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Surface Roughness Prediction For Robotic Gmaw-Manufactured Beads Through Different Machine Learning Algorithms

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Abstract

WAAM has been proven a promising alternative to the fabricate medium and wide-scale metal parts with a high depositing rate and automation level. However, the production quality may deteriorate due to the poor deposited layer surface quality. In this paper, a 3-D profilometer is used for surface roughness measurement. To improve the surface integrity of deposited layers by WAAM, different machine learning models, including ANN, Decision tree, Random forest regression and linear regression, were developed to predict the surface roughness. Furthermore, the ANN model was optimized by using different number of hidden layer and adam optimizer. Full factorial experiments were conducted to obtain the training data, and the K-fold Cross-validation strategy was applied to train and validate machine learning models. The comparison results indicate that Random forest regression has superiority in predicting surface roughness. The RMSE, MAE and MAPE for Random forest regression were 65.0021, 1.93516, 14.15% respectively. This study could also provide inspiration and guidance for surface roughness modelling in multipass arc welding and cladding.

Keywords: Wire Arc Additive Manufacturing (WAAM), Random Forest regression, Machine learning, Surface roughness, 3-D profilometer, Artificial neural network (ANN)

1. INTRODUCTION

Wire and Arc Additive Manufacturing (WAAM) is a type of 3D printing technology that uses wire as the feedstock and an electric arc as the heat source to melt and deposit the material onto a build platform in layers. WAAM is classified as a type of metal additive manufacturing (AM), which is a process that uses 3D printing techniques to build parts layer by layer using metal materials. WAAM has several advantages over other metal AM technologies, such as selective laser sintering (SLS) and selective laser melting (SLM). For example, WAAM has a relatively low cost of equipment and materials and it can process a wide range of metal alloys, including ferrous and non-ferrous materials. WAAM can also produce parts with high accuracy and good surface finish, and it has a high production rate compared to other AM technologies. The dimensional accuracy of the component, manufactured through WAAM is±1 mm [1].

In recent years, Additive Manufacturing (AM) technology has gained wide attention due to its superiority in fabricating complex components. Additive manufacturing slices 3D objects into multiple layers of two-dimension in CAD, and then deposits feedstock layer by layer. Compared with traditional manufacturing methods, AM technology simplifies the manufacturing process when producing complex components, saves the production time, and provides a solution for the variety of repairs and direct forming. According to Frazier (2014) [2], the metal AM technology can be mainly classified into three types: powder bed systems, powder feed systems, and wire-feed based systems. Among them, the wire-feed process has a higher deposition rate and material utilization (up to 100%) (Karmuhilan 2018) [3]. The energy source for wire-feed AM usually includes laser, electron beam and welding arc. Compared with laser and electron beam-based AM, wire arc additive manufacturing (WAAM) has the advantages in terms of lower equipment expenses and higher deposition efficiency (Xia et al. 2020) [4]. Usually, the deposition rate for AM using laser or electron beam is about 2–10 g/min, while the deposition rate for WAAM is about 50–130 g/min (Brandl et al. 2011; Karunakaran et al. 2010; Frazier 2014) [5].

Khan et al. [6] designed and developed a barrel finishing machine for improving the surface finish of parts produced by WAAM where the part was submerged in a barrel filled with dry or wet abrasives and the barrel was rotated with the part inside it. Some researchers used a hybrid manufacturing process combining WAAM with milling for a better surface finish [7,8]. But they predicted the surface roughness after milling from the input milling parameters. Li et al. [9] predicted the roughness of parts produced by WAAM after machining from the input machining parameters using the 2nd order regression model and Tian et al. [10] did this using Response Surface

Methodology. Laser polishing after machining for improving surface quality has also been investigated too [11]. However, if the surface roughness of WAAM can be modeled and predicted, the milling process might be eliminated or reduced to a large amount, and this is more important for achieving efficiency and reducing material wastage.

The surface roughness of WAAM was predicted using the process parameters in [12]. Three approaches are used-Adaptive neuro-fuzzy inference system (ANFIS), Extreme Machine Learning (ELM), and Support Vector Regression (SVR), to predict the surface roughness from the process parameters including- travel speed, wire feed speed, and bead step-over distance. They found that surface roughness decreased with increasing step-over distance for multi-bead deposition with a straight pass. Travel speed and wire feed speed showed a non-linear relationship with surface roughness. They collected 27 sets of experimental data and used the K-fold cross-validation for machine learning implementation. Among the three machine learning methods, ANFIS gave the best results. The three machine learning methods used in their research have also been used several times by other researchers for predicting various welding performance characteristics [13,14].

