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Original Article

Weld Bead Prediction in Electron Beam Welding Using Machine Learning

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Abstract *- Machine Learning (ML) enhances the effectiveness of process parameter optimization, even in well-established manufacturing industries. By utilizing this data-centric approach, we can unveil the complex and nonlinear patterns present in the data and transform them into models. These models were subsequently utilized to refine and optimize the process parameters. This study focuses on the utilization of machine learning algorithms for forecasting the weld bead geometry in EBW(electron beam welding) of Ti6Al4V. Input weld process parameters considered included accelerating voltage(kV), beam current(mA), and welding speed(m/min). The weld process parameters varied at three different levels through a series of experiments, and the resulting EBW weld bead geometry was measured for each set of input parameters. The source data were analyzed using machine learning techniques, resulting in the creation of a correlation matrix for the process parameters. The analysis revealed a strong positive correlation with the current as a process variable. An extra tree algorithm yielded a higher coefficient of determination than Random Forest and XG Boost.*

Keywords *- Machine learning, Process parameters, Bead geometry, Correlation, Coefficient of determination*.

1. Introduction

Machine Learning (ML) is an emerging and specialized domain within the wider scope of Artificial Intelligence (AI) that focuses on applying models and algorithms to enable computer systems to acquire knowledge, forecast results, and make informed decisions. In the welding industry, ML can serve as a potential instrument for optimizing and refining the overall quality and efficiency of the process. ML enhances the stability and precision of the welding process by functioning as an adaptive control system.[1] A scheme for selecting and evaluating different sources of manufacturing data in injection molding using ML has been demonstrated [2,12]. A 3D printing or additive manufacturing process uses a machine learning method that relies on a neuro-fuzzy method to estimate the fatigue life of a laser additive process under high-cycle conditions. The model demonstrated accurate predictions compared to existing literature data, showing variability in the results. By integrating the literature findings into the retraining process, the model's performance was enhanced. [3]. For a Directed Energy Deposition (DED) method, a data-centric model was developed using ML to estimate the melt pool temperature. Two predictive models were created using the XG Boost (extreme gradient boosting) and the LSTM (long short-term memory) algorithms. The investigational results exhibited that both the XG Boost and LSTM accurately predicted the melt pool temperature. Notably, XG Boost demonstrated higher computational efficiency than LSTM, while LSTM excelled in terms of prediction accuracy and robustness [4]. Identifying the potential impact of the noise and the size of temperature data during real-time on the prediction accuracy has highlighted one of the primary hurdles that data-driven approaches encounter. The Extreme Gradient Boosting (XG Boost) algorithm has been developed to address this challenge. XG Boost is renowned for its scalability and proficiency in effectively addressing diverse problems. This was accomplished using automatic parallel computation and tailored tree structures. Undoubtedly, XG Boost has been extensively documented to exhibit a ten times faster speed than alternative machine learning algorithms while demonstrating superior generalization capabilities compared to traditional boosting-tree algorithms [5]. Regression model algorithm was used to establish a relation between the independent variables, such as reinforcement and matrix, and dependent variables, such as yield strength, and to predict the mechanical properties. The feature of importance analysis identified the factors most influencing the independent variable on mechanical properties. This study explored the role of ML in a fabrication process [6]. Evaluating the reliability of lattice structures can be challenging, particularly

for the non-destructive assessment of failure in metal additive manufacturing lattice structures. Failure identification depends on whether the applied force exceeds the yield stress limit. An enhanced meta-heuristic Type 2 fuzzy model was developed for metal lattice structures to predict yield stress. Consequently, this model assesses whether a given sample will fail under stress [7]. In metallic materials, an NFML(Neuro-Fuzzy Machine Learning) method was developed to predict the life of multiaxial fatigue. Both fuzzy interface systems and neural networks were combined to capture and identify the correlation between fatigue damage parameters and multiaxial fatigue life. To estimate the premise parameter of the model, the Adam algorithm was employed with the objective of reaching a fast and accurate convergence.

Finally, subtractive clustering was utilized to connect the input variables and output a, thereby improving prediction effectiveness [8]. A novel computational framework, driven by data, has been formed to support the simulation and design of novel structures and material systems [13-14]. The application of ML in predicting the bead geometry of electron beam welding presents a novel and unexplored approach. It should be noted that the optimization of parameters for achieving the desired geometry lacks a precise equation, given the multitude of influencing factors, such as voltage, current, speed, beam oscillation, bead-to-work distance, and their complex interactions [9–11,16]. The presence of these parameters introduces an additional level of intricacy, which poses a difficulty in formulating an analytical equation to compute the bead geometry using process parameters. Consequently, machine learning algorithms (ML) have emerged as a challenging solution aimed at addressing this challenge. ML can learn from datasets, make predictions, and optimize the necessary parameters for determining the bead geometry.

