models (decision tree, random forest, and XGBoost models) performance for a FSW joined AA 6061-T6 aluminium alloy. The models were trained to check the effect of input parameters on the yield strength of the FSW joined AA6061-T6 alloy. Area under the curve metric and confusion matrix was used to evaluate performance of models. Among the three models XGBoost model showed a maximum accuracy of 95.24%. Thus the ML model can be used to predict the combination of parameters to get the required strength of the FSW joint.

Vidakis et. al. [8] investigated the weldability of 3D printed plates of Polyamide 6 plates joined with FSW. They used full factorial experiments, to assess the effect and optimize levels of rotational speed, travel speed of the tool and pin geometry of the tool. Tensile tests were performed on the FSW welded and unwelded 3D printed specimens of Polyamide 6 plates. Scanning Electron and optical Microscopy were performed to study the welding zones. A threaded cylindrical pin profile with rotational speed of 1200 rpm and travel speed 3 mm/min resulted in a welding efficiency of up to 120.40%. The results showed the feasibility of joining 3D printed plates of Polyamide 6 with FSW.

Guan et. al. [9] predicted friction stir welding defects and their types by using force-data-driven machine learning models. They studied the characteristics of the three component forces in FSW namely: traverse force, lateral force and plunge force. It was found that when a defect was formed there was abnormal increase in average force. This is due to the buildup of redundant material transported to the retreating side. The machine learning model was built with the input of 15 force features. They achieved 95.8% accuracy in detecting defects and 98.0% accuracy in classifying the defects into tunnels and porosities.

Xie et. al. [10] performed a combined strategy for mapping the macro- and microstructural responses of FSW joints of AA2195-T8 alloys. The AA2195-T8 alloys were selected for FSW by authors due to their more complex phase composition and precipitation. The study was done using a combined model for the prediction of tensile strength of FSW joints. The combined model included computational fluid dynamics model, precipitation evolution model, dynamic recrystallization and recovery model, and computational solid mechanics model. Comparison between the experimental results and the combined model was also done to check the accuracy, and it was found to be satisfactory. This combined model will be used by authors to generate datasets for further research using neural network methods.

Nejad et. al. [11] examined the fracture behavior and fatigue crack growth rate of the FSW joined 2024-T351 aluminum alloy. Fracture toughness and fatigue crack growth rate of the specimens were studied experimentally. Artificial neural network was used to predict fatigue crack growth rate and fracture toughness. The concluded that ANN had better accuracy in predicting results as compared to fitting methods.

Verma et. al. [12] predicted the tensile strength of friction stir welded AA6082 by machine learning by using rotational speed and feed rate as input variables. Authors used full factorial design to perform the experiments. The experimental results were validated by random forest regression, M5P tree regression, and artificial neural network (ANN). Absurdity in actual and predicted data was analysed by machine learning models. The rotational speed was found to be the most influencing factor for tensile strength. Whereas the best performing machine-learning approach to predict the tensile strength of FSW joints was found to be Random forest regression.

Thapiyal et.al.[13] used machine learning to establish relationship between tool rotational speed, tool traverse speed, shoulder diameter, pin diameter, tool tilt angle and ultimate tensile strength. The machine learning models were trained and tested on 119 experimental data set for the pure copper system taken from peer-reviewed literature. This dataset was subjected to four machine learning classification Models, i.e., K-Nearest Neighbours, Decision Tree with Gini Index, and information gain as criteria and Neural Network classification. The machine learning model suggested that shoulder and pin diameter of the tool were the most significant parameters influencing the ultimate tensile strength. Further maximum accuracy of 94% in predicting the tensile strength was achieved by using artificial neural network.

Hartl et. al. [14] detected cavities inside the friction stir welds by non-destructive approach using convolutional neural networks. 120 FSW joints of aluminum alloy EN AW-6082-T6 were produced to train the convolutional neural networks model. FSW welds with cavities were also produced purposely for training the model. These 120 FSW welds were examined by ultrasonic testing and labeled as good or defective. Authors used three types of artificial neural network namely; convolutional neural networks, fully connected neural networks and recurrent neural networks to predict the cavities in FSW welds. The authors found that use of convolutional neural networks resulted in highest accuracy (79.2%) among the other three for monitoring surface and internal defects of FSW welds.

Mishra and Pathak [15] determined the grain size parameters such as an equivalent diameter, perimeter, area, orientation etc. in the microstructure of stir zone seam of Friction Stir Welded magnesium AZ31B alloy plates by machine learning algorithm. The algorithm was developed using Python programming. The authors concluded that the developed algorithm determined various grain size parameters accurately.

Mishra et.al. [16] developed a cloud-based remote and real time monitoring and control scheme to prevent weld defects in FSW. Authors used multiple sensors to measure force, torque, power and transmit this data in real time to the cloud. This data was processed and analyzed by machine learning techniques to give feedback for controlling the feed, torque and power in real time. Thus they made FSW complaint with Industry 4.0. They developed two seperate ANNs for predicting ultimate tensile strength and modified weld parameters for improvement in weld quality.

Sudhagar et. al. [17] trained Support Vector Machines to detect and classify defective FSW welds using the images of weld surface. The FSW joints were produced by varying tool rotational speed, welding speed, tool shoulder diameter and pin diameter were recorded by camera and processed. Maximally stable extremal region (MSER) algorithm was used to extract features of weld. 95.8% accuracy was achieved by the SVM model in classification of good and bad FSW weld joint.