Some researchers also used tree-based methods such as Decision Tree [15,16] and Random Forest [15] in arc welding and WAAM [17]. They deposited a single layer with a straight pass and predicted bead width and height from input parameters including current, cladding voltage, deposition velocity, and initial interlayer temperature. Random Forest, known for its suitability for modeling non-linear processes, will be investigated in this paper. The performance of Random Forest will be compared with that of MLP for predicting the layer roughness for a given set of input parameters such as travel speed, wire feed speed, weaving amplitude, and wavelength. This paper makes the following contributions:

- Modeling layer roughness deposited using a robotic weaving path which has not been done before;
- Comparing the effectiveness of Random Forest and MLP for layer roughness modeling in robotic WAAM.

For conducting the experiments, the WAAM process parameters welding parameters (travel speed, wire feed speed and standoff distance) selected. After a layer is deposited, the layer roughness is measured after collecting the profile of the surface with 3-D profilometer. Then modeling methods based on Random Forest, Artificial neural network, Decision tree and linear regression are implemented to predict the surface roughness of a deposited layer for a given set of WAAM process parameters and the experimental results are analyzed and compared.

2. Proposed methods

The objective of this research is to predict the roughness using the WAAM process parameters. The WAAM process model can be expressed using,

$$y = f(X) + \varepsilon \quad (1)$$

where y is the layer roughness; X is a vector of WAAM process parameters including travel speed, wire feed speed and standoff distance; ε is noise.

To construct a roughness prediction model, datasets must be collected first. Suppose the following datasets are obtained:

$$y = [y1, y2, \ldots, yn] \quad (2)$$

$$X = [X1, X2, \ldots, Xn] \quad (3)$$

where y and X are the vectors of output and input respectively; yi is the i th collected roughness data and Xi the ith set of WAAM process parameters; n is the number of collected datasets. The datasets will be divided into training and testing datasets for modeling and testing a model constructed using Random Forest respectively.

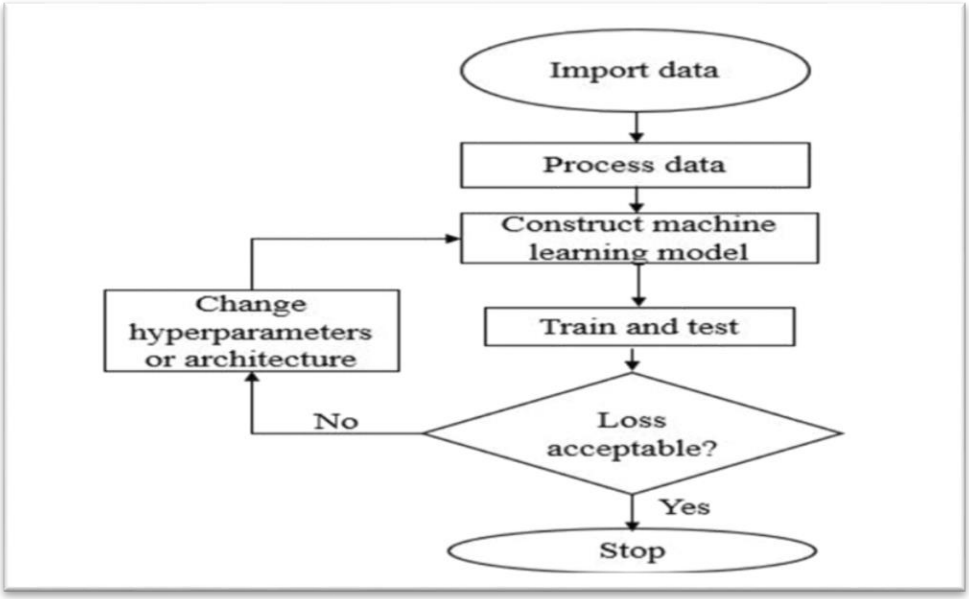

Figure 2-1. construction procedures of a machine learning model.

