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# DEVELOPMENT OF METHODOLOGY FOR STRESS PREDICTION OF CRANKSHAFT USING MACHINE LEARNING

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## ABSTRACT

A system that calculates the critical stress value of the crank pin fillet from six design variables of the crankshaft was developed using an XG Boost Classifier & Regressor. The learning dataset was generated based on the Finite Element Analysis by using 3 Point Bending Method and Standardization Descaling Technique was used to adopt the learning calculations. In trained XG Boot Classification & Regression Machine Learning model having Mean Absolute Error (MAE) 8.3, is within our acceptable limit because it gives us satisfactory prediction of stress values in critical stress area (Crank Pin Fillet), which closer to stress value calculated by FEA method. Hence, for prediction of unknown parameter with this trained and tested Machine Learning Model of XG Boost Classifier and Regressor can be used.This methodology is useful to calculate critical stress values along with unknown design variable of crankshaft in short time as compared to FEA methodology, hence it save time and cost.

**Keywords:** Crankshaft, Decision Tree Classifier and Regressor, Linear Regression, ML - Machine Learning, PFP - Peak Firing Pressure, Random Forest Classifier and Regressor, XG Boost - Extreme Gradient Boosting .

## 1. INTRODUCTION

In IC engine Crankshaft failure is savior problem. Crankshaft is subjected to bending and torsion during operation. The crankshaft design is performed according to bending and torsional stress. The crankshaft must be capable of withstanding the intermittent variable loads acting on them. During transfer of torque to the output shaft, the force deflects the crankshaft. This deflection occurs due to bending and twisting of the crankshaft. Bending and torsional stresses can be achieved by using material with the correct physical properties and by minimizing stress concentration. The crankshaft is put in series to all the other components of the engine in the fault crankshaft analysis and the reliability of the whole system heavily depends on the reliability of the crankshaft. The alternating load can lead to bending fatigue failure of the crankshaft which is started at the stress concentration area. So the effective way of increasing crankshaft bending fatigue intensity is reducing the maximum bending stress in the premise of constant maximum load. Traditional methods of increasing crankshaft bending fatigue intensity are increasing crankshaft overlap, increasing connecting rod and the shaft fillet, adding the slot, increasing the risk cross-section width. However these design approaches have a certain degree of blindness and require a higher experience of the designer. With the development of the finite element analysis (FEA) technology, engine components' strength analysis using this method for has become the common method for engine design and check. The numerical finite element simulation of crankshafts with multiple constraints is often time consuming even quite accurate if the aim is to evaluate the stress -strain behavior at the notched area and verify the component. The development of a simplified numerical model would prove effective to reduce the time needed to reach a good approximation design of the crankshaft. In this study contains stress concentration for a crankshaft in bending loading state. This study is an updating study. Data obtained from FEA was converted into numerical values. The charts data converted numerical data. Machine Learning model was developed in new format. With using the method, unknown values can be obtained without perform FEA or any interpolation etc. with high reliability.

## 2. PROBLEM STATEMENT:

Earlier stages of crankshaft development involve several iterations in FEA analysis and it is required to follow all FEA steps and these are time consuming. Reducing the number of CAD -FEA iterations will save cost and time in terms of man hours required to carry out necessary CAD and FEA works. ."For this, a Methodology involving Machine Learning is proposed to predict the crankshaft design parameters to achieve correctness in the first step itself. This will eliminate further iterations which may be required otherwise. This Model will learn from a dataset containing previous design data and FEA results of various crankshaft designs".

## 3. METHODOLOGY

Methodology is divided in to two parts : 1) Dataset generation to train Machine Learning Model by using FEA 2) Development of Machine Learning Model by model training and testing.

### 3.1 Dataset Generation by using FEA:

In this process Dataset is generated by using FEA of Crankshaft by using Bending with shear force method of Crankshaft.

This dataset is generated by considering six variables: 1) Crank Radius 2) Crank Journal Diameter 3) Crank Pin Diameter 4) Crank Fillet Radius 5) Crank Journal Fillet Radius 6) Peak Firing Pressure of Engine. This FEA dataset is used to train and validate the Machine learning model. CAD Model with Dataset variables.

