Machine Learning Based Prediction of Fatigue Crack Growth Rate in Carbon Steel

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Abstract: There are various models out there, both theoretical and experimental, which are used to predict the fatigue crack growth in metals. Machine learning based computational models have been recently developed to predict such crack growth rate in a more comprehensive manner. This paper presents a supervised machine learning model with a better accuracy than the existing machine learning models. The experimental data obtained from the fatigue test carried out on CT specimen of material SA516Gr70 is used to test and train the model. The machine learning model XGBoost, which is implemented in this paper, is not only more accurate but also less likely to over fit when exposed to unseen data. Three alternative algorithms are investigated and by the process of elimination, best one is chosen. The paper shows the results received from some of those models, which were important in order to select the best one. The metrics used to filter and tune the model's performance are R2 score and mean squared error. The procedure for finding the optimal model and its results have been discussed.
Keywords: Fatigue Crack Growth Rate, Machine Learning, XGBoost.

INTRODUCTION

Predicting crack growth rate accurately can be of great use as these factors prove to be crucial while designing and analyzing the residual life of any engineering structure. The theoretical approach has been to predict the crack growth rate (da/dN) from the stress intensity factor (ΔK). The fatigue crack growth is classified into three stages (Fig. 1) based on the nature of the crack growth rate.

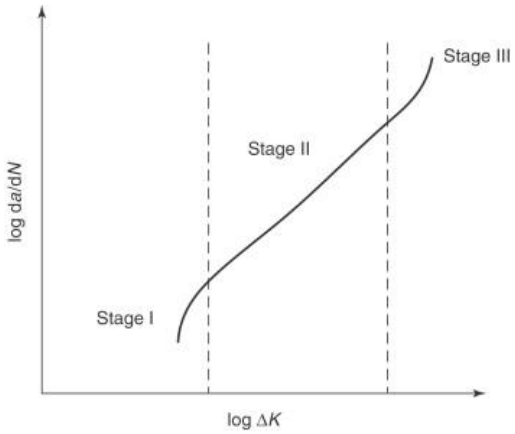


Fig. 1 Stages of fatigue crack growth.

Paris and Erdogen [1] present the Paris Law, a fundamental model for calculating the crack growth rate. This model is accurate within the stage-II which accounts for most of the stable crack propagation zone for various materials. Factors like crack instability and stress ratio 'R' are considered in [2], which further refined the model. A new method for getting similar results as that of Paris law without considering the stress intensity factor is presented by [3,4]. A new driving force parameter is introduced by [5], which turned out to be a good feature to predict crack growth. An interesting way to integrate sensor data along with the crack growth rate was discussed in [6]. An AI based approach was used [7,8] to predict the cracks under heavy or random loading or other specific conditions. Pestana et al. [9] integrated Finite element approach and machine learning to get better accuracy. ASTM E647 [10] provides a standard

procedure to measure these crack growth rates, by using COD gauges. The readings from these gauges are real time and can be used to calculate the crack growth parameters using ASTM standards [11,12].

Kamble et al. [13] have developed a ML model to estimate the fatigue crack growth rate in carbon steel. Similar Machine Learning models have been developed to predict the fatigue crack growth in Alloys [14,15]. Some papers discuss the novel models which were used for predicting these crack extensions, like using a Bi-LSTM model for predicting progressive crack using fatigue data [16] or sometimes even using real time data as the crack progresses [17] while others discuss the limitations and challenges faced during crack assessment using an ML model [18].

This paper explores more machine learning models which would give more accurate predictions about the crack growth in carbon steel than those obtained by [13]. The performance of proposed models is compared to the existing model.

DATA GENERATION AND ACQUISITION

The data used in this work in obtained from the experiments conducted by [13] on compact tension (CT) specimens. The CT specimen was a carbon steel of SA516 Gr 70 material with ultimate tensile strength of 650 N/mm^2 and yield strength of 260 N/mm^2. Fig. 2 shows the dimensions of CT specimen.

