DEVELOPMENT OF A MACHINE LEARNING ALGORITHM BASED ON RANDOM FOREST MODEL FOR LOCALIZATION OF CRACK IN THE COMPOSITE BEAMS

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Abstract:
The Random Forest method, which is a well-known generalized, high-accuracy supervised machine learning method and hence it is used as damage evaluation algorithm. The composite materials are more popular in several defense and aerospace applications, so present paper is focused on damage monitoring based on vibration data obtained from cracked composite beams. The trained machine learning models can be used for real-time health monitoring and damage detection in composite structures which can help prevent catastrophic failures and reduce maintenance costs. The Random Forest algorithm is a technique based on decision trees and it is further improved in present paper for effective localization of damage by adding additional features for efficient selection, processing and hyperparameter tuning based on input features. The experimental data collected from natural frequency test is used training the Random Forest algorithm to predict crack location in cracked composite structures. The data collected from experiments are used to train Random Forest algorithm. In the present paper 80% of experimental data is used for train the Random Forest model and remaining data is used for test the generated Random Forest model. Further to improve the efficiency of Random Forest model, the train and test data is scaled using minmax scaler. The developed Random Forest model is well fitted for prediction of crack localization as per the input parameters of first three natural frequencies of cracked composite beam.

Keywords: *Crack localization, machine learning algorithm, Random Forest algorithm, cracked composite beam, natural frequency test, natural frequencies, composite beam.*

1. Introduction

The Random Forest method, which is a well-known generalized, high-accuracy supervised machine learning method and hence it is used as damage evaluation algorithm. The algorithm works by training multiple decision trees on different subsets of the data, and then averaging the predictions of all the trees to make a final prediction. Wind turbine blades, aerospace structures, bridge decks and pressure vessels are made of composite materials and are subject to cracks and other forms of damage. Machine learning algorithms based on the random forest model can be used to analyze data from sensors on the structures and detect the presence of cracks. Machine learning based on the random forest model can be a powerful tool for crack localization and health monitoring in composite beams. With the ability to analyze large amounts of data and make accurate predictions, these algorithms can help prevent costly failures and improve the safety of composite structures. Prashant et al. [1] performed an experimental modal analysis on rectangular cantilever beam to obtain natural frequencies, mode shapes, and modal damping. Initial excitation is given by impact hammer as connected with FFT analyzer and NI Lab VIEW software was utilized to extract modal data. Karandikar et al. [2] performed an experimental modal analysis on cracked and un-cracked beam. Fast Fourier Transform (FFT) set up was utilized to perform modal analysis on the cantilever beam with a single crack. These cracks were situated at different locations and having varying sizes. The results from a modal analysis performed in ANSYS were contrasted with experimental results. Modal testing is more reliable as the percentage of error between among these methods within the acceptable level. Ashish et al. [3] studied various vibration based crack identification methods for detection of damage in a fiber reinforced composite. Presence of cracks in the structure influence the static as well as dynamic response attributes. Cracks in a beam modify the natural frequency, mode shape and stiffness. It is discovered that detection of crack size, crack location in cantilever beam depends on natural frequencies and mode shapes.

Chandan Kumar et al. [4] determined natural frequency of different modes of a cantilever beam analytically and experimentally. Both theoretical and experimental results are contrasted for Aluminum and Mild Steel. It is found that results found by theoretical and experimental methods are nearly the same. Vader et al. [5] evaluated variation in natural frequencies of cantilever composite fabricated with glass epoxy. The effect of crack location and depth on the natural frequency of a beam with a transverse open crack is analyzed. The numerical results from ANSYS were found in good concurrence with the experimental results. Khalkar et al. [6] presented a technique for determination of first mode frequency of a healthy beam in bending mode. Modal analysis is performed in ANSYS workbench to get modal frequencies. Finally, there is a good conformity between the modal frequencies calculated from proposed technique and ANSYS workbench.

Kumar et al. [7] performed finite element analysis of a cantilever beam to get modal frequencies using MATLAB code and ANSYS APDL and the results compared with experimental results. It is observed that modal frequencies are decreased when mass at the tip of beam is increased. Pragnesh et al. [8] calculated the natural frequencies of a beam made of various materials such as aluminium and steel using experimental modal analysis. The beams were energized by an impact hammer and the modal spectrums are obtained by lab view software. Kumar sahu [9] designed an experimental setup, in which a woven fiber and glass cantilever plates is excited by an impact hammer and the response is obtained by using an accelerometer which attached to the plate. An experimental investigation was carried using modal analysis technique with Fast Fourier Transform analyzer, PULSE lab shop, impact hammer and contact accelerometer to obtain the frequency response functions. **P**ushparaj [10] analyzed the effect of change in the matrix material, hybridization, and laminate stacking sequence on the natural frequencies and mode shapes are also investigated. It is found that hybridization and orientation of the outermost layer has more significant influence on the natural frequencies of the laminated composite plates compared to fiber volume fraction and change in the matrix material. Melville et al. [11] has used a deep learning interpretation of ultrasonic guided waves to achieve fast, accurate, and automated structural damage detection. To achieve this full wavefield scans of thin metal plates are used. Daskalakis et al. [12] has presented a framework for damage detection and localization using neural networks. Several results obtained with numerically simulated data illustrate the effectiveness of the proposed approach. Adam et al. [13] has proposed hybrid identification method based on Deep Learning Approach, which is examined for cracks on concrete bridge images.

2. Experimental Analysis

An E-Glass composite beam with dimensions 300mm×50mm×3mm is considered in the present work to carryout impact hammer test to find the first three natural frequencies of cracked composed beams. One end of cracked composite beam is rigidly fixed with the help of bench vice and accelerometer placed other end of beam. Impact hammer is used to create the free vibration in the beam. Both accelerometer and impact hammer is connected to dynamic signal analyzer to acquire and process the signals. The frequency range is set it to 1440 Hz. The impact hammer sensitivity value as 10 mv/g and accelerometer sensor sensitivity as 9.68 mv/g. An accelerometer is placed at the selected locations and initial excitation is given by the impact hammer. During an impact hammer test, initial excitation is given by with an impact hammer and measure the resulting vibrations using an accelