Residual Stress Prediction of Welded Joints Using Gradient Boosting Regression

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Abstract. Welding residual stress (WRS) estimation is highly nonlinear process due to its association with high thermal gradients generated during welding. Accurate and fast estimation of welding induced residual stresses in critical weld geometries of offshore structures, piping components etc., becomes important from structural integrity perspective. Fitness for services (FFS) codes like API 579, BS7910 recommend residual stress profiles are mainly based on three approaches, out of which nonlinear finite element modelling (FEM) results coupled with residual stress experimental measurement, have been found to be most conservative and realistic. The residual stress estimation from thermo mechanical FEM models is computationally expensive as it involves a large degree of interactions between thermal, mechanical, metallurgical and phase transformations etc. The destructive and non-destructive measurement techniques also carry a large amount of uncertainly due to lack of standardization and interpretation variability of measurement results. To mitigate the aforementioned challenges, response surface models (RSMs) have been proposed in this study, for the estimation of WRS at a significant confidence. This paper examines the applicability of 12 different Response Surface Models (RSMs) for estimating WRS. The training and testing data is generated using FEM, Abaqus - 2D weld interface (AWI) plug-in. To compare the accuracy of the RSMs, three metrics, namely, Root Mean Square Error (RMSE), Maximum Absolute Error (AAE), and Explained Variance Score (EVS) are used. An illustrative case study to demonstrate the applicability of the response surface model to predict WRS is also presented.

Keywords: Welding residual stress, Response surface model, Gradient Boosting Regressor.

1 Introduction

Residual stresses are defined as internal self-balanced stresses, which are inherently present in the material without the application of external load. Residual stress acts in three distinct length scales [1] defined as type I (long range macro stresses), type II (grain dimension inter-granular stresses) and type III (sub grain or atomic scale stresses), where type I are often used in practice for maintaining structural integrity of welded joints. Residual stresses estimation has always been a subject of interest for designers, manufacturers, and integrity engineers as harmful tensile residual stress have been found to accelerate crack propagation in welded joints. Accurate estimation of stress intensity factor due to residual stresses can further help in better prediction of remaining fatigue life of welded joints while using fracture mechanics procedures of welded joints. In various defect assessment procedures of fitness for service codes (FFS) like BS 7910, API-579 [2, 3], welding residual stresses (WRS) profiles for

This is a post-peer-review, pre-copyedit version of a conference proceeding published in INTAP 2021: Intelligent Technologies and Applications, 4th International Conference, Revised Selected Papers, which is part of the Communications in Computer and Information Science book series (volume 1616). The final authenticated version is available online at DOI: https://doi.org/10.1007/978-3-031-10525-8_4

distances away from weld toe or welds placed at close proximity like critical offshore brace joints, piping's welds etc. are not available [4] often leading to conservative assessment. Challenges due to harmful tensile residual stress at distance away from welds have been well documented in [5] causing failures due to stress corrosion cracking in welded austenitic steel piping's of nuclear plants.

Finite Element Methods (FEM) is still considered a fast and inexpensive method for determining residual stresses. However, due to the multi physics phenomenon of complex fluid and thermo dynamics associated with the weld pool during melting, coupled with the global thermo-mechanical behavior of the weld, FEM consumes a large amount of computational time. Consequently, to overcome the aforementioned shortcomings of FEM, Response Surface Models (RSMs) may be used to closely predict the WRS for any values of dimensional parameters for these weld joints. Previously, authors have used RSM to predict Stress Intensity Factor (SIF) for assessing fatigue degradation of offshore piping [6, 7]. Thus, the main objective of this manuscript is to predict WRS of welded joints using RSMs. Different Machine learning (ML) algorithms are trained on the training dataset (obtained from the Abaqus simulation) and compared to each other based on the metrics such as RMSE, MAE, EVS. K-fold cross validation is used to for dividing the dataset into training and testing. Finally, the most accurate algorithm is used to estimate the WRS values for the test dataset.

The remainder of the paper is structured as follows: In Section 2, the manuscript discusses the uncertainty associated with FEM simulation of WRS and various other methods to evaluate it. Thereafter in Section 3, a small discussion regarding the RSM is presented. Subsequently, in Section 4, an illustrative case study is presented. Finally, the paper is concluded in Section 5.