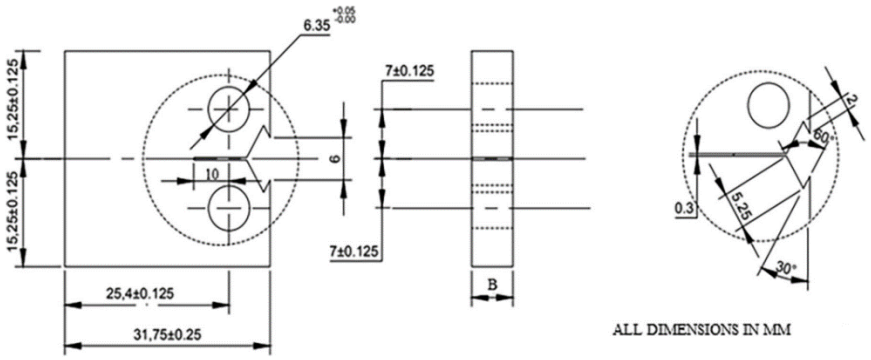


Fig. 2 Dimension of CT Specimen (B = 5mm and 6.2mm) [13].

The experiment was performed on UTM with maximum threshold for load being 25 kN. Thus machine was used to perform the Variable Amplitude Fatigue crack propagation test (VAFCP) as shown in Fig. 3. An adequate amount of sample points were defined for crack length estimation for the model to learn from. Too many points and the model might over fit, while too little and the model will not learn enough.

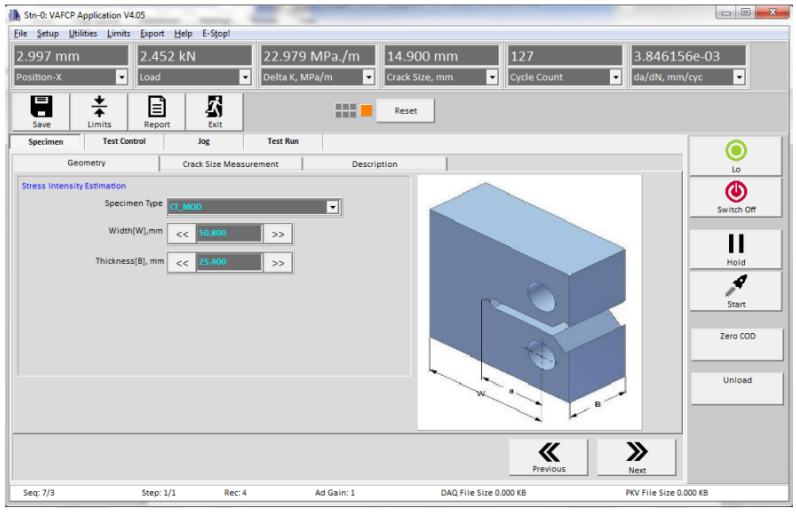


Fig. 3 Performing VAFCP Test on Specimen.

Compliance and SIF constants are taken according to the ASTM standards for standard specimens. For every preset increments of cycle count, data will be logged into the results file. Parameters from the six experiments (Table 1) conducted are used to develop the new model. Data from experiment number 1,3 and 6 were used to train the model and the rest were used for testing.

Table 1. Description of Parameters used in Experimental Cases as given in [13].

Experiment No.	Thickness of Specimen (in mm)	a/W	P_{Max} (in KN)	P_{Min} (in KN)	Loading Frequency (Hz)
1	6.2	0.39	1.75	0	50
2	5	0.39	1.50	0	50
3	5	0.39	4.3	0	1
4	6.2	0.39	4.5	0	1
5	5	0.39	1.75	0	25
6	6.2	0.39	2.25	0	25

METHODOLOGY

The raw data obtained from the experiments contained 29 features and by observing the data, it was clear that most of the features were redundant and would have thus harmed the model. Thus, exploratory data analysis and feature selection was performed to simplify the data. The features used to predict the crack growth rate (da/dN) were the stress intensity factor range (ΔK), and loading frequency (f). The loading frequency parameter tends to bring unnecessary variance into the data and thus, is also dropped. After this, we combine the data conducted from the experiments 1,3 and 6 and use them as the training dataset. Three models were used to train on this dataset, namely Ridge Regression with Polynomial Features, Random Forest and XGBoost.