2. Experimental Work

The machine setup used for experimentation is shown in Figure 1.

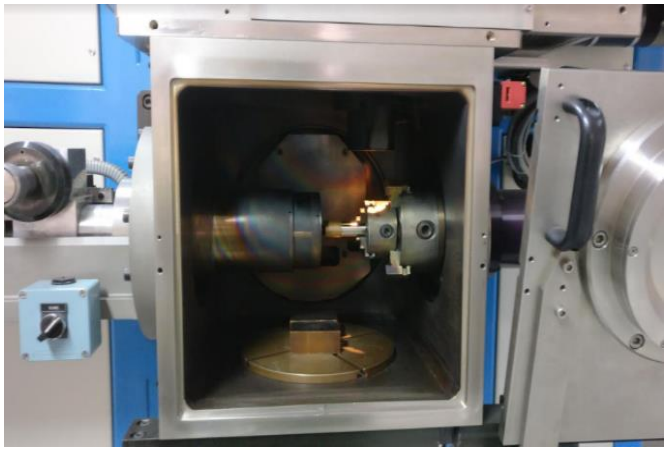
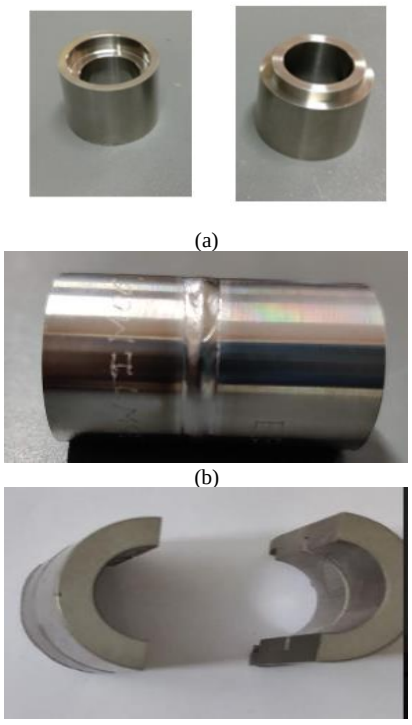


Fig. 1 Machine used for electron beam welding

The current study utilizes Titanium Grade 5 (Ti6Al4V) as the base material. Before welding, the composition of Titanium Grade 5 is verified through EDX analysis, as shown in Table 1. The specimens are prepared using CNC Turning Figure 2(a). The experiment involved conducting bead-on-plate trials by adjusting the Voltage(kV), Beam Current(mA), and Speed(m/min) parameters, as depicted in Figure 2(b). The other welding conditions, including the vacuum pressure in the welding chamber, distance from the electron gun to the workpiece, position of focus, and cleaning procedure before welding, were kept constant throughout the trials [25]. After welding, the specimens were tested for defects using radiographic equipment Figure 3. From the radiography results, it was clear that the weld joints have no defects like porosity cracks. The only defect identified was an incomplete penetration depth. As shown in Figure 2(c), samples were obtained along the longitudinal cross-section to analyze the weldment profile. Following the etching process, weld profiles were examined to determine the bead width and penetration depth.

Table 1. Weldment composition

Element	Weight Percentage
Aluminum	5.5
Vanadium	3.7
Carbon	2.9
Iron	0.2
Oxygen	0.3
Titanium	87.4



(a)

(b)

(c)

Fig. 2 (a) The specimens used in this experiment (b) EBW specimens after welding (c) Samples

Fig. 3 Radiography equipment

Fig. 4 Flowchart for implementing ML Model

Machine learning algorithms, random forest, extra tree, and XG Boost regressors were employed to analyze the data [21-24], specifically for forecasting the bead penetration and width. Figure 4 shows a flowchart for ML.

2.1. Random Forest Regressor

During the training process, an (RF) (Figure 5) builds numerous decision trees by utilizing various subsets of the training data. A random forest selects the most advantageous split at every node when building a decision tree. Subsequently, this procedure is iterated on a distinct subset of the data with different features until the designated number of trees is created. After acquiring the results from all trees, the final prediction is derived from the majority voting for classification. However, a high number of trees leads to increased complexity and computational time, ultimately prolonging the training process. Moreover, bias may be introduced through sampling of subsets [9,15].