2 Uncertainty in estimation of welding induced residual Stress

To estimate WRS various FEM based numerical methods are available [8] which often consumes large computational time as welding process involves a complex interaction between thermal, mechanical, phase transformations, metallurgical a shown in figure 1 [9]. FEM model of welds involves many parameters, such as 2D or 3D approaches, heat source calibration, filler, parent metal temperature dependent properties, heat loss consideration, efficiency of welding process, phase transformations, constraint conditions, etc. These models are able to estimate long-range type-1 residual stresses [1] at the macro level, as they follow a continuum mechanics approach. Weld modeling can be dealt with at a complex fluid and thermo dynamics level, where conservation of mass and momentum of various parameters are considered in thermal modeling. Hence, to conservatively model complex residual stress distribution during welding, improve heat source calibration based on analytical models, isotropic hardening models where mixed hardening models are not available and the use of annealing transitional temperature ranges are adopted [8].

However, in general applications, the structural mechanics approach of sequentially coupled thermal and thermo-mechanical method is employed to model single and multi-pass welds. 2D axisymmetric models have been used in past due its time saving, however 3D models are well known to capture realistic welding conditions which consumes more computational time. Various other, simplified thermo elastic plastic time saving technique like sub-structing, block dumping [11], inherent strain method [12] have been known to reduce large computational time for WRS estimation. In recent times, various machine learning based predictive models [13] have also gained popularity in estimating WRS but relies heavily on accuracy of input numerical and experimental data and training and testing of developed algorithms.

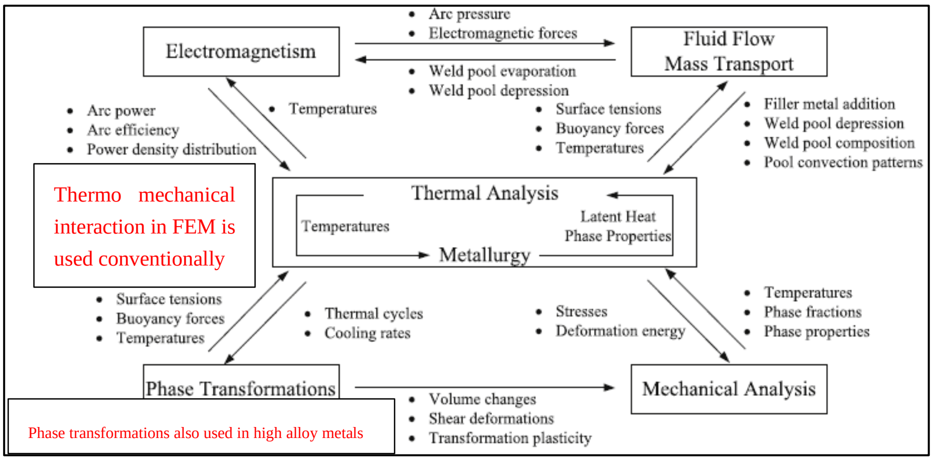

Fig. 1. Interactions of different parameters and processes in arc welding of ferritic steel adapted from [10]

3 Response Surface Modeling

As discussed in Section 1, the main purpose of RSMs is to act as a replacement to the computationally expensive and/or time-consuming simulations, without compromising the accuracy of the output. In total, 12 regression algorithms, namely, multi linear regression (MLR), least absolute shrinkage and selection operation (LASSO), Ridge, Bayesian Ridge, Support Vector Machine (SVM), k-nearest neighbor (kNN), Tree, Random Forest, Bagging, AdaBoost, Gaussian Process Regression (GPR) and Gradient Boosting Regression (GBR), have been used to predict the value of Residual Stress in the weld. The mathematical details of a few of the aforementioned regression algorithms have been discussed by the authors in [6, 7]. As will be shown in the next section, that GBR is the most accurate algorithm amongst the aforementioned algorithms to predict WRS.