2.1. Modeling based on Random Forest

Random Forest is a supervised and ensemble machine learning technique that consists of many decision trees as its building blocks. As a supervised machine learning technique, random forest learns to build the relationship between the input X and output y in the training stage. Once the training is done, we test the model using the testing datasets. Random forests can model complex and highly non-linear relationships. It is also generally not affected by outliers and noise, and also a faster process.

2.2. Modeling based on ANN

A neural network is a type of machine learning model that is inspired by the structure and function of the brain. It is composed of layers of interconnected "neurons," which process and transmit information. Each neuron receives input from other neurons, performs a computation on that input, and produces an output that is passed on to other neurons in the next layer.

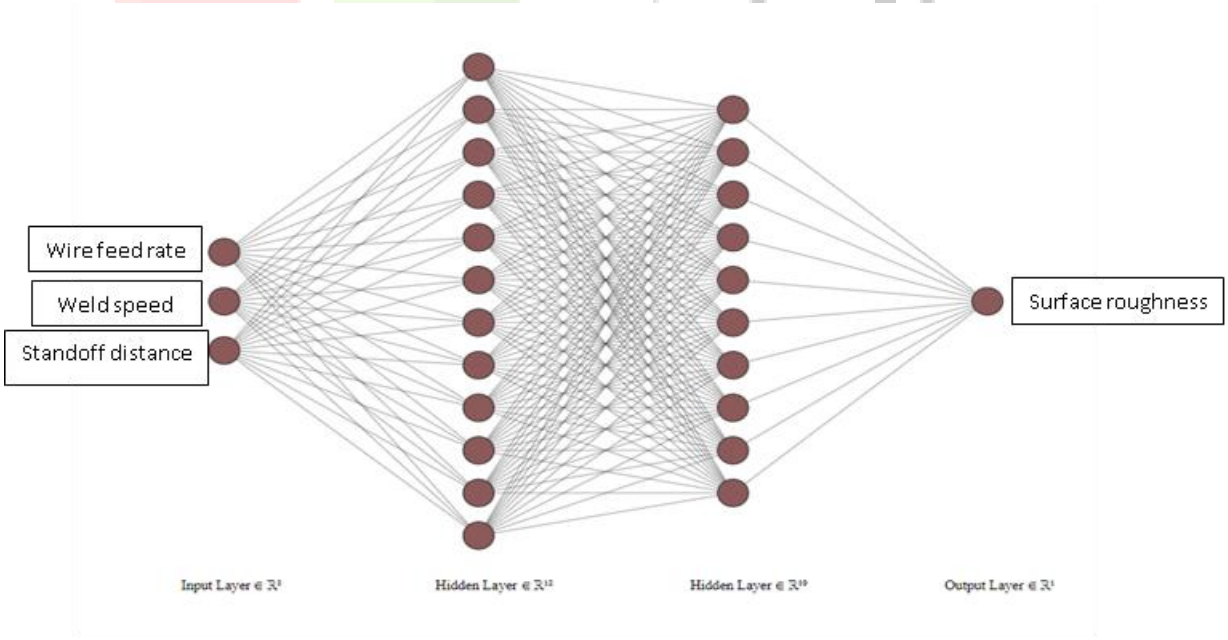

Figure 2.2 Artificial neural network architecture

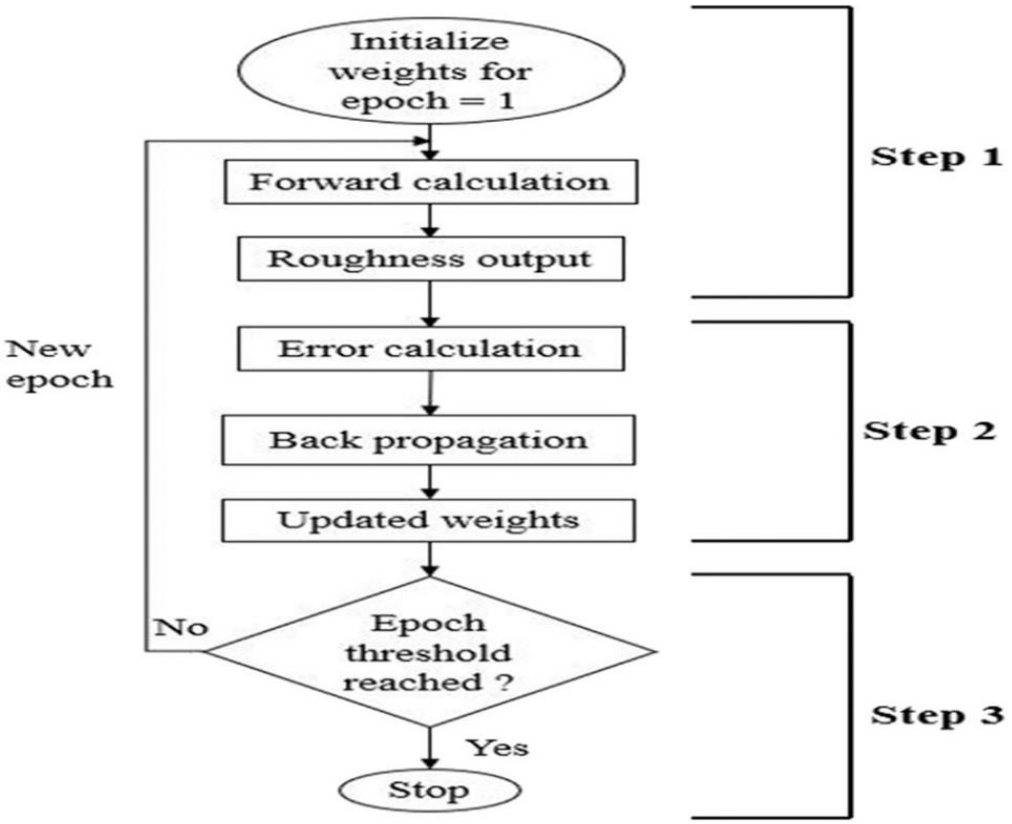

Figure 3.3 Step of ANN

In this study, the development and the training of the network was performed on a PC using Jupyter notebook application tool. For modeling Tensor flow keras library was used. The transfer function for the hidden neurons was a Rectified linear function and a linear function was used for the output neurons. Learning rate was set as 0.01. The number of neurons in the hidden layer was varied from 9 to 15. Different structures of the neural networks were trained. The performance function was the mean square error (MSE) minimization by updating the weights through the gradient descent approach. The best architecture was found as 2-128-64-1 with minimum MSE.

2.3. Modeling based on decision tree

A decision tree is a machine learning algorithm that is used for classification and regression tasks. It is a tree-like model in which an internal node represents a feature or attribute, and the branches represent the decision rules based on the attribute's value. The leaves of the tree represent the class labels or the predicted value for a given input.