Ridge Regression with Polynomial Features

Ridge Regression is basically a L2 Regularized Linear model. This model was chosen as by manually inspecting the data, one can guess that the best model to predict the crack growth would be a polynomial of fairly low degree. Thus, by introducing a basic polynomial model, a rough estimate as to what the model lacks can be found out. For this model data columns are filtered and it is found to be dependent on only the Delta K column. We then performed feature scaling using min-max scaler and hyper tuned the model by changing the degree of polynomial used and the regularization parameter. The tolerance and solver and degree of the model was also tuned. By iterating through some code, all the optimized models would be collected in a list. Then, by using an elimination approach the order of polynomials were decreased until there was a model which could give about the same accuracy as the model prior to it in the list with relatively higher polynomial. The model heavily depended on the degree of Polynomial. Although it gave a good prediction towards the test dataset combined as shown in Fig. 4 by giving a R^2 score of 95.85% and a mean squared error of 1.34×10^{-14}. Its results on individual experiments were bad as, being a low degree polynomial with fairly less features, it had a lot of bias in dataset and thus couldn't predict well for small datasets with higher variances. From this, inference was taken so as to choose a model which would be able to take into account all the variances in the dataset and thus maintaining a low bias.

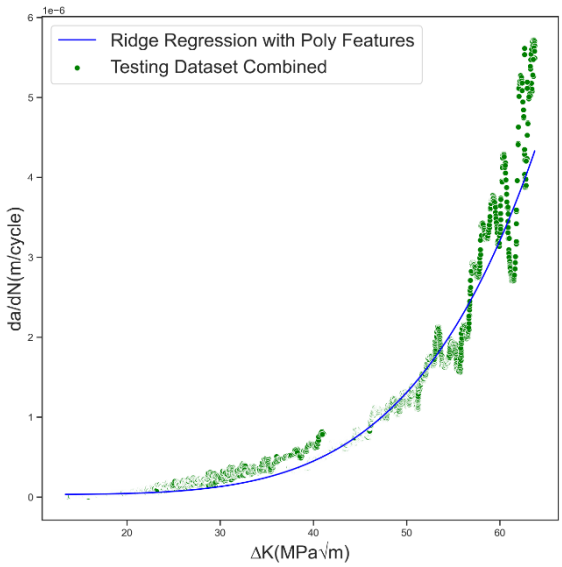


Fig. 4 Prediction of Ridge Regression with Polynomial degree 5
on combined test dataset consisting of Experiments 2,4 and 5.

Random Forest

As there are many variances throughout the data, it was assumed that Random Forest could be a perfect suit. There was no need to scale the data for a decision based model. It turned out that as it tried to split the values throughout its tree depth, it over fit on the training set and thus couldn't give good test predictions. Since the ideal fit was supposed to be not that complex, this model had a hard time giving a good test prediction as it fit a higher degree model no matter how much the model was tuned.

XGBoost

While the Random Forest uses fully grown decision tress trying to classify every point with minimum error and thus reducing variance, XGBoost uses weak learners, parametrized by high bias and low variance. Thus, while the random forest will try to perfectly fit the training model, XGBoost will retain its bias and thus give a good fit to the test dataset. It controls its complexity by directly restricting the trees using parameters like max depth, min child weight, etc. Not only that, but it also makes the model robust by adding randomness to data by using subsample and colsample_bytree.

RESULTS AND DISCUSSION

Table 2 provides the R^2 Score and the Mean squared error values of the three machine learning models used in this work. Fig 5 (i,ii,iii) show prediction by each of the models for unseen data of Experiment 2. The predictions by Paris Model are included for the purpose of comparison. Fig 5. (iv) shows the prediction by the Nearest Neighbor Regression (NNR) Model which was found to be the most accurate model according to [13]. It can be observed that the XGBoost model has the best fit amongst the proposed models.

Table 2. Comparison of Different Machine Learning Models.

Experiment Number	Load (KN)	Thickness (mm)	Frequency (Hz)	Performance of Model on Experimental Data					
				Mean Squared Error (m^2/$cycle^2$)			R^2 Score		
				Ridge Regression with Polynomial Features	Random Forest	XGBoost [19]	Ridge Regression with Polynomial Features (%)	Random Forest (%)	XGBoost [19] (%)
1*	1.1750	6.2	50	0.74×10^{-15}	1.16×10^{-16}	0.932×10^{-16}	58.33	97.18	97.74
2	1.50	5	50	0.92×10^{-15}	1.98×10^{-16}	0.94×10^{-16}	23.45	95.15	97.69
3*	4.3	5	1	0.90×10^{-13}	0.33×10^{-16}	0.32×10^{-14}	91.9	99.97	99.72
4	4.5	6.2	1	0.32×10^{-13}	0.66×10^{-13}	0.63×10^{-13}	94	89.34	89.92
5	1.75	5	25	0.34×10^{-14}	1.58×10^{-15}	1.36×10^{-15}	4.6	86.40	88.28
6*	2.250	6.2	25	0.24×10^{-14}	0.23×10^{-15}	0.92×10^{-15}	90.5	99.37	97.42

(* Data is used to train the ML models under consideration).