2.2. Extra Tree Regressor

Extremely Randomized Trees, commonly referred to as Extra Trees (ET) (Figure 6), build numerous trees similar to RF when training on the complete dataset. Throughout the training process, Extra Trees are created for each observation in the dataset using varying subsets of features. In addition, the extra tree algorithm randomly splits nodes when constructing each decision tree. ET is much faster than RF because node splits are random [9,15].

XG Boost regression (Figure 8) combines coupled strategies to minimize variation. It first employs bagging for ensembled learning to decrease variance errors and then incorporates gradient boosting to decrease bias errors. XG Boost regression builds a robust predictive model by combining multiple weak models. This method is recognized for its high speed, achieved through the fusion of gradient-boosting machine principles with cause-based decision trees [9,18].

To predict the quality of the model, the following regression metrics are calculated: MSE (mean standard error), MAE (mean absolute error), and R^2 (coefficient of determination) [16]. These metrics are used to evaluate the model's error rates and performance in regression analysis. The MAE (mean absolute error) quantifies the variance between the actual and forecasted bead geometry by computing the average of the absolute variances in the dataset.

$$MAE = \frac{1}{N}\sum_{i=1}^{N}|y_i - \hat{y}|$$

Where $\hat{y}$ – Predicted value of y and $\bar{y}$ – mean value of y

The MSE (Mean Squared Error) quantifies the variance between the actual and forecast by squaring the mean deviation across the dataset.