GBR is a generalization of gradient boosting and involves three elements, namely, a loss function (which needs to be optimized), a weak learner (used for making predictions) and an additive model (to add weak learners to minimize the loss function) [14]. The principal idea behind this algorithm is to construct the new base-learners to be maximally correlated with the negative gradient of the loss function, associated with the whole ensemble [14]. The loss functions applied can be arbitrary, but if the error function is the classic squared loss, then the learning procedure would result in consecutive error-fitting. Furthermore, the prediction accuracy of GBR also depends upon the hyperparameter selection such as the number of estimators, learning rate etc, which shall be discussed in the next section.

4 Illustrative case study

In this manuscript, the single bead-on-plate analysis of the European Network Task Group, NeT Task [15] Group 1, has been analyzed on type 316L steel, as shown in figure 5, by performing a thermo-mechanical analysis in Abaqus using a 2D weld interface (AWI) plug-in. The single bead was modeled using dimensions from weld macrography and temperature-dependent physical and tensile material properties referenced from [16]. Due to symmetry, with respect to the weld section centerline, half symmetry was used to reduce the model size.

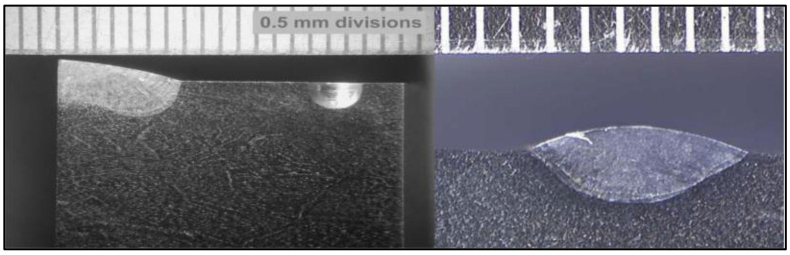

Fig. 2. Single Bead Mid-Length Macrograph Of Net Specimen Adopted From [15]

4.1 Abaqus 2D Weld modeler Interface (AWI)

The 2D weld modeler is a plug-in for Abaqus CAE, compatible with its 2017 version. This plug-in imports the basic geometry, having materials, sections assigned, and parts meshed with no imposed boundary conditions. It can automatically generate and define weld passes, by facilitating easy assignment of the weld bead sequence, which is very effective in the modeling of multi-pass welds. In the pass control section of this plug-in, the time required to ramp up the heating cycle to melting and the hold time can be inserted for each pass. Similarly, the cooling time can be inserted, accordingly. Surface film conditions and radiation heat transfer properties can be assigned simultaneously. Subsequently, AWI generates thermal and mechanical models, which can be edited to assign mesh elements and related boundary condition. The model change feature allows AWI to activate and deactivate weld beads in torch hold and pause step and controls the amount of heat transferred to the model, to avoid overheating. In mechanical analysis, torch temperature is capped, avoiding excessively large thermal strains. The annealing temperature can be set in material properties, to avoid a large accumulation of plastic strains

4.2 Finite Element Modeling

A 4-node linear heat transfer quadrilateral DC2D4 element was used in the thermal analysis, along with 4-node bilinear generalized plane strain quadrilateral CPEG4 element in the mechanical model. A total of 2497 elements were created for the entire model. A generalized plain strain CPEG4 element was used in the mechanical model, as it has been demonstrated to give higher accuracy results, compared to those of plane strain element. An annealing temperature of 1200°C was used in the modeling, to avoid the accumulation of plastic strain, and elastic perfectly plastic conditions was used in the analysis.

4.3 Thermal and mechanical model in AWI

In the Abaqus AWI plug-in, torch hold time is calculated as shown in table 1&2, from linear 2D heat input approximation [17]. Welding parameters are referenced from [16] for the linear heat input Q (J/mm) calculation. Ramp and hold time were used in the thermal model, followed by convective cooling as thermal boundary condition. To remove rigid body motions and to introduce symmetry conditions in the 2D model, appropriate boundary conditions were employed in the mechanical model. Contour plots of nodal temperature distribution and longitudinal stresses are shown in figure 3.

