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Heat input prediction during dissimilar welding of steel using different machine learning model

Yeshwanth Dendi[1*], Wasim Akram[2]

[1,2,]Assistant Professor, Department of mechanical Engineering, Presidency University, Bengaluru, Karnataka, India, 560064

Corresponding Author[*]: yeshwanthreddy806@gmail.com

ABSTRACT

In the current research work, different machine learning model such as random forest (RF), support vector regression (SVR), XGBoost and Linear regression (LR) is used to predict the heat input involved in dissimilar welding of AISI 304 stainless steel and AISI 1020 carbon steel. The welding is accomplished using gas metal arc welding with different input parameter such as welding speed, welding current and torch angle. The acceptability of different model is checked based on coefficient of correlation (CC)and root mean square error (RMSE). The RMSE for test data for random forest model and XGBoost model are found to be 10.99 and 9.97 respectively. The corelation coefficient (CC) for test data for random forest model and XGBoost regressor model is found to be 0.9965 and 0.9962 respectively.

Keywords: Random forest, linear regression, XGBoost regression, support vector regression, Machine Learning, dissimilar welding,

INTRODUCTION

Dissimilar welding is significantly used in different industry such as pressure vessel, shipbuilding and automobile to manufacture a component subjected to different chemical and mechanical load in different parts of the component. For example, carbon steel welded with austenitic steel is significantly used in power generation sector, petrochemical industry as a structural material [1,2]. Austenitic steel has a better corrosion resistance whereas carbon steel is having better wear resistance and is less costly. From the past literature it is evident that heat input during welding has significant effect on the properties of the final weldment. Higher heat input leads to the formation of intermetallic phase, residual stress, weld distortion, elemental segregation and other defects[3,4]. For measurement of heat input , most of the calorimetric technique used for the measurement of heat input produce results that have systematic errors due to uncontrolled heat loss from the sample from the time welding start to the end. During welding, some part of the heat input to the plate gets dissipated to the environment by radiation mechanism and also by convection from the heated bead [9].

A significant number studied were conducted on dissimilar welding for better understanding the underlying concept to produce the sound weld in terms of better mechanical properties of the joint.A large number of experiment needs to be conducted by varying the different input parameter in order to produce sound welds which is certainly a time consuming process and also it requires significant human effort.To resolve these issue, researcher round the world are using different machine learning models to predict the output characteristics based on the given input variables which effect these characteristics [5,6,7,8].A team of researcher [10] developed a hybrid model combining support vector machine (SVM) and relevance vector machine (RVM) to predict the bead geometry during gas metal arc welding of metallic parts. The performance measured in terms of root mean square error (RMSE) is observed to be 0.0257 and 0.0447 in predicting the height and width of the bead respectively.

The objective of the present study is to predict the gross heat input under welding performed with different input parameter using different machine learning model.

EXPERIMENTATION

In present work dissimilar welding is carried out between 1020 low carbon steel and 304 stainless steel using GMAW process. The selected plate dimension for welding is (length = 200mm, width = 100mm and thickness =

6mm). The welding experiment is performed by varying the input parameter such as welding speed, welding current and torch angle. The detail of different level of input parameter used in the current study is shown in Table.1. The images of some of the welded sample is shown in Fig.1. The gross heat input is calculated by subtracting the heat lost by convection and radiation from the heat input to the weld.

Table 1. Welding input parameter and their level

	-1	**0**	**+1**
welding speed(mm/sec)	4	6	8
welding current (A)	60	80	100
torch angle (degree)	-20	0	20

The gross heat input during welding at different input parameter is shown in Table.2

Exp No.	Torch angle (degree)	Welding speed (mm/s)	Welding current (A)	Gross heat input (J/mm)
1	-1	-1	-1	318
2	-1	-1	0	471
3	-1	-1	1	597.4
4	-1	0	-1	249.4
5	-1	0	0	368
6	-1	0	1	475.5
7	-1	1	-1	153.2
8	-1	1	0	213.9
9	-1	1	1	274.1
10	0	-1	-1	334.7
11	0	-1	0	471.79
12	0	-1	1	597.4
13	0	0	-1	254.4
14	0	0	0	360.7
15	0	0	1	466
16	0	1	-1	159
17	0	1	0	221.6
18	0	1	1	287.6
19	1	-1	-1	318
20	1	-1	0	484.2
21	1	-1	1	582.5
22	1	0	-1	249.4
23	1	0	0	353.8
24	1	0	1	456.8
25	1	1	-1	141.3
26	1	1	0	195.7
27	1	1	1	256

