A Tree-Driven Ensemble Learning Approach to Predict FS Welded Al-6061-T6 Material Behavior

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***Abstract*—This paper proposes a machine learning approach to forecast the mechanical behavior of an aluminum alloy, Al6061-T6, in the case of friction stir welding. Essentially, we investigate the performance of the bagged trees regression (BT) in forecasting the stress-strain curve of an aluminum alloy. This choice's motivation is due to BT's ability to improve the performance of machine learning models by combining multiple learners versus single regressors. Actual data was gathered by performing uniaxial tensile testing on both base material and joined using FSW at a deformation speed of $10^{-3}s^{-1}$. Then, the performance of the BT model is compared to that of the Support Vector regression, and it proved to be more accurate.**

***Keywords*—machine learning, bagged trees, data-driven methods, FSW**

I. INTRODUCTION

The welding institute (TWI) first proposed friction stir welding (FSW) in 1991 as a solid-state material joining process [1]. FSW has proven to be a high-speed, high-quality material connecting method. Because the total heat generated during the welding process is below the melting temperature (about 80% of the base material's melting temperature), this welding approach can greatly decrease or eliminate problems that may develop when employing traditional welding techniques, such as severe distortion. FSW is widely used in many industries, mostly in aerospace industry [2], robotics [3], In the shipbuilding and marine industries [4], In the armor industry [5], and the automotive industry [6], and it also permits to weld dissimilar materials combinations [7], [8]

The effect of varying friction stir welding parameters such as rotation speed, advance speed and cooling rate on the mechanical properties of aluminum alloy welds was experimentally investigated by several researchers [9][10].

Artificial intelligence (AI) is a broad field of computer science that focuses on creating intelligent machines or programs that can accomplish activities that would generally necessitate human intelligence and is widely applicable in materials science. Moreover, AI has known an increasing interest in the Friction Stir Welding applications; it has been used to detect defects in materials degradation [11], to forecast the mechanical properties of materials [12], and tensile strength prediction [13].

In recent years, there has been an increasing interest in employing artificial neural networks to forecast the tensile strength of FSW (ANN). Neural networks have a high capacity for detecting and identifying patterns, which can be used to forecast or anticipate the mechanical properties of materials [14].

[15] used an FSW cell environment to evaluate various machine learning approaches such as principal component analysis (PCA), K-nearest neighbor (KNN), multilayer perceptron (MLP), support vector machine (SVM), and random forest (RF) to predict defective welds under a variety of process conditions, alloys, and joint configurations. The authors stated that the acquired results could make a significant contribution to the optimization of process parameters.

On the other hand, [16] used machine learning techniques to predict the best FSW process parameters for joints. The authors first gathered experimental results on AA2024/AA7075 that were distinct in terms of ultimate tensile strength and hardness. These data were analyzed using a support vector machine (SVM) model and a new artificial neural network (ANN) model that included the Nelder-Mead algorithm, as well as an effective parametric combination to actually confirm tensile strength and hardness. The authors came to the conclusion that the ANN approach outperforms SVM strategies. Simulation studies were used to demonstrate the validity and accuracy of the suggested method.

In another study, [17] investigated the prospect of using machine learning techniques in the welding sector. The authors reported that machine learning (ML) is a valuable tool for resolving problems in different welding methods such as Tungsten inert gas welding (TIG), Friction Stir Welding (FSW), Laser welding, Resistance Welding, Metal inert gas welding (MIG) and Plasma arc welding. Furthermore, the authors stated that ML has the potential to improve the welding process as well as the quality control procedure, it has aided in the real-time detection of defects during welding.

[13] examined how machine learning approaches including Gaussian process regression (GPR), support vector machine (SVM), artificial neural network (ANN), and linear regression

(LR) may be used to analyze and predict the tensile behavior of friction stir welded AA7039 aluminum alloy. The authors demonstrated that all of the models utilized can predict the tensile behavior of the material under study. Furthermore, as compared to other machine learning methods, the ANN modeling approach is substantially superior at predicting the tensile behavior of FS welded AA7039.