To build a decision tree, the algorithm begins by selecting the feature that best splits the data into classes or predicts the target value. The process is then repeated on each child node, recursively splitting the data until the leaf nodes are pure, meaning that they contain only samples from a single class or a single target value.

2.4. Modeling based on linear regression

It is a linear approach to modeling the relationship between a dependent variable (the target or output) and one or more independent variables (the features or inputs).

In linear regression, the goal is to find the line of best fit that minimizes the difference between the predicted values and the true values. This is done by estimating the coefficients (weights) of the independent variables and the intercept (bias) term, which are used to predict the dependent variable.

Linear regression can be used to model the relationship between a single independent variable and a dependent variable, in which case it is called simple linear regression. It can also be used to model the relationship between multiple independent variables and a dependent variable, in which case it is called multiple linear regression.

3. Experimental details

3.1. Material

Aluminum5356 alloys filler wire of diameter 1.2 mm was used for the deposition of single bead according to the DoE. The Al6061-T6 aluminum plate of dimension $200mm \times 200mm \times 20mm$ was used as substrate for the deposition.

3.2 Single bead design of experiment (DOE) for surface roughness measurement

An ABB 6-axis robot (model IRB140) is used to control the welding torch as shown in Fig. 12. The experimental setup is shown in Fig. 13 and the robot is controlled using its controller (model-IRC5). The welding machine is Thermal Arc PowerMaster 500 and the wire feeder is Miller r-115 with 1.2 mm diameter steel wire (ER70S-6). This wire contains higher level of Si and Mn than other carbon steel wires, enabling them to weld steels with a moderate amount of rust. Also, the presence of Si provides more puddle and wetting action. The shielding gas with a combination of 90% Argon and 10% CO2 is utilized with a gas flow rate 31.78 ft3 /h. Direct current reverse polarity (DCRP) is used for connecting the welding machine with the MIG gun and substrate.