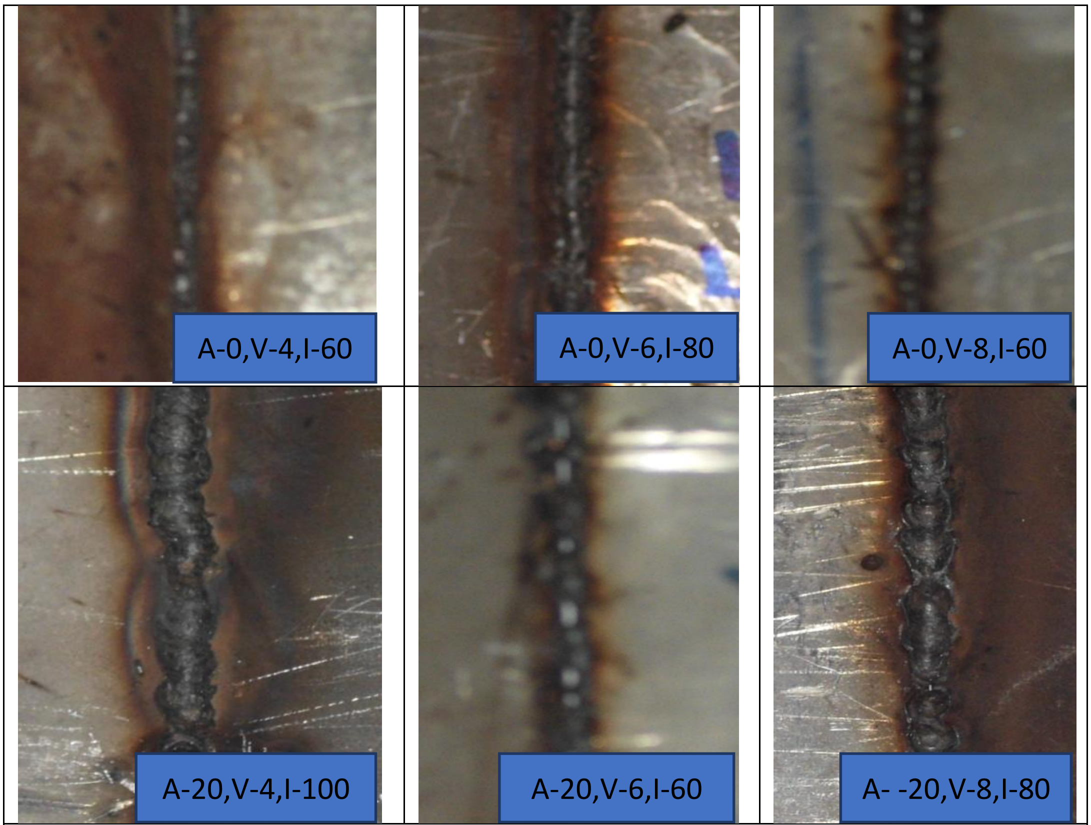

Fig.1 The actual welding image at different input parameter

Machine learning Modelling of Heat input.

The modelling of heat input is performed using different machine learning technique such as LR, SVR,RFR and XGBoost. Among the whole dataset , 80% of the datapoint is used for training the model whereas rest 20% is used for testing. The training dataset is used for training the model whereas test dataset is used for computing the performance of the developed model.

RESULTS AND DISCUSSIONS

Fig.2 shows the RMSE value for the different ML model for the training as well as the test dataset. The RMSE value for SVR regression model is found to be higher for both training as well as test dataset for the different kernel. For Example, the RMSE value for train dataset as well as test dataset for SVR model with radial basis kernel is found to be 139.6 and 119.46 respectively. Similar for the other kernel the RMSE value is high for both the dataset. This shows that the SVR model is not appropriate for the current problem statement. Similarly for other ML model like LR with different kernel the observed RMSE for train and test data is found to be high. The XGBoost model RMSE for train and test data is observed to be 2.10 and 9.97 respectively. This very low RMSE value for XGboost model shows a better applicability of the model for the current problem.