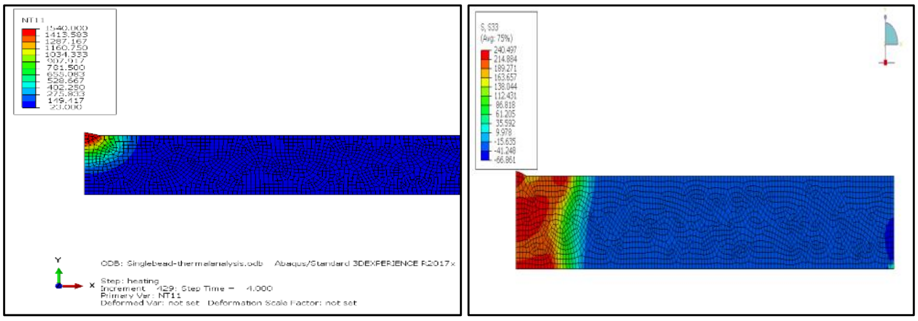

Fig. 3. Nodal temperature & longitudinal stresses distribution in Abaqus

4.4 Data Preparation and Model Evaluation

Two different data sets corresponding to Longitudinal Stress (LS) and Transverse Stress (TS) generated from FEM are used to train and test the performance of different RSMs. The dataset is shown in Table 1 and Table 2. The values of the following input parameters "current, voltage and traveling speed" are referred from the cases study presented in [15], while the input parameters "heat input to the metal, Length of weld pool, Hold time" are analytically derived. A correlation matrix for the training dataset is shown in Fig. 4 and 5. It can be seen from Fig 4, that LS has a strong negative correlation with the parameter "Distance from center of weld", while in Fig. 5, TS has a positive correlation with the same parameter, which is in agreement with the physical observations due to the fact that stresses perpendicular to the weld are more deleterious to structural integrity due to its loading direction. In order to gain maximum advantage of the predictive power of the machine learning algorithms, scaling of the data using Standard Scaler function of Sckitlearn library was performed. Thereafter, a ML pipeline consisting of all the algorithms was created in order to prevent data leakage. Since, we had limited number of data, therefore K-fold cross validation technique (10 folds and 10 repeats) was used to evaluate different ML models. In order to compare the accuracy of the regression algorithms, three metrics, namely, Root Mean Square Error (RMSE), Mean Absolute Error (MAE), and Explained Variance Score (EVS) are used. Mathematically, these are written as:

$$RMSE = \sqrt{\frac{\left(\sum_{i=1}^{n}(y_i - \hat{y}_i)^2\right)}{n}}$$

$$MAE = \frac{\sum_{i=1}^{n}|y_i - \hat{y}_i|}{n} \qquad (1)$$

$$EVS = 1 - \frac{Var(y_i - \hat{y}_i)}{Var(y_i)}$$

Table 1: FEM based Training data set input

S.no	Current (amps)	Voltage (V)	Traveling speed (v) (mm/s)	Heat Input to the metal (J/mm)	Length of weld pool (mm)	Hold time (sec)=l/v
1	202.73	9.03	2.49	552.24	4.34	1.74
2	218.66	7.55	2.61	475.21	4.02	1.54
3	207.41	10.01	2.51	621.10	4.80	1.91
4	213.71	7.62	2.66	459.03	4.73	1.78
5	206.88	9.35	2.65	548.10	4.18	1.58
6	212.46	8.55	2.48	549.44	4.15	1.67
7	211.64	8.40	2.68	498.30	4.41	1.65
8	217.23	9.89	2.44	660.48	4.44	1.82
9	212.71	9.21	2.41	610.94	4.31	1.79
10	204.06	9.03	2.30	600.35	4.03	1.75
11	216.44	9.33	2.53	599.32	4.44	1.76

Table 2: FEM based Testing data set input & output

S.no	Current (amps)	Voltage (V)	Traveling speed (v) (mm/s)	Heat Input to the metal (J/mm)	Length of weld pool (mm)	Hold time (sec)=l/v
1	203.51	8.13	2.65	467.70	4.59	1.73
3	219.46	8.70	2.55	561.05	4.00	1.57
4	207.97	9.13	2.37	600.95	4.34	1.83
5	215.55	7.88	2.62	485.59	4.64	1.77