In the past two decades, ensemble learning-driven methods, which integrate several single models, have shown a promising solution compared to the traditional machine learning methods. Importantly, ensemble models are characterized by their ability to reduce the model's variance while getting a low bias, making them very appealing to enhance prediction precision. This study presents a data-driven approach to forecast FSW Al-6061-T6 material's behavior. Specifically, we adopted the bagging ensembles of decision trees because it is an effective prediction method that takes the benefit of numerous relatively weak individual trees to improve prediction accuracy. Additionally, it decreases the overall error and can merge several models. As we know, the Bagging trees approach has not been exploited for material behavior forecasting.

Real measurements were gathered by conducting uniaxial tensile testing on the base material, and friction stirred welded are employed to demonstrate the performance of the investigated methods. We compared the performance of the bagged trees (BT) method with support vector regression (SVR). Results revealed the BT approach's promising and superior prediction capacity compared to the SVR.

II. Materials and Methods

A Gantry friction stir welding machine was employed to weld 50×100×3 mm Al6061-T6 plates using a steel alloy FSW tool having a conical threaded pin having a superior and inferior radius of 1.6 mm and 1.45 mm respectively, and a 10 mm shoulder diameter. A conventional clenching system was used to hold the plates, as shown in figure 1.

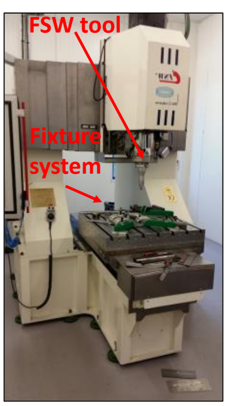

Fig. 1. FSW machine setup.

The chemical elements (%) of the Al6061-T6 aluminum alloy used to carry out the present study is following the ASTM B308 standards [18] (Table I). The working plates were cut in the rolling direction to permit the joint lane to be aligned with the rolling direction of the plates.

1600 rpm tool spinning and 1000 mm/min tool traversal speeds with a 3° tool pitch inclination were used to carry out FSW operation. FSW tensile examination specimens were acquired orthogonally to the obtained joints and were mechanically ground to take out any weld surface defect. Tensile experiments were implemented at various heat degrees of 25°C, 100°C, 200°C and 300°C to contrast the effect of temperature on mechanical aspects of the welded and the as-received materials.

TABLE I. The Chemical Composition of Al6061-T6 (ASTM-B308/B308M-10, 2010)

Wt. %	Al	Mg	Si	Cu	Cr	Fe	Zn	Mn	Ti	Other each	Other, total
Min	95.8	0.8	0.4	0.15	0.04	-	-	-	-	-	-
Max	98.6	1.2	0.8	0.4	0.35	0.7	0.25	0.15	0.15	0.05	0.15

A. Materials and Methods

In the present investigation, tensile testing was carried out using a screw-driven MTS insight tensile testing machine with a 30 kN load cell, an LBO-series Thermocraft LabTemp laboratory oven, and a PC. The tensile test samples were mechanically made using a CNC machine, and the dimensions followed ASTM guidelines [19]. They were cut perpendicular to the weld direction and ground with 180 grit silicon carbide paper, preceded by 1200 grit silicon paper to discard wrinkles and any bottom defects. Tensile samples made from as-received material were sectioned orthogonally to the rolling direction to get a direct comparison between the obtained joints and the as-received material. Furthermore, tensile testing at elevated heat was carried out according to ASTM standards [20].