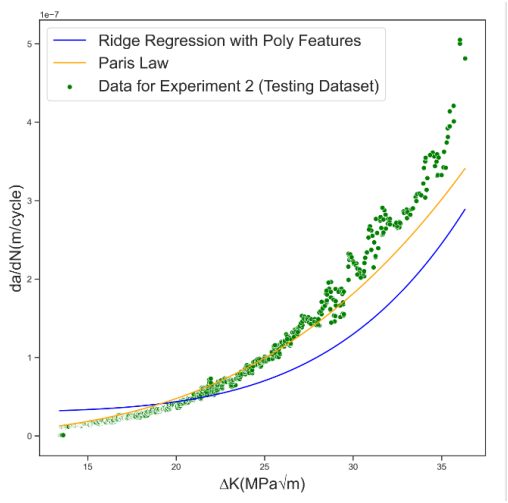


Fig. 5 (i) Prediction of Ridge Model of Polynomial Degree 5 on Data from Experiment 2 (Testing Dataset).

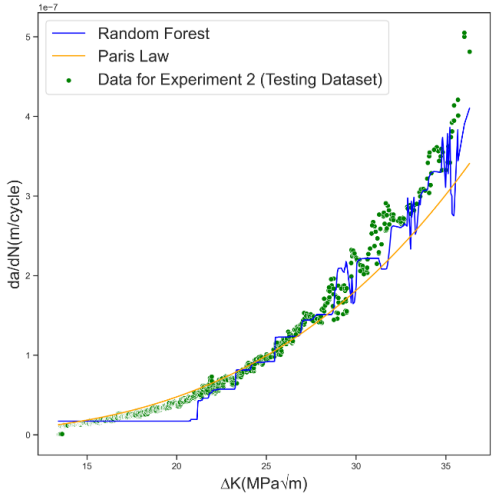


Fig. 5 (ii) Prediction of Random Forest Model on Data from Experiment 2 (Testing Dataset).

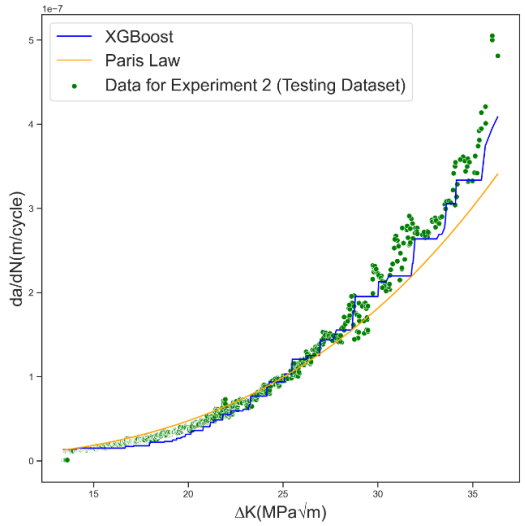


Fig. 5 (iii) Prediction of XGBoost Model on Data from Experiment 2 (Testing Dataset).

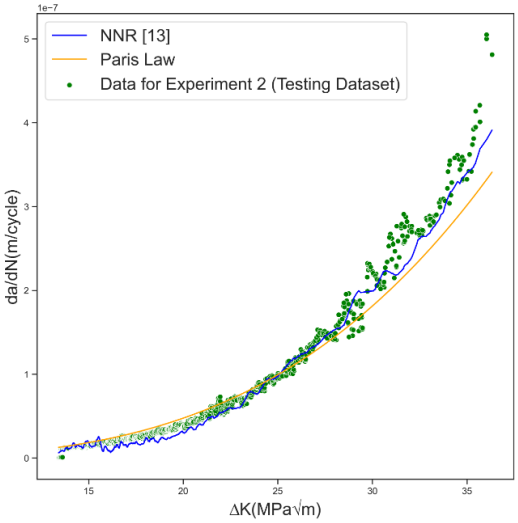


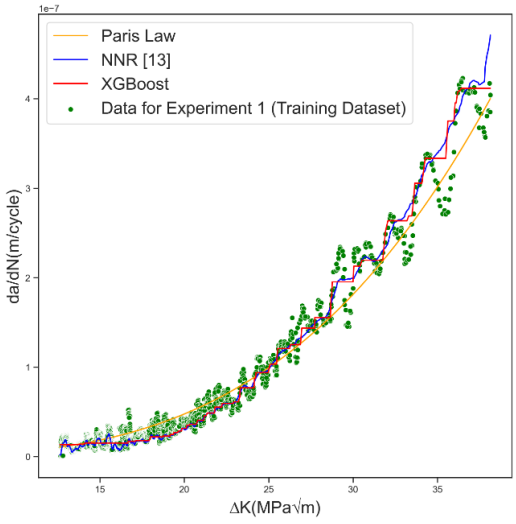
Fig. 5 (iv) Prediction of NNR [13] Model on Data from Experiment 2 (Testing Dataset).