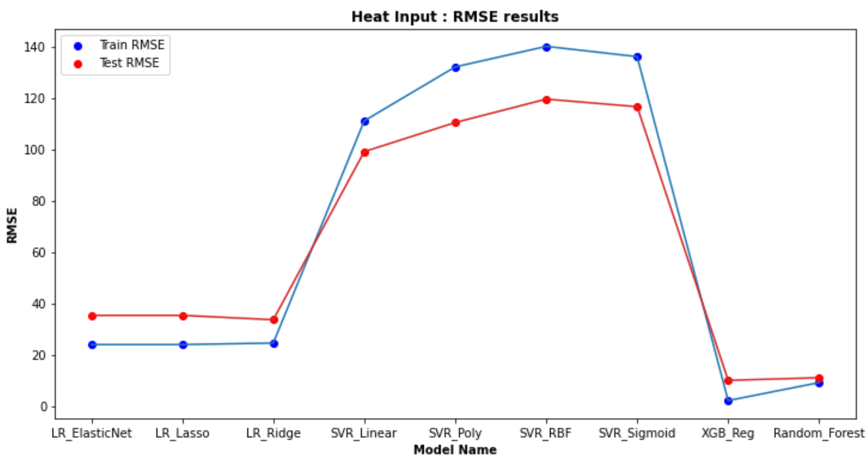

Fig.2 The RMSE value for different ML models

The performance of the different model is further evaluated by calculating the correlation coefficient . Fig.3 shows the correlation coefficient for different model obtained on training as well as test dataset. The correlation coefficient for XGboost model is found to be 0.99989 for train dataset and 0.996261 for test dataset. Both the correlation coefficient value for XGboost model is very close to 1 which shows the better performance of the model.

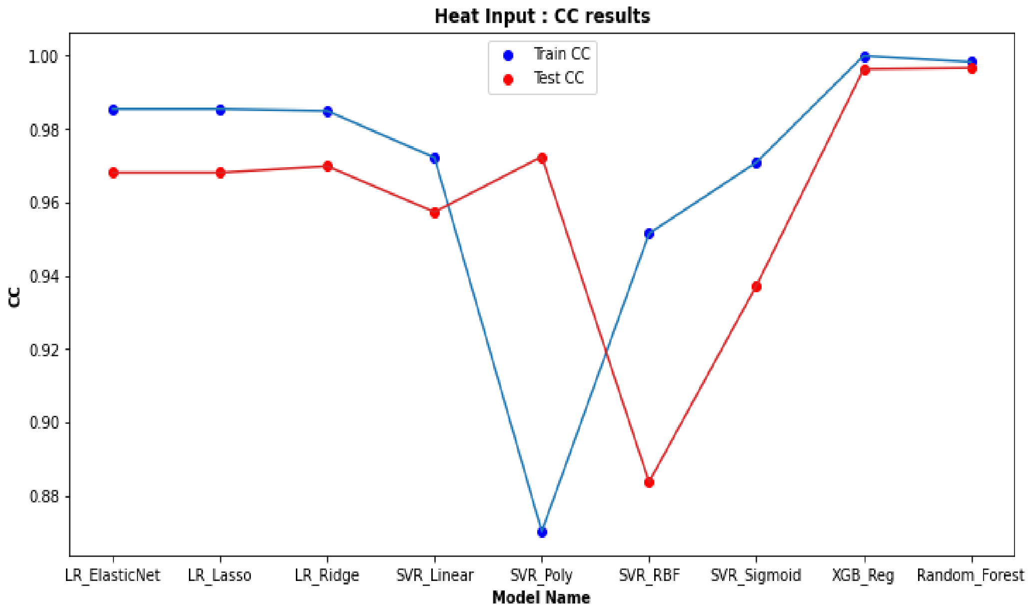

Fig.3 The Correlation coefficient value for different ML models

After the model is trained, the predicted value from the model and the actual value from the experiment is compared to check the accuracy of the model. The actual and predicted value for the train dataset is shown in Fig.4 whereas the actual and predicted value for the test dataset is shown in Fig.5. From the figure it can be depicted that the actual value of gross heat input and the predicted value of the heat input is very close to each other for the XGBoost model for both the dataset. The actual and predicted value from the XGboost model for train and test dataset is shown in Fig.6 and Fig.7 respectively.