B. Microstructure

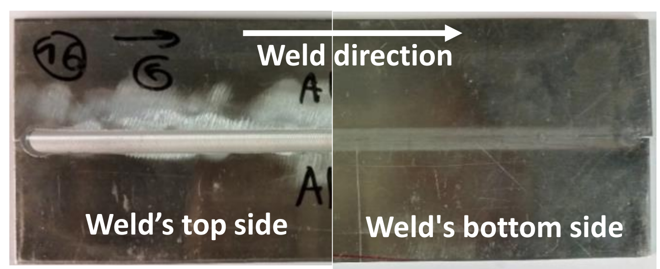

Fig. 2. Top and bottom sides of the weld surface.

Figure 2 shows the images of the weld junction using a spindle speed of 1600 rpm and a tool advancement speed of 1000 mm/min. The top image shows the weld's upper side, with no visible defects such as surface galling, lack of fill, or excessive flash. The bottom image, on the other hand, shows the weld's bottom side, with no visible faults such as lack of penetration or fusion, as stated in [21], [22].

C. Bagged Trees Regression Approach

The main idea of bootstrap aggregating (bagging) trees primarily proposed by Breiman [23] is based first on the construction of multiple similar but independent predictors, then the outputs of such predictors are averaged to obtain the final prediction. This allows the reduction of the variance error as pointed out in [24]. In bagging trees/ensembles of decision trees methods, a large number of individual models (trees) are combined with each other (see Figure 3) to improve the quality of prediction of the model. The use of the BTs predictive model is of great importance because it allows us to reduce the variance of regression trees and address the overfitting problem in a single tree. Recently, the BT-based prediction method demonstrated good performance in different applications, including wind power prediction [25] and swarm motion speed prediction [26]. Figure 3 illustrates the basic concept of the bagging trees prediction approach. According to such a figure, new training datasets of the same size n are first created from the original data by selecting n out of n samples uniformly with replacement from the original training dataset. Then, a training process starts, where each tree in the ensemble is trained individually on the corresponding training new sets. In the present work, 30 trees are used in the bagging trees approach. Lastly, the average of all output predictions is computed to obtain the final prediction. The prediction of the bagging trees model has the following form:

$$\widehat{\mathbf{y}} = \frac{1}{N}\sum_{i=1}^{N} f_i(\mathbf{X}), \tag{1}$$

where $f_i(\boldsymbol{X})$, $i = 1, \ldots, M$ are regression trees.

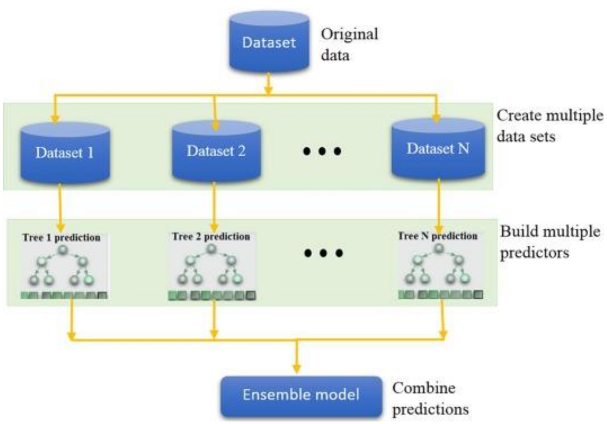

Fig. 3. Illustration of the BT-driven prediction model.

III. Results and Discussion

A. Stress-Strain Data

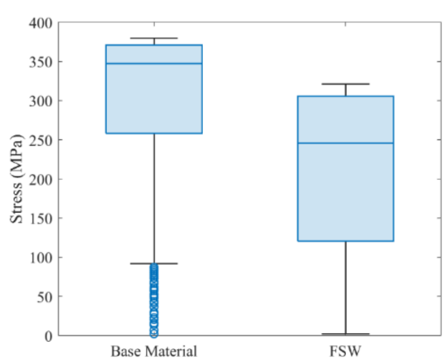

Fig. 4. Stress data distribution of the base material and FSW.