The XGBoost model [19] was used to train on Experiments 1,3 and 6, and then tested on Experiments 2,4 and 5 as shown in Fig. 6 (i,ii,iii,iv,v,vi). It gave the best prediction out of all the tested models. This model was then compared using R^2 Score and Mean Squared Error for the prevailing ML model. The model which was used in [13] was Nearest Neighbors Regression with number of neighbors = 60. The XGBoost model proposed in this paper gave a better prediction that the NNR model both in terms of mse value and R^2 Score as shown in Table 3. Here too the predictions by Paris Model are included for comparison. The NNR model [13] with such large value of neighbors, would certainly have overfitted on the training dataset and might fail for new experiments, or different loading conditions. By contrast, the XGBoost model is tuned by selecting the best model with the least parameters to prevent overfitting. Also, being a scalable and controlled tree branching system, it will not over fit its trees and thus give an accurate generalized prediction. By this process, the best model comes out to be one with estimators=100. It even gave much better results for the training data as compared to the NNR [13] model.

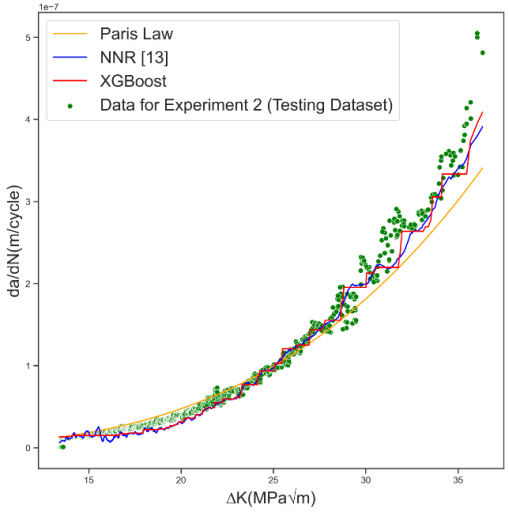
Table 3. Comparison of the Proposed Model to the ML Model by [13]

Experiment Number	Load (KN)	Thickness (mm)	Frequency (Hz)	Performance of Model on Experimental Data					
				Mean Squared Error (m^2/$cycle^2$)			R^2 Score		
				NNR [13]	XGBoost [19]	Paris Law	NNR [13] (%)	XGBoost [19] (%)	Paris Law (%)
1*	1.1750	6.2	50	0.961×10^{-16}	0.932×10^{-16}	1.43×10^{-16}	97.65	97.74	96.53
2	1.50	5	50	1.07×10^{-16}	0.94×10^{-16}	1.71×10^{-16}	97.36	97.69	95.81
3*	4.3	5	1	0.16×10^{-13}	0.315×10^{-14}	0.52×10^{-12}	98.55	99.72	53.82
4	4.5	6.2	1	0.79×10^{-13}	0.63×10^{-13}	2.25×10^{-13}	87.36	89.92	63.87
5	1.75	5	25	1.43×10^{-15}	1.36×10^{-15}	1.71×10^{-15}	87.62	88.28	85.21
6*	2.250	6.2	25	1.18×10^{-15}	0.92×10^{-15}	2.63×10^{-15}	96.68	97.42	92.61
Average Value				0.16×10^{-13}	0.11×10^{-13}	0.12×10^{-12}	94.20	95.13	81.31

(* Data is used to train the ML models under consideration).