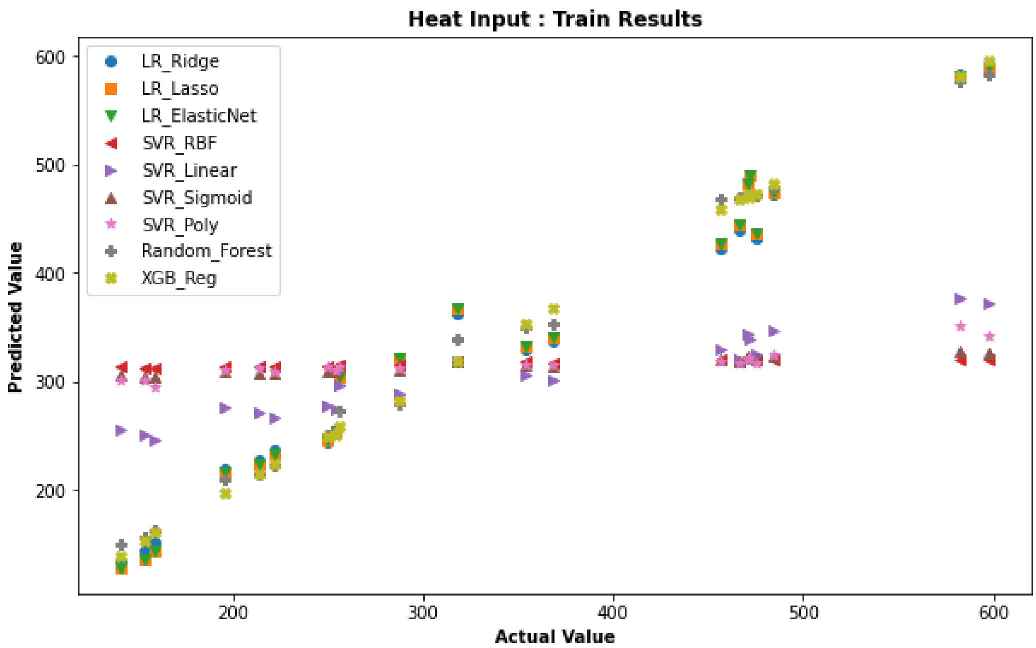

Fig.4 The Actual and predicted value for different ML models on train dataset

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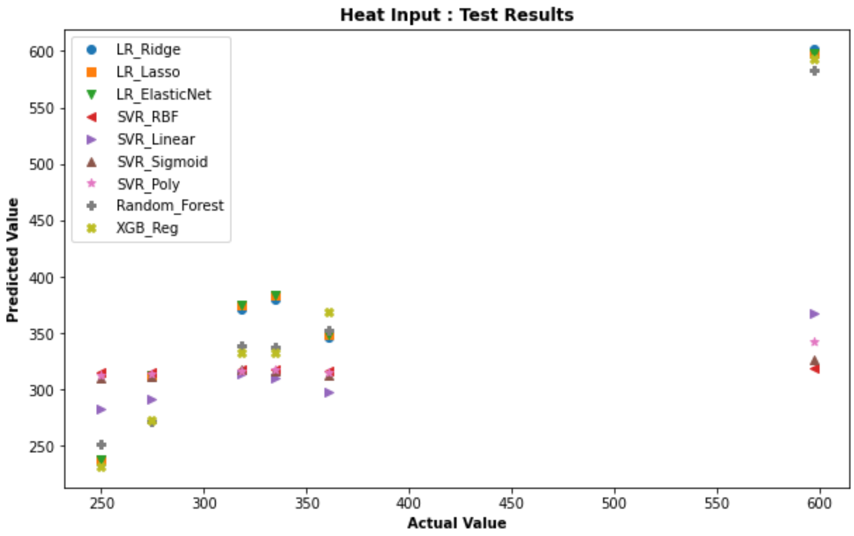