4.5 Result Discussion

The regression model which has lowest value of RMSE and MAE and for which EVS are closer to 1 is the most accurate model**.** The value of the three metrics for 12 algorithms for the analysis has been shown in Table 3. The collective time taken by all

12 algorithms for training and making predictions was less than 2 minutes, and for GBR, the time taken was 45 seconds. From Table 3 it is seen that Gradient Boosting Regression (GBR) is the most accurate algorithm as it has lowest errors (i.e. RMSE, MAE) and EVS closest to 1. The value of various hyperparameters for GBR used in the case study are learning rate = 0.5, number of estimators = 200 (as seen from Fig. 6). The value of RS obtained from FEM and GBR on the validation data set is shown in Fig. 7. As can be seen from Fig. 7 that there are very few outliers and in general the trend between the actual and predicted Longitudinal RS and Transverse RS is almost linear, thus indicating good prediction accuracy of the GBR. Thereafter authors used the trained GBR to predict the value of Longitudinal and Transverse RS on the test dataset (shown in Table 2) the results of which are presented in Fig. 8 – 11, which clearly depict that GBR is able to predict the WRS with significantly higher accuracy.

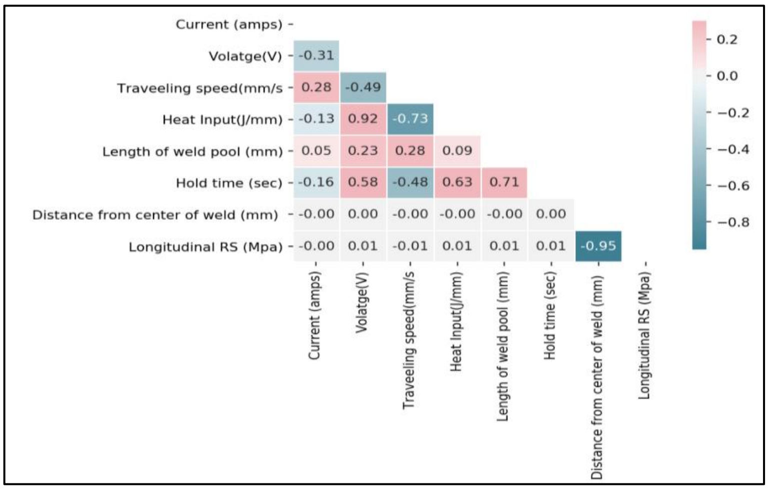

Fig. 4. Correlation Matrix for Longitudinal RS

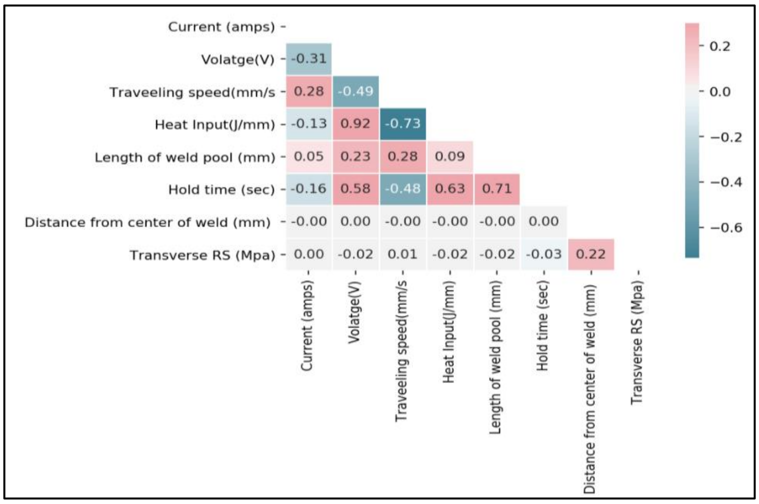

Fig. 5. Correlation Matrix for Transverse RS

Table 3. Different RSMs Comparison for Longitudinal & Transverse RS

RSM	RMSE		MAE		EVS	
	Long	Trans	Long	Trans	Long	Trans
MLR	58.1	39.7	48.2	30.2	0.881	-0.173
LASSO	56.7	39.5	46.9	30.0	0.885	-0.148
Ridge	61.9	39.1	49.1	29.7	0.844	-0.13
BayesRidge	56.9	36.5	46.9	28.0	0.883	-0.001
SVM	46.0	29.1	37.9	20.5	0.915	0.353
kNN	61.7	19.3	49.8	16.3	0.848	0.72
Tree	13.3	22.3	8.3	15.7	0.995	0.661
RandomForest	4.0	2.6	2.1	1.9	0.996	0.995
Bagging	4.1	2.7	2.1	1.9	0.998	0.994
AdaBoost	4.0	6.6	2.7	4.8	0.998	0.966
GPR	41.7	15.0	31.5	9.7	0.921	0.87
GBR	4.0	1.3	2.0	0.9	0.999	0.999