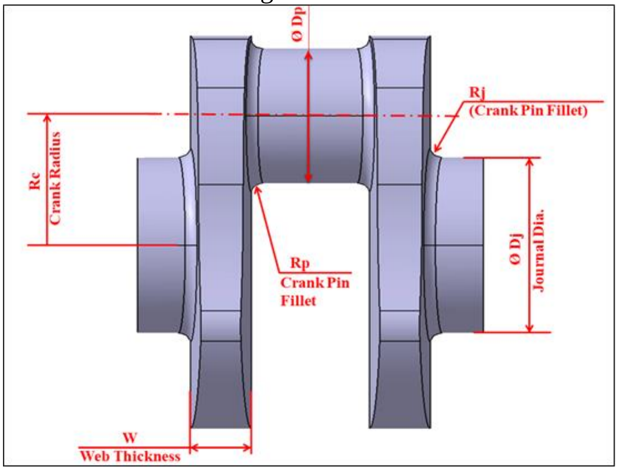


**Figure 1:** Crankshaft CAD Model with Dataset Variable.

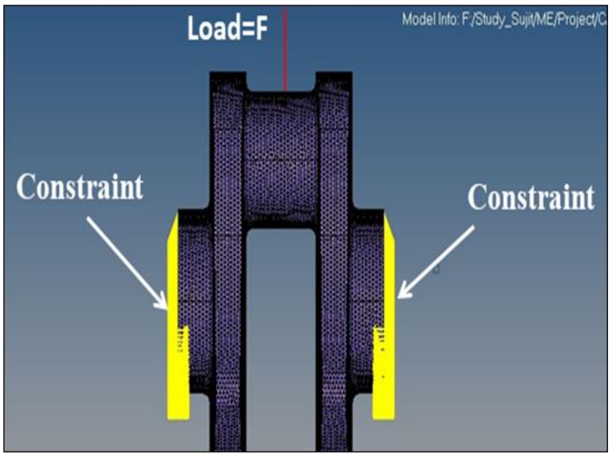


**Figure 2:** Load Case and Boundary Condition of Crankshaft

Dataset includes 500 observations of FEA can be used to learn and validate the ML model developed for stress and unknown design parameter calculation.

**Table 1**. FEA Dataset For Ml Model Development

| Sr. No. | Crank Radius | Crank Journal Dia | Crank Pin Dia | Crank Fillet | PFP | Force in 'N' | Stress Value In MPA |
|---|---|---|---|---|---|---|---|
| 1 | 50 | 65 | 48 | 3.5 | 150 | 97343.9 | 653.7 |
| 2 | 50 | 65 | 48 | 3.5 | 130 | 84364.7 | 566.5. |
| 3 | 50 | 65 | 48 | 3.5 | 110 | 71385.6 | 566.5 |
| 4 | 50 | 65 | 48 | 3.5 | 90 | 58406.4 | 479.4 |
| 5 | 50 | 65 | 48 | 3.5 | 70 | 45427.2 | 392.2 |
| . | | | | | | | |
| . | | | | | | | |
| . | | | | | | | |
| . | | | | | | | |
| 500 | 102.5 | 60 | 71 | 52 | 5.5 | 3569.3 | 258.1 |

### 3.2 Machine Learning Model training and testing:

Data is split for training and testing dataset training dataset from 0 to 350 numbers and testing dataset from 351-500 numbers. In this process dataset is imported in Machine learning algorithm in .csv format. Learning Dataset containing input known parameters are called independent parameters and output FEA results stress value called dependent variables. Based on split learning data, model will develop train by fitting line from given data points of all variable (like graphical method) and this line or train used to predict unknown variables of crankshaft geometry. Test dataset split used for validation of Machine Learning Model. Crankshaft FEA generated datasets simple dataset and stress value to be predicted, so supervised regression Machine learning is proposed to build Machine learning Model. In this study following models are tried and tested for output result:

**a. Linear regression**

**b. Decision Tree Classifier and Regressor**

**c. Random Forest Classifier and Regressor**

**d. XG boost Classifier and Regressor**

For all above Machine Learning model code Scikit-Learn Library in Python is used. Out of these tested models.

**a. Linear regression:**

Here in Linear regression Machine Learning Model average of mean absolute error is 39.8 which is not acceptable so we cannot use this Linear regression model for stress prediction.

b. Decision Tree Classifier and Regressor

In Decision Tree Classifier and Regressor Machine Learning Model average of mean absolute error is 54.8 which are not acceptable so we cannot use this Decision Tree Classifier and Regressor model for stress prediction.

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**c. Random Forest Classifier and Regressor**

Here in Random Forest Classifier and Regressor Machine Learning Model average of mean absolute error are 54.8 which are not acceptable so we cannot use this Random Forest Classifier and Regressor model for stress prediction.