Fig.5 The Actual and predicted value for different ML models on test dataset

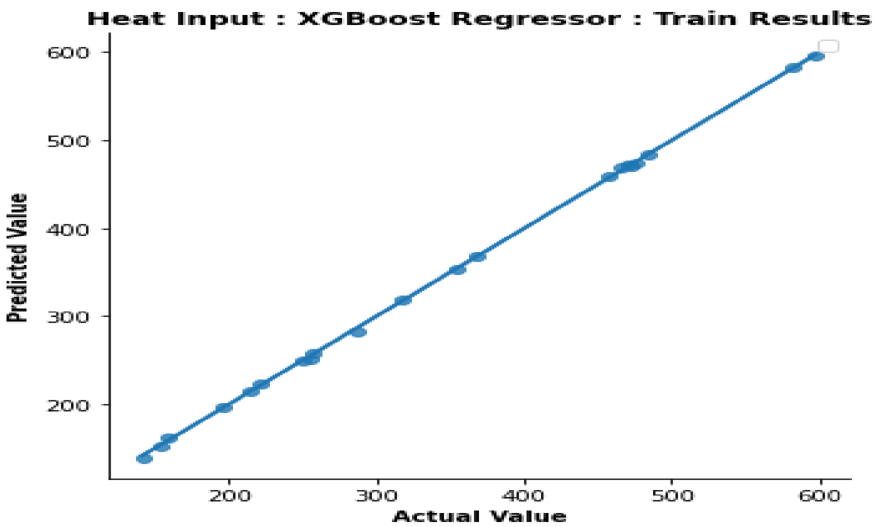

Fig.6 The Actual and predicted value for XG Boost model for train dataset.

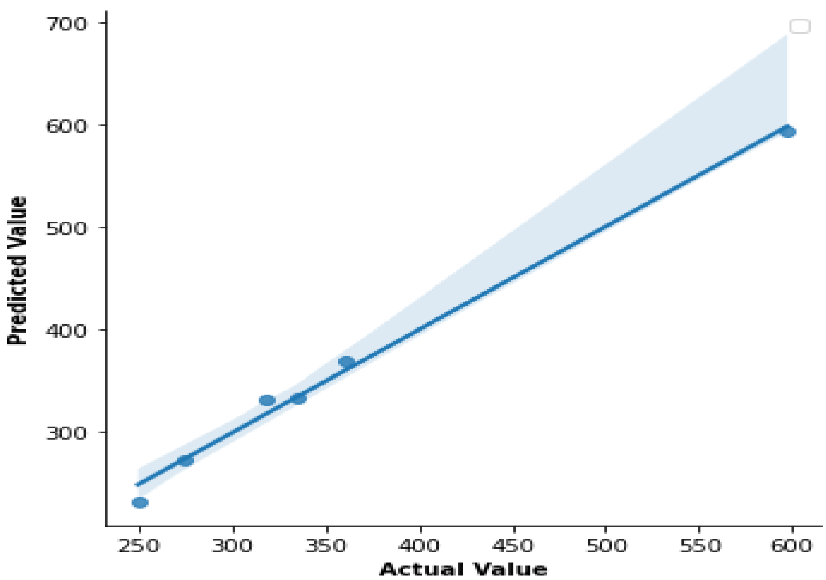

Fig.7 The Actual and predicted value for XG Boost model for test dataset.

CONCLUSION

The effect of Input parameter on gross heat input during dissimilar welding is assessed using M/L models. The underlying conclusion can be drawn from the current study.

- ML models such as Linear regression, support vector regressor are found to have very high root mean square error and very low corelation coefficient which shows that these models cannot be used for prediction of gross heat input.

- XGBoost regressor model is found to predict the gross heat input with better accuracy. The RMSE for test data for XGBoost model is found to be 2.10 and 9.97 respectively for train and test data. The corelation coefficient (CC) for test data for XGBoost regressor model is found to be 0.99989 for train dataset and 0.996261 for test dataset respectively.

- From the current study, it is interesting to note that ML model is very efficient in drawing the prediction of gross heat input during welding and thus a large number of experiments can be avoided leading to faster and economic production.

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