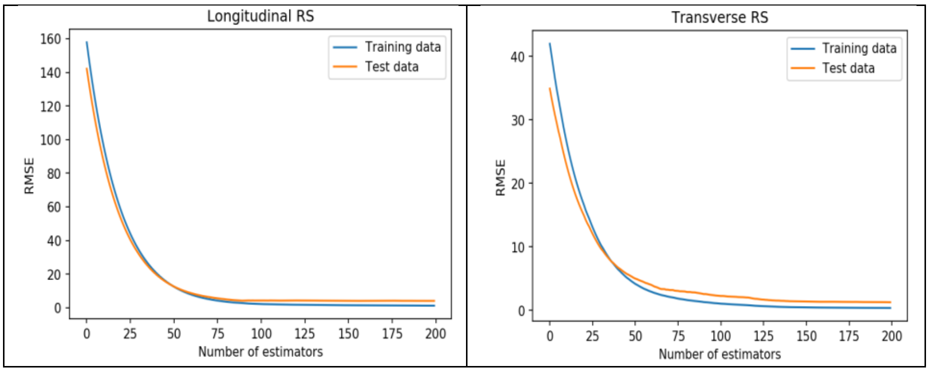

Fig. 6. Estimator selection for GBR

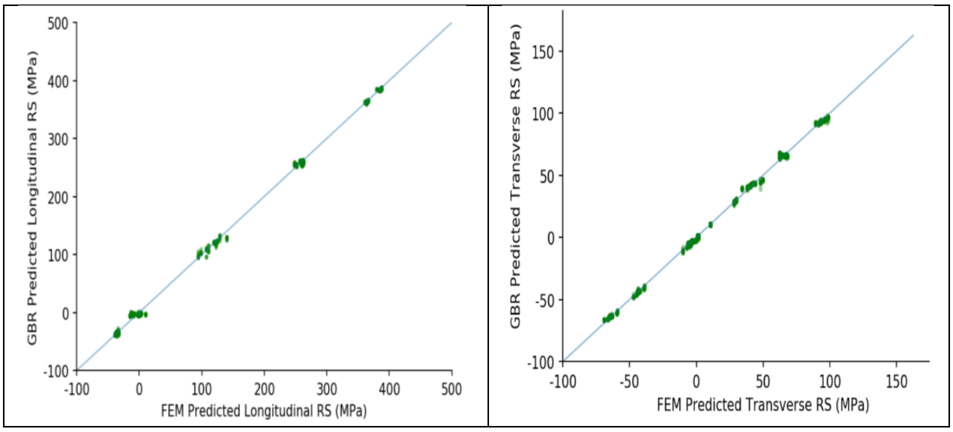

Fig. 7. RS predicted by FEM and GBR for test data set

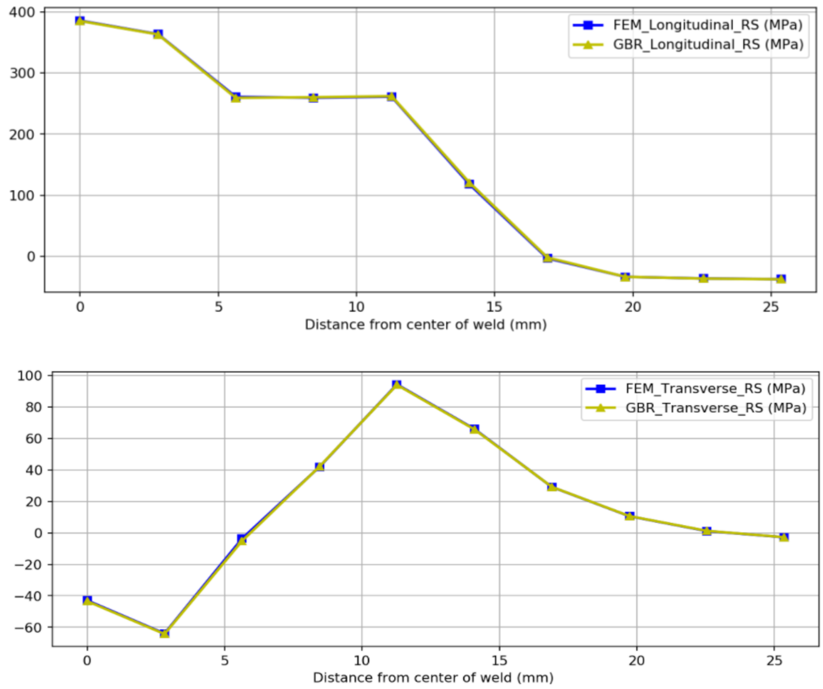