Figure 3.1 Experimental setup

The spray transfer mode of GMAW is implemented to reduce spatter and produce quality weld. Robot programming is done using the robot teach pendant (Fig. 13) to move the robot to the desired positions. The program for moving the robot with the MIG gun along the weaving path is written using the ABB robotic programming language RAPID with the software Robot Studio. In this research, numerous trial experiments were done and we found that with increasing travel speed and wire feed speed using it causes more spatter. Considering these issues, we chose the parameters for the experiments whose ranges are given in Table 1. 50 datasets were used to train and validate (using cross-validation) the proposed Machine learning methods. In order to test the proposed methods, another 22 data set are used. The values of the parameters of these 22 experiments were chosen randomly based on the sklearn test train split method.

S.No.	Feed Rate (m/min)	Weld Speed (mm/s)	Standoff distance (mm)	surface roughness (Sa)
1	8	2.5	8	117.402
2	9	2.5	8	140.716
3	10	2.5	8	139.8
4	8	3	8	101.772
5	9	3	8	125.086
6	10	3	8	127.3
7	8	3.5	8	86.142
8	9	3.5	8	109.456
9	10	3.5	8	114.8
10	8	4	8	70.512
11	9	4	8	93.826
12	10	4	8	102.3
13	8	4.5	8	119.846
14	9	4.5	8	144.076
15	10	4.5	8	155.254
16	8	5	8	110.62
17	9	5	8	134.85
18	10	5	8	148.523
19	8	2.5	10	119.662
20	9	2.5	10	142.976
21	10	2.5	10	142.875
22	8	3	10	104.032
23	9	3	10	127.346
24	10	3	10	130.375
25	8	3.5	10	88.402
26	9	3.5	10	111.716
27	10	3.5	10	117.875
28	8	4	10	131.332
29	9	4	10	96.086
30	10	4	10	105.375
31	8	4.5	10	122.106
32	9	4.5	10	146.336
33	10	4.5	10	103.77
34	8	5	10	112.88
35	9	5	10	137.11
36	10	5	10	161.34
37	8	2.5	12	121.922
38	9	2.5	12	145.236
39	10	2.5	12	145.95
40	8	3	12	106.292
41	9	3	12	129.606
42	10	3	12	133.45
43	8	3.5	12	90.662
44	9	3.5	12	113.976
45	10	3.5	12	120.95
46	8	4	12	75.032

47	9	4	12	98.346
48	10	4	12	108.45
49	8	4.5	12	124.366
50	9	4.5	12	148.596
51	10	4.5	12	142.826
52	8	5	12	115.14
53	9	5	12	139.37
54	10	5	12	133.6
55	8	2.5	14	124.182
56	9	2.5	14	147.496
57	10	2.5	14	144.72
58	8	3	14	108.552
59	9	3	14	131.866
60	10	3	14	132.22
61	8	3.5	14	92.922
62	9	3.5	14	116.236
63	10	3.5	14	119.72
64	8	4	14	77.292
65	9	4	14	100.606
66	10	4	14	154.312
67	8	4.5	14	126.626
68	9	4.5	14	150.856
69	10	4.5	14	145.086
70	8	5	14	117.4
71	9	5	14	141.63
72	10	5	14	135.86

3.3 Analysis of surface of bead

Sa is the areal (3D) equivalent of two-dimensional Ra. Sa is the “areal average roughness,” the average height of all measured points in the areal measurement. The “S” parameters refer to measurements of a “surface,” as opposed to the “R” parameters which are calculated from the roughness profile.

After a part is fabricated, the part surface was scanned using a zygoneyview 90003-D profilometer, and the point cloud data were collected using the 3-D profilometer. Among various definitions of surface roughness such as average roughness, root-mean-square (RMS) roughness, and maximum peak to valley roughness, used in industries, average roughness is the most effective index of product quality.