**d. XG boost Classifier and Regressor**

"In XG Boost Classification and Regression Machine Learning model having Mean Absolute Error 8.3, is within our acceptable limit because it gives us satisfactory result to decide design parameters of crankshaft. For prediction of unknown parameter this trained and tested Machine Learning Model of XG Boost Classifier and Regressor can be used."

## 4. EXPERIMENTAL RESULTS

**Table 2.** Experimental Results of Tried and Tested ML Mode

| Sr. No. | Machine Learning Model | Average Stress Value by FEA | Average Stress Prediction Value by ML | Mean Absolute Error |
|---|---|---|---|---|
| 1 | Linear Regression | 452.41 | 445.42 | 39.80 |
| 2 | Decision Tree Classifier & Regressor | 436.15 | 435.43 | 54.80 |
| 3 | Random Forrest Classifier & Regressor | 452.41 | 439.09 | 137.95 |
| 4 | XG Boost Classifier & Regressor | 448.08 | 447.02 | 8.22 |

ls

The results, shown in above Table 2, confirm that the ML models, when developed properly, could be used as a surrogate for an FEA considering their high accuracy and precision in predicting Von-Mises stress value in crankshaft critical region Crank-Pin Fillet and Journal Fillet Radii.. However, this conclusion does not hold for the ML models, Linear Regression, Decision Tree Classifier and Regressor, Random Forrest Classifier and Regressor. XG Boost is a new and highly popular method that works for many regression cases successfully. The main challenge in the use of ML algorithm as surrogate finite elements lays in the necessity of large training sets, consisting of thousands of data entry and must encompass the expected loading conditions that the dynamic system will encounter. In addition, additional analysis is required to establish the optimal locations for the reference locations. The result shown in every model we have tried and validated among that Mean Absolute Error of ML predicted stress and FEA analyzed stress value for XG Boost Classifier and Rgressor is 8.22 which satisfy our requirement of Stress Prediction. XG Boost ML Model prediction can be used for new requirement of crankshaft design. Using these design variables we can design the crankshaft and validated by FEA. Then we can trigger for proto type part manufacturing of crankshaft. This can reduce our overall development cost and man hours required for several FEA iteration otherwise. In the four machine learning algorithm development mean absolute error shown by Linear Regression Model is 39.8 is lesser than Decision Tree Classifier & Regressor (MAE=54.80) also less than Random Forest Classification and Regrssor (MEA=137.95), So these two developed machine learning model is not useful better to with Linear Regressor. Linear Regressor Model MAE value is 39.8 which shows considerable difference between FEA predicted stress values. Thus this also gets eliminated, next XG Boost Classifier and Regressor shows MAE value '8.22' this can predict closer to stress calculated by FEA method. Hence this ML model can be used for stress and unknown design parameters prediction.

## 5. VALIDATION

Testing and Validation developed machine learning model is completed by using spited FEA dataset 150 numbers used out of 500, for validation purpose. In validation activity we will compare the Machine Learning Model stress prediction versus Stress Value calculated by FEA. As said above all models are tested approximately for 134 numbers dataset and Mean Absolute Error are predicted on that basis Machine Learning Model is finalized for stress calculation.
Following are the validation summary of each model:

### 5.1 Linear regression

As said above data is split in two section 1-350 numbers for learning of ML model and 151-500 numbers for validation of Machine learning model. In linear regression Machine Learning model Average mean absolute error found is 39.8 hence this prediction by the Model is not acceptable. It shows Linear Regressor Model MAE value is 39.8 which shows considerable difference between FEA predicted stress values.

### 5.2 Decision Tree Classifier and Regressor

Here in Decision Tree Classifier and Regressor Machine Learning Model average of mean absolute error are 54.8 which shows predicted value shows considerable difference comparing with FEA test split dataset, it's not acceptable so we cannot use this Decision Tree Classifier and Regressor model for stress prediction.

### 5.3 Random Forest Classifier and Regressor

Here in Random Forest Classifier and Regressor ML Model average of mean absolute error are 54.8 which are not acceptable so we cannot use this Random Forest Classifier and Regressor model for stress prediction.

### 5.4 XG boost Classifier and Regressor

"In XG Boot Classification and Regression Machine Learning model having Mean Absolute Error 8.3, is within our acceptable limit because it gives us satisfactory prediction of critical area stress value (Crank Pin Fillet), which closer to stress value calculated by FEA method. Hence, for prediction of unknown parameter this trained and tested Machine Learning Model of XG Boost Classifier and Regressor can be used."