Shehabeldeen et. al. utilised a modified version of the adaptive neuro-fuzzy inference system (ANFIS) integrated with harris hawks optimizer (HHO) called ANFIS-HHO model to predict ultimate tensile strength of FSW joint. The ultimate tensile strength was predicted as a function of welding speed, tool rotational speed, and plunge force. They observed that the tool rotational speed was the most effective parameter affecting the ultimate tensile strength of FSW joint.

V. Conclusions

Most of FSW work is done on Aluminium as Al alloys. Other materials used for FSW are magnesium, steel, copper. Even some researchers have joined metal matrix composites using FSW.

Some research is done to predict, control the quality of weld by using Artificial intelligence, machine learning, artificial neural networks, simulation, cloud etc.

References

[1] Thomas, M., Nicholas, E.D., Needham, J.C., Murch, M.G., Temple Smith, P. and Dawes, C.J. (1991) The Welding Institute, TWI, International Patent Application No. PCT/GB92/02203 and GB Patent Application No. 9125978.8

[2] C. Dawes and W. Thomas: 'Friction stir joining of aluminium alloys', TWI Bull., 1995, 6, 124–127

[3] R.S. Mishra, Z.Y. Ma, "Friction stir welding and processing", Materials Science and Engineering: R: Reports, Volume 50, Issues 1–2, 2005, Pages 1-78,

[4] P. Prabhuraj, S. Rajakumar, Tushar Sonar, Mikhail Ivanov, I. Rajkumar, D. Elil Raja, "Effect of retrogression and reaging (RRA) on pitting and stress corrosion cracking (SCC) resistance of stir zone of high strength AA7075-T651 alloy joined by friction stir welding", International Journal of Lightweight Materials and Manufacture, Volume 6, Issue 2, 2023, Pages 264-277

[5] Luesak, P., Pitakaso, R., Sethanan, K., Golinska-Dawson, P., Srichok, T., & Chokanat, P. (2023). "Multi-Objective Modified Differential Evolution Methods for the Optimal Parameters of Aluminum Friction Stir Welding Processes of AA6061-T6 and AA5083-H112", Metals, 13(2), 252.

[6] Wang, Y., Chen, Y., Zhou, L., Shao, Y., Liu, L., & Jiang, J. (2023), "Improving the corrosion resistance of friction stir welding joint of 7050 Al alloy via optimizing the process route", Journal of Materials Research and Technology, 24, pp 8098-8108.

[7] Kumar, A. Kiran, Mulugundam Siva Surya, and P. Venkataramaiah. "Performance evaluation of machine learning based-classifiers in friction stir welding of Aa6061-T6 alloy", International Journal on Interactive Design and Manufacturing (IJIDeM) 17.1 (2023): 469-472.

[8] Vidakis, N., Petousis, M., Mountakis, N., & Kechagias, J. D. (2023) "Optimization of friction stir welding for various tool pin geometries: the weldability of Polyamide 6 plates made of material extrusion additive manufacturing", The International Journal of Advanced Manufacturing Technology, 124(7-8), 2931-2955.

[9] Guan, Wei, Yanhua Zhao, Yongchang Liu, Su Kang, Dongpo Wang, and Lei Cui. "Force data-driven machine learning for defects in friction stir welding." Scripta Materialia 217 (2022): 114765.

[10] Xie, Y., X. Meng, and Y. Huang. "Entire-process simulation of friction stir welding—Part 1: Experiments and simulation." Welding Journal 101, no. 5 (2022): 144-159.

[11] Nejad, Reza Masoudi, Nima Sina, Danial Ghahremani Moghadam, Ricardo Branco, Wojciech Macek, and Filippo Berto. "Artificial neural network based fatigue life assessment of friction stir welding AA2024-T351 aluminum alloy and multi-objective optimization of welding parameters." International Journal of Fatigue 160 (2022): 106840.

[12] Verma, Shubham, Joy Prakash Misra, and Dipesh Popli. "Modeling of friction stir welding of aviation grade aluminium alloy using machine learning approaches." International Journal of Modelling and Simulation 42, no. 1 (2022): 1-8.

[13] Thapliyal, Shivraman, and Akshansh Mishra. "Machine learning classification-based approach for mechanical properties of friction stir welding of copper." Manufacturing Letters 29 (2021): 52-55.

[14] Hartl, Roman, Andreas Bachmann, Jan Bernd Habedank, Thomas Semm, and Michael F. Zaeh. "Process monitoring in friction stir welding using convolutional neural networks." Metals 11, no. 4 (2021): 535

[15] Mishra, Akshansh, and Tarushi Pathak. "Estimation of grain size distribution of friction stir welded joint by using machine learning approach." ADCAIJ: Advances in Distributed Computing and Artificial Intelligence Journal 10, no. 1 (2021): 99-110.

[16] Mishra, Debasish, Abhinav Gupta, Pranav Raj, Aman Kumar, Saad Anwer, Surjya K. Pal, Debashish Chakravarty et al. "Real time monitoring and control of friction stir welding process using multiple sensors." CIRP Journal of Manufacturing Science and Technology 30 (2020): 1-11.

[17] Sudhagar, S., M. Sakthivel, and P. Ganeshkumar. "Monitoring of friction stir welding based on vision

system coupled with Machine learning algorithm." Measurement 144 (2019): 135-143.

[18] Shehabeldeen, Taher A., Mohamed Abd Elaziz, Ammar H. Elsheikh, and Jianxin Zhou. "Modeling of friction stir welding process using adaptive neuro-fuzzy inference system integrated with harris hawks optimizer." *Journal of Materials Research and Technology* 8, no. 6 (2019): 5882-5892.