(i)



(ii)

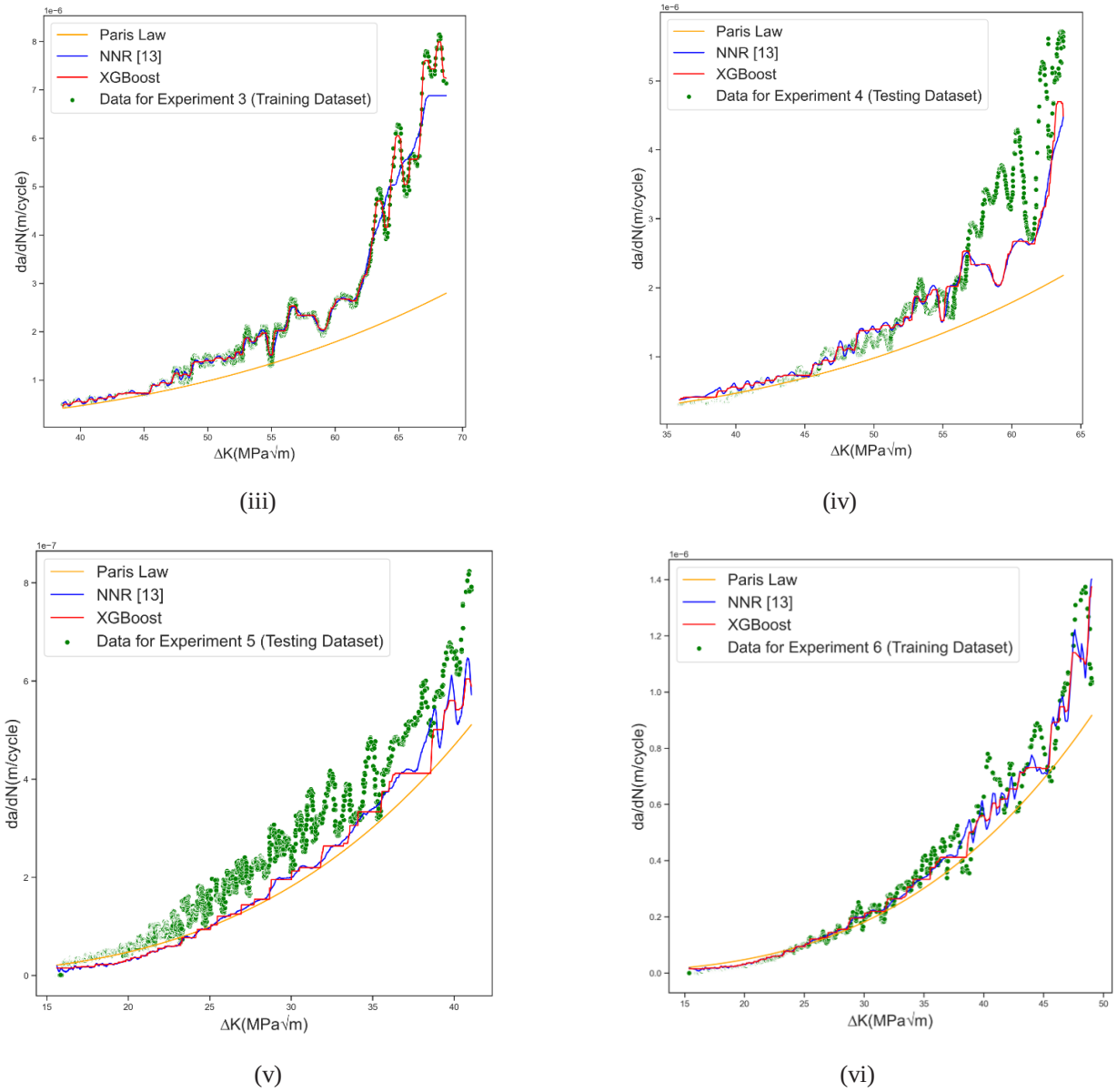


Fig. 6 Comparison of Crack Growth Prediction by XGBoost Model on data from (i) Experiment 1, (ii) Experiment 2, (iii) Experiment 3, (iv) Experiment 4, (v) Experiment 5 and (vi) Experiment 6.

The proposed Machine Learning Model can be made more generalized after including data from further experiments which may include variation in experimental parameters such as cyclic loading conditions, specimen thickness, material types, etc.

CONCLUSION

The paper presents a better and more regularized model used to predict the fatigue crack growth rate in carbon steel. Three models were considered, namely Ridge Regression with Polynomial Features, Random Forest and XGBoost, out of which XGBoost outperformed the rest. The XGBoost model gave an average mean squared error of 1.1×10^{-14} and average R^2 Score of 95.13% against the test dataset. The average mse value of the XGBoost model is 31.2% lower than the average mse value of previous machine learning model [13]. The average R^2 value of the proposed model is better than the previous model as well.

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