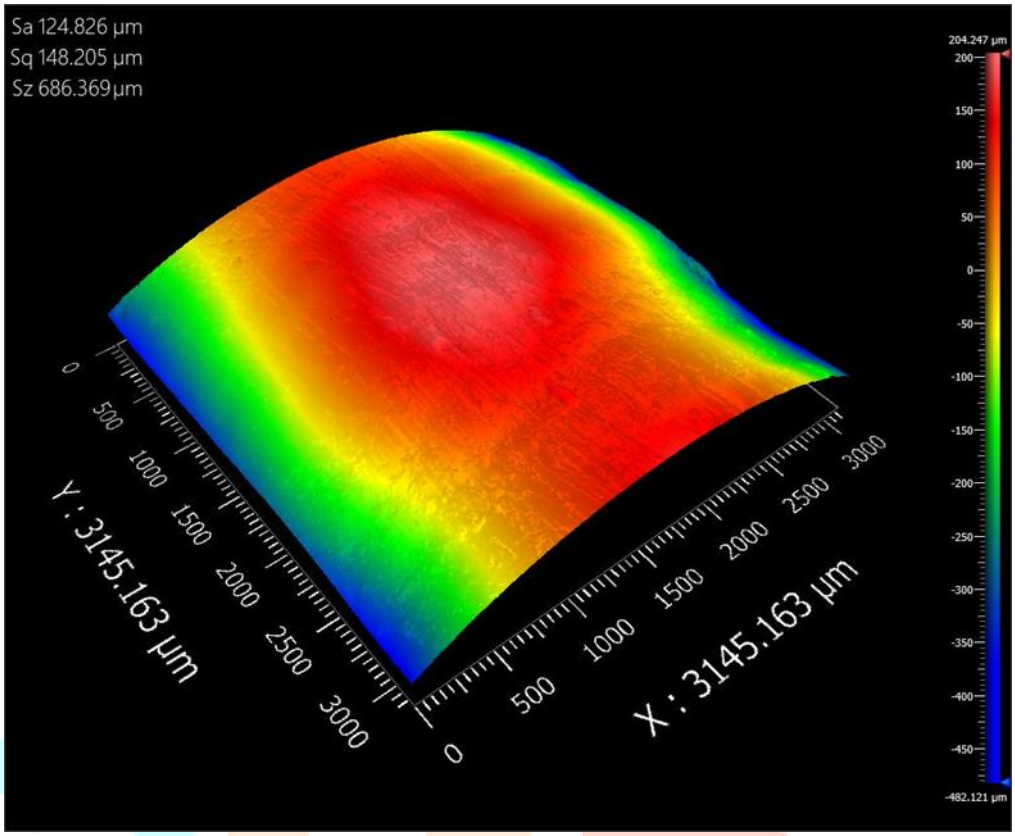

Figure 3.2 surface profile

4. Result and discussion

4.1 Prediction of result

The prediction graph of Random Forest for the 72 cross-validated training datasets is shown in Fig. 20. The mean squared error is 65.0021 and the average error percentage (also known as mean absolute percentage error (MAPE)) is 5.64% (maximum 12.58% and minimum 0.47%). The prediction graph of Random Forest for the 22 testing datasets is shown in Fig. 21. The mean squared error is 103.1964 and the average error percentage is 5.77% (maximum 13.74% and minimum 1.25%). The prediction graph of ANN for the 50 cross-validated training datasets is shown in Fig. 22. The best ANN architecture is 4-10-1 with a minimum MSE of 0.00052 and an average error percentage of 4.94% (maximum 17.10% and minimum 0.23%).The mean squared error is 0.00087 and the average error percentage is 7.37% (maximum 20.32% and minimum 0.80%)

In both Random Forest and MLP, the validation (cross-validated) MSE and MAPE were better than the testing MSE and MAPE. For the 50 training (cross-validated) datasets, even though the MAPE of MLP is slightly better than that of Random Forest, but the maximum error rate of MLP (17.10%) is larger than that of Random Forest (12.58%). The MSE is about the same for both methods. Hence, for the 50 training datasets, we can conclude that Random Forest provides better results than MLP. For the 22 testing datasets, Random Forest has better results than MLP for all the performance indices. Moreover, Random Forest took less time compared to MLP since Random Forest has few hyperparameters.