This study investigates Al6061-T6 aluminum, which was welded employing the FSW procedure and tensile tested at room temperature and utilizing a deformation speed of $10^{-3}s^{-1}$. Figure 4 shows the stress data distribution for base material and FS welded plates. From Figure 4, we observe that the ultimate tensile strength of the plates is relatively larger than that of the FSW plates, which confirms the results in [27]. Specifically, this is because of the presence of several areas with varying grain dimensions in the welded joint.

B. Stress-Strain Modeling

At first, a preliminary step to convert the time-series forecasting problem into a supervised learning problem is required to use the considered machine learning methods. This enables the creation of pairs of input and output data points. The prediction models will use the data at the previous time *t-1 to* predict the value of time *t (see* [28] *for more details).* At that, we split the data into two sets: training (80%) and testing (20%). To construct the prediction models, we used a training set. A 5-fold CV procedure has been adopted in training to avoid overfitting. For the BT model, 30 trees are used, and for the SVR model, we used a Gaussian kernel. Figure 5 (a-b) displays the actual and predicted strain-stress values of FSW and base material using BT and SVR models based on training data. Results in Figure 5 indicate the good prediction capacity of the two used models based on training data.

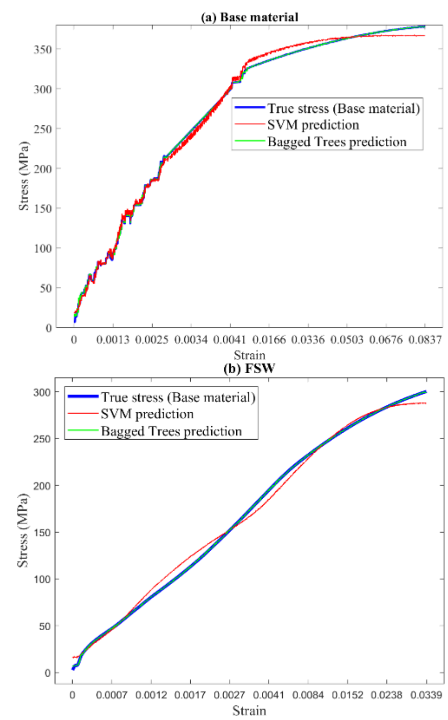

Fig. 5. Measured vs predicted stress-strain curves using BT and SVR models based on training data (a) base material and (b) FSW.

C. Stress Strain Forecasting

Now, we verify the prediction ability of the trained models using new testing data. Figure 6(a-b) shows the actual stress-strain curves and predictions based on the BT and SVR models for the based material and FSW. We observe that the BT model achieves satisfactory prediction performance. However, the SVR model is not providing acceptable prediction performance for both the base material and FSW.

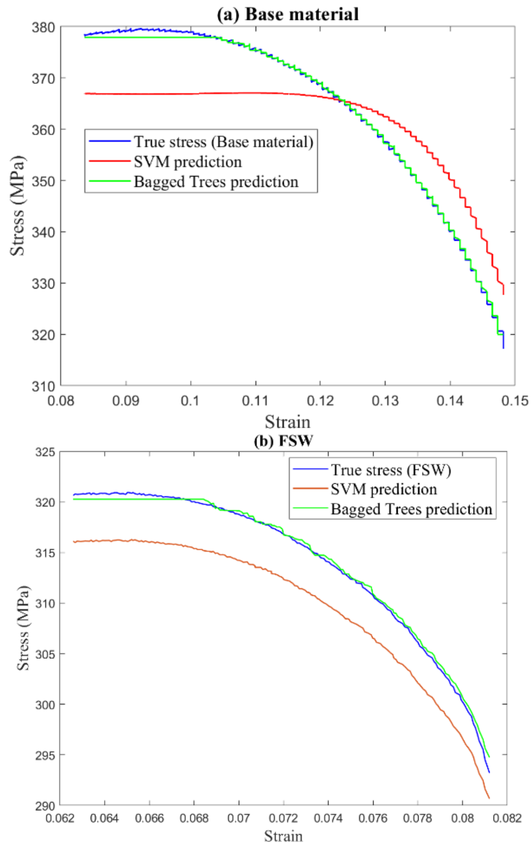

Fig. 6. Actual vs. forecasted stress-strain data using BT and SVR models based on testing data under 25°C (a) base material and (b) FSW.