Fig. 8. RS predicted by FEM and GBR for test data set (1st Test Set)

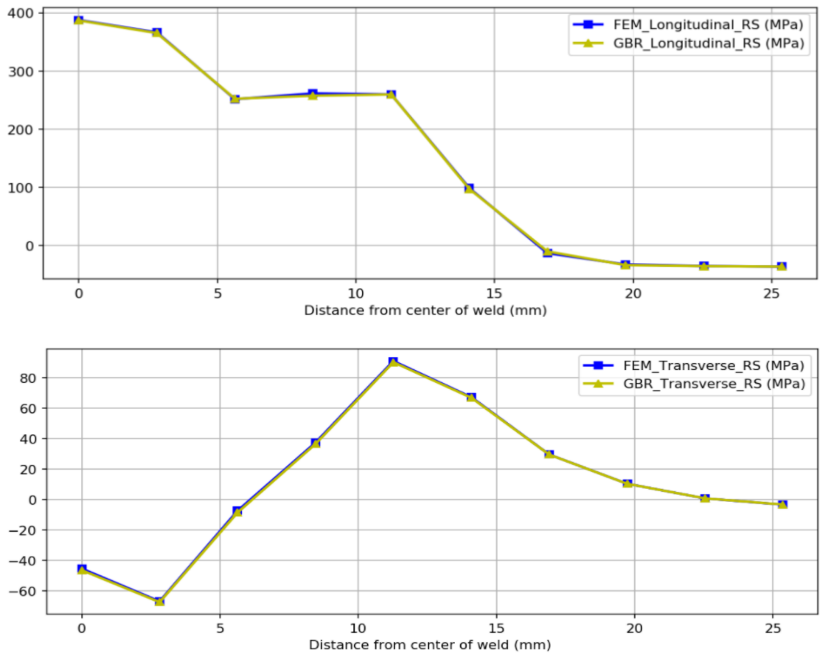

Fig. 9. RS predicted by FEM and GBR for test data set (2nd Test Set)