4.2. Selecting the most accurate model

For verifying predictable accuracy of the neutral network, decision tree, random forest regression and the linear regression models, the scatter diagrams of predicted versus measured surface roughness from all the models by using training data are shown in Figs. 5. The performances of all models are evaluated by the mean value of the error rate (ER) and the standard deviation of the ER. The ER is defined as follows:

$$ER_{(n)} = \frac{|G_{predicted(n)} - G_{actual(n)}|}{G_{actual(n)}} \times 100\% \quad (4)$$

where $G_{redicted(n)}$ is the predicted bead geometry based on the model,

$G_{actual(n)}$ is the measured bead geometry,

and n is the experiment index.

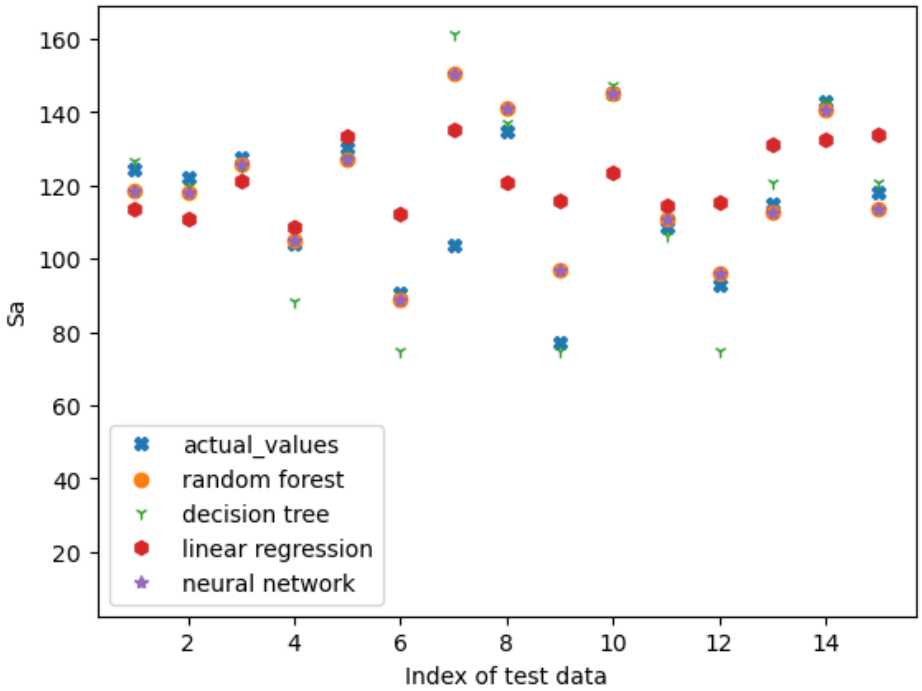

Figure 4.1 actual vs predicted result for different models

Table 2 Error analysis between different models

Model	R^2 value	mean square error (MSE)	mean absolute error (MAE)	mean absolute percentage error (MAPE)
ANN	**.8202**	**103.1964417**	**6.123564**	**5.7702**
Random forest regression	**.7956**	**65.00210892**	**1.935768889**	**5.6426**
linear regression	**.6526**	**341.0518926**	**15.65344503**	**21.210442**
decision tree	**.8124**	**81.0298634**	**8.996066667**	**18.14025**

Detailed error analysis for surface roughness using all models is shown in Table 2. The maximum errors of Surface roughness predicted by all models are no more than 21.21%, within the range of reasonable accuracy. For the bead width and height, the network model has a lower mean value and a lower standard deviation of ER than the values predicted from the second-order regression model. It can be concluded that the neural network model exhibits a better predictive ability than the regression model in actual applications. The reason why the neural network model has a better performance than the second-order regression model is that the neural network, with a hidden layer establishing a nonlinear mapping between the inputs and outputs, has strong capability of approximating any nonlinear processes.

5. Conclusion

The paper investigates the surface roughness for robotic WAAM using a surface profile. Random Forest, ANN, decision tree and linear regression models were developed that were able to predict the surface roughness given a set of robotic WAAM parameters. Experiments were performed and the results show that both methods are effective in modeling the relationship between robotic WAAM parameters and layer roughness, however, the modeling method using Random Forest achieves better results than that using MLP. The developed Random Forest model was able to predict the weld bead roughness from the given input parameters with an average error rate below 6% for both validation and testing. Since Random Forest is not computationally expensive, it can be extended for online roughness modeling for quality control purposes.

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