We also quantitatively evaluate the prediction accuracy of the considered models (BT and SVR) based on Root Mean Square Error (RMSE), mean absolute error (MAE), Coefficient of determination (R2), and mean absolute percentage error (MAPE) (Table II). We can see that the BT model achieved high prediction performance in terms of the computed statistical scores.

TABLE II. EVALUATION METRICS OF FORECASTING USING TEST DATA

Methods	**RMSE**	**MAE**	**R^2**	**MAPE**
SVR (Base material)	9.19	8.41	0.70	2.33
BT (Base material)	0.72	0.54	1.00	0.15
SVR (FSW)	4.32	4.31	0.64	1.39
BT (FSW)	0.43	0.37	1.00	0.12

Figure 7 depicts the boxplots of the prediction errors using the BT and SVR models for the base material and FSW. We observe that the prediction error of the BT method is around zeros, which means that the BT model can follow the future trend in strain-stress data for both the base material and FSW. However, the prediction error from the SVR model diverges from zeros, highlighting the difficulty of this model in capturing the variation in strain-stress data. Hence, these boxplots confirm the superior performance of the BT models over the SVR.

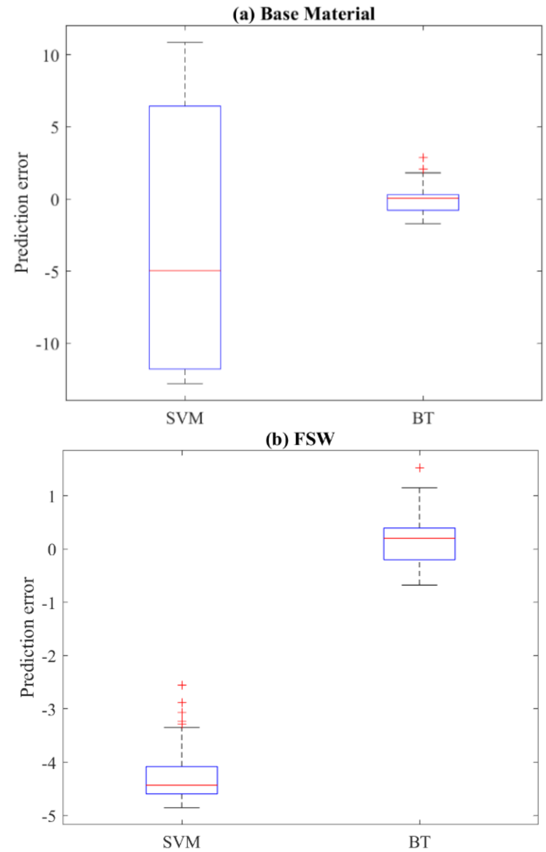

Fig. 7. Distribution of prediction errors using BT and SVR models based on testing data under 25°C (a) base material and (b) FSW.

IV. CONCLUSION

Precise prediction of mechanical properties is undoubtedly crucial to reduce the number of experimental testing and thus save time and costs. This paper investigated the desirable features of the bagged trees method to improve the prediction of the stress-strain curves of Al6061-T6 base material and FSW joints. This study demonstrated that using an ensemble model (i.e., BT) helps reduce the prediction error. Also, we compared the BT-based prediction method to that of the SVR method.

In future work, it would be interesting to investigate other machine learning-driven prediction methods, such as ANN and Gaussian process regression, for predicting material behavior of other types of material alloys and heterogeneous FSW of different materials. Another direction of improvement consists in employing Bayesian optimization to tune the BT hyperparameters in training for improved prediction performance. Furthermore, it would be crutial to investigate the ability of BT and SVR machine learning models in predicting the material's behavior of various metal alloys at different temperatures and strain rates.

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