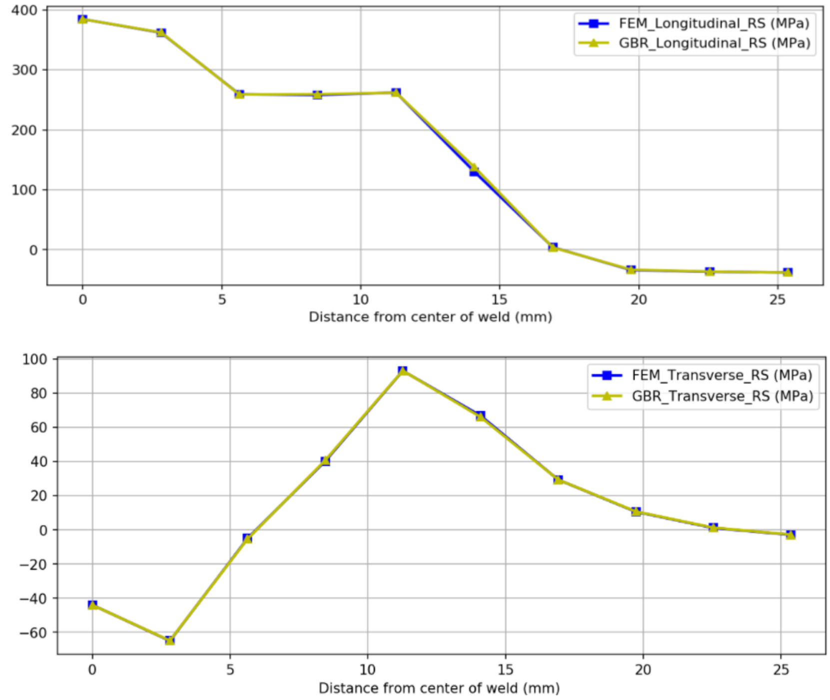

Fig. 10. RS predicted by FEM and GBR for test data set (3rd Test Set)

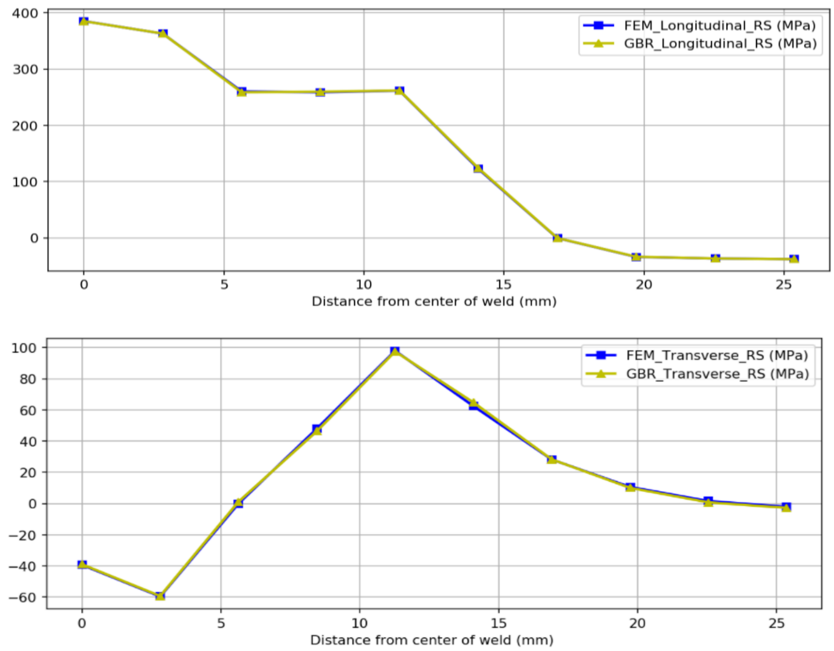

Fig. 11. RS predicted by FEM and GBR for test data set (4th Test Set)

The Gradient boosting regression model used in this case study for predicting the non-linear pattern of WRS is an attempt to highlight the application of ML in structural integrity world. Welding input parameters used for given case study are limited in range hence expected outcomes from GBR and FEM models have a better correlation. Training of these regression models from wider range of input parameters having varying weld geometries in combination with outputs of various experimental & numerical methods (considering non linearities associated with welding) will be way forward.

5 Conclusion

The main conclusion of the paper is as follows:

- Welding residual stresses (WRS) estimation away from weld center becomes important from structural integrity aspect especially in constrained geometries of offshore jackets and piping's welds
- Longitudinal stresses (LS) equal or more than yield magnitude of material in plastic zone formed adjacent to fusion zone can help in determining full field WRS profile from weld center till they fully vanish.
- Transverse stresses (TS) distribution estimation away from weld center can help in SIF determination due to WRS and help in efficient determination of crack propagation rates used in fracture mechanics procedures.
- Gradient Boosting Regressor accurately predicted the WRS in the longitudinal and transverse direction on the test dataset. The time taken for training and testing the GBR model was 45 seconds which in comparison to FEM is quite fast the FEM simulations took approximately 30 minutes.
- The trained GBR may be used as an alternative to FEM for predicting WRS in similar problems without compromising the accuracy, nevertheless saving simulation time.

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