$$MSE = \frac{1}{N}\sum_{i=1}^{N}(y_i - \hat{y})^2$$

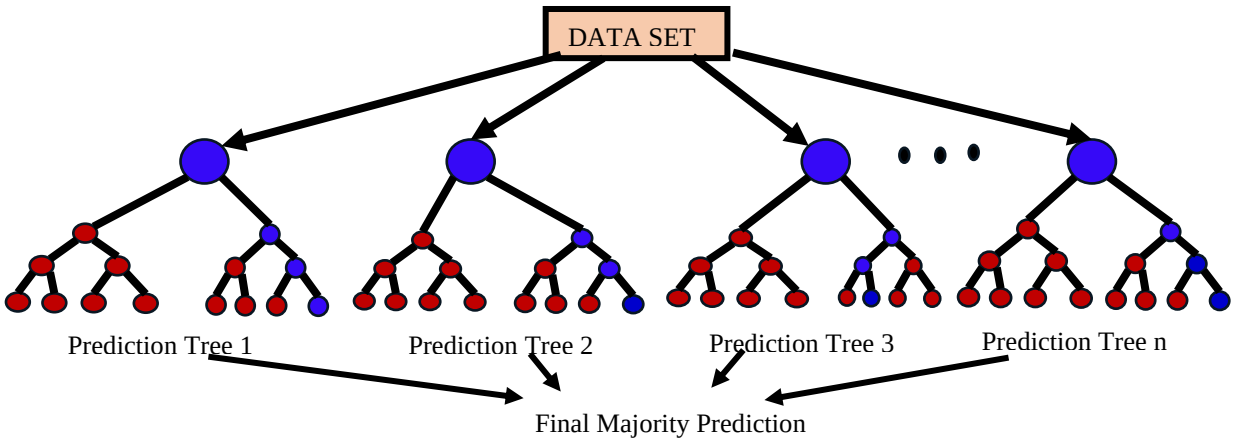


Fig. 5 Graphical representation of random forest regression

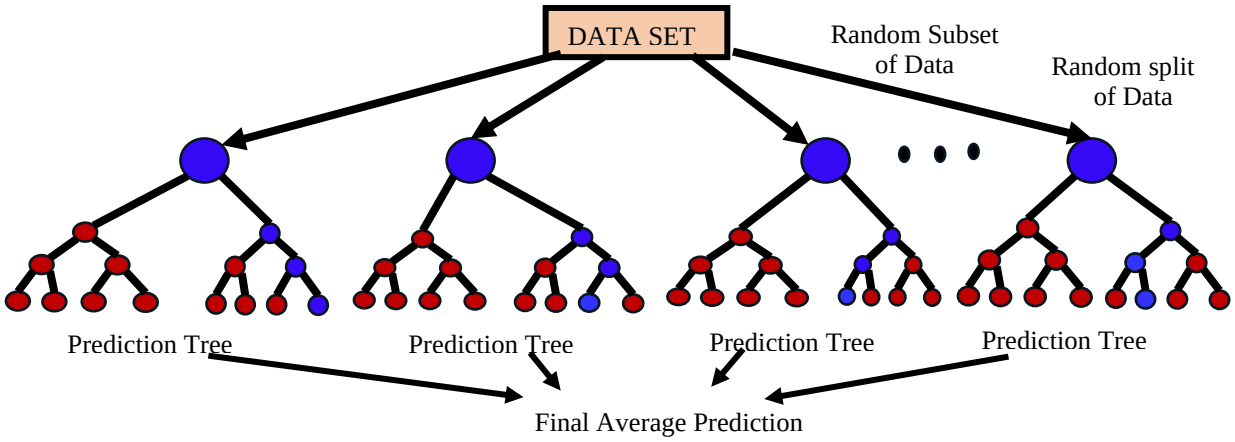


Fig. 6 Graphical representation of extra tree regression

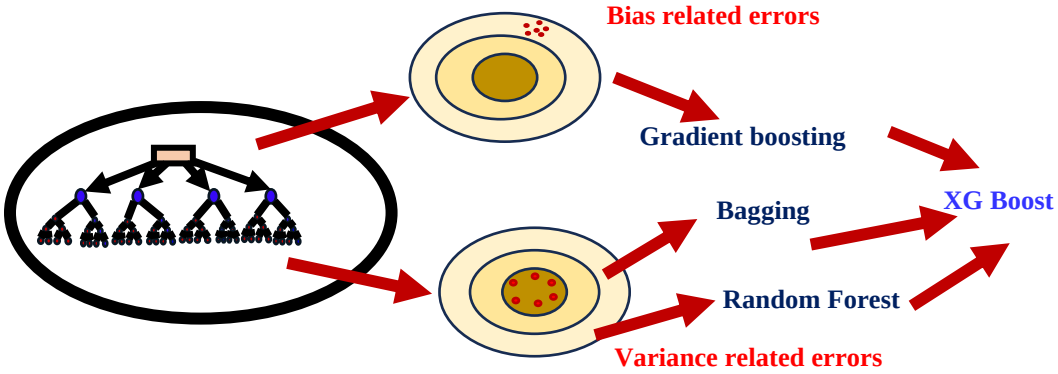


Fig. 7 Graphical representation of XG boost regression

The R^2 (Coefficient of determination) indicates the degree to which the predicted values align with the original values. It is expressed as a value between zero and one. A higher R^2 value signifies a better-fitting model.

$$R^2 = 1 - \frac{\sum (y_i - \hat{y})^2}{\sum (y_i - \bar{y})^2}$$

3. Results and Discussion

The geometry of the bead during welding plays a crucial role in determining the weld joint's capacity to endure stress, affecting its performance in different real-time service conditions [17,19]. The optical projector was used to measure the bead width and depth, and the values are tabulated in Table 2.

Table 2. Bead geometry from the experiments

	Process Parameters			Bead Geometry	
Experiment No.	**Voltage (kV)**	**Current (mA)**	**Speed (m/min)**	**Penetration of Bead (mm)**	**Width of Bead(mm)**
1	45	5	0.8	0.97	0.74
2	60	5	0.8	1.8	1.58
3	45	25	0.8	1.7	1.47
4	60	25	0.8	2.73	1.61
5	45	5	1.2	0.73	0.56
6	60	5	1.2	1.33	0.92
7	45	25	1.2	1.89	1.23
8	60	25	1.2	2.48	1.49
9	45	15	1	1.31	0.91
10	60	15	1	2.23	1.38
11	50	5	1	1.09	0.79
12	50	25	1	1.93	1.23
13	50	15	0.8	1.37	1.14
14	50	15	1.2	1.45	0.98
15	50	15	1	1.41	1.01
16	50	15	1	1.56	1.03
17	50	15	1	1.39	0.98
18	45	5	0.8	1.01	0.82
19	60	5	0.8	1.81	1.55
20	45	25	0.8	1.68	1.36
21	60	25	0.8	2.84	1.45
22	45	5	1.2	0.82	0.52
23	60	5	1.2	1.35	0.96
24	45	25	1.2	1.8	1.11
25	60	25	1.2	2.38	1.47
26	45	15	1	1.31	0.91
27	60	15	1	2.24	1.27
28	50	5	1	1.17	0.83
29	50	25	1	1.98	1.25
30	50	15	0.8	1.28	1.01
31	50	15	1.2	2.12	0.92
32	50	15	1	1.41	1.12
33	50	15	1	1.56	0.93
34	50	15	1	1.39	1.01
35	45	5	0.8	0.62	0.78
36	60	5	0.8	1.79	1.42
37	45	25	0.8	1.72	1.54
38	60	25	0.8	2.71	1.47
39	45	5	1.2	0.77	0.63
40	60	5	1.2	1.38	0.91
41	45	25	1.2	1.72	1.25
42	60	25	1.2	2.32	1.79
43	45	15	1	1.26	1.12
44	60	15	1	2.22	1.34
45	50	5	1	1.13	0.86
46	50	25	1	1.91	1.23
47	50	15	0.8	1.39	1.13
48	50	15	1.2	1.86	0.96
49	50	15	1	1.41	1.22
50	50	15	1	1.56	0.95
51	50	15	1	1.59	1.02