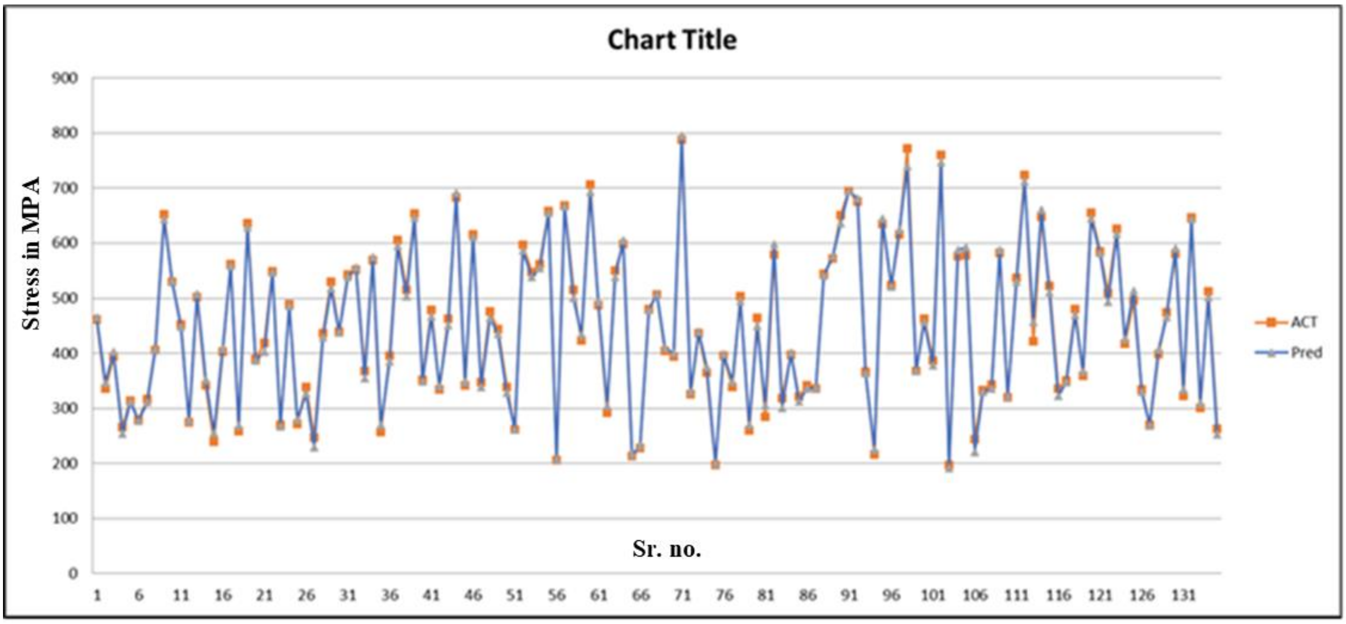


**Chart 1:** Actual Vs. Predicted Stress Value Comparison for Validation

## 6. CONCLUSION

A system that predicts the stress value developed in crankshaft fillet radius (in critical zone of crankshaft failure) by three point bending method of analysis crankpin fillets was developed using THE XG Boost Classifier and Regressor Model (from Python Scikit Learn Library). This system was constructed based on the database consisting both of the geometry of the crankshafts and the higher stress values generated in critical zone. By using this system, the von mises stress value in crankshaft fillet radius can be predicted precisely in a short time without further iteration required in FEA. The predicted values compared to the 92 to 93 % accuracy. This study presents Machine Learning Application to FEA will enhance our accuracy as First Time Right Design Approach. It reduces number of iterations while doing FEA of Crankshaft. It reduces over all product development cost by saving man hours required for repetitive FEA iterations.

## 7. FUTURE SCOPE

i. Developed Machine Learning model in this research work, designers can easily analyze the stress sensitivities of the crankshafts by themselves. It's becomes easier to optimize the crankshaft geometry considering to parts commonization related to the crankshafts under the limitations of a production facility. The prediction errors are small in application use, but methodology is required to improve the prediction precision and to enlarge the range of applicable crankshaft shapes.
ii. This developed methodology helps us to predict design parameter of crankshaft, which can be helping us to avoid initial FEA iterations involved.
iii. It can be helping us to reduce development time and cost of an IC Engine Crankshaft.
iv. This type of methodologies can be helpful for other mechanical parts design which can save development time and cost for iteration require. These can be implement all type of part analysis, Structural, CFD & Thermo structural analysis. System that predicts the stress value developed in crankshaft fillet radius (in critical zone of crankshaft failure) by three point bending method of analysis crankpin.

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