Table 2, with three input parameters and two output parameters, is used to represent the dataset for machine learning. The data were analyzed using machine learning, employing various regression techniques for predicting continuous data, such as bead geometry, bead penetration, and bead width. In this research, MAE, MSE, and Var are the metrics considered to estimate each model's error rates, which are widely employed in machine learning algorithms. It is to be considered that assessing the performance of a regression model solely through these errors can lead to a misconception, as each metric presents a unique perception of the errors and fails to provide a broad understanding of the model's overall usefulness. Hence, apart from considering the MAE and MSE, R^2 values were included. R^2 offers a glimpse into the extent to which a model can clarify the variability of the dependent variable, whereas MAE and MSE offer insight into the scale and spread of errors.

Table 3. Metrics of ML algorithm

S.No.	Method	R^2	MAE	MSE	var
1	Random Forest	0.9257	0.0651	0.0057	0.9288
2	Extra Tree	0.9286	0.0628	0.0055	0.9333
3	xgboost	0.9241	0.0649	0.0059	0.9259

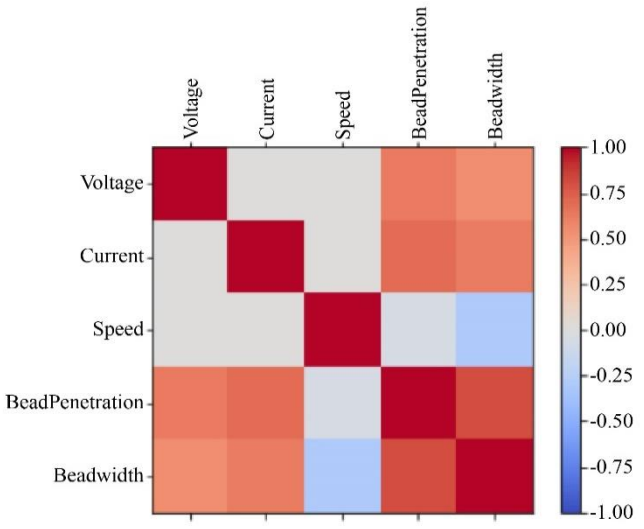


Fig. 8 Correlation matrix

Table 3 shows the different values of error and R^2 observed for each regression model. The highest R^2 was 0.9286 for the Extra Tree regressor, and the model presented the smallest errors based on MAE and MSE values of 0.0628 and 0.0055, respectively. Based on the results in Table 3, the Extra Tree regressor model exhibits a substantial R^2 value and the lowest error, making it the optimal choice for data prediction.

The correlation matrix depicted in Figure 7 displays the relationship between all parameters using color-coded values [20]. Gloomier red shades signify a correlation coefficient (>0), i.e., positive, whereas gloomier blue shades indicate a correlation coefficient (<0), i.e., negative. The coefficient of correlation was approximately 1, indicating a strong relationship. Specifically, the voltage, current, bead penetration and bead width were positively correlated, suggesting a strong connection. However, Speed and Bead geometry displayed a negative correlation.

4. Conclusion

The study's primary aim was to predict titanium's bead geometry by employing various regression model algorithms through Machine Learning. This was achieved by utilizing three input parameters and two output parameters. After analysing the results, the following conclusions were reached.

Extra tree regression emerged as the top-performing model for predicting bead geometry compared with other regression models. An impressive R^2 value of 0.9286 was achieved. Additionally, it demonstrated superior performance with the least error rates for an MAE value of 0.0628 and MSE value of 0.0055, respectively. Based on the paired correlation coefficients in Figure 7, the resulting conclusions can be drawn regarding the cross-parametric correlations:

- Current exhibits a strong positive correlation (0.75).
- Voltage also shows a relatively high positive correlation (0.5).
- The remaining factor pairs demonstrate low or very low correlation levels.
- Additionally, it is worth noting that the beam current was highly correlated with Bead Penetration (0.75) and Bead Width (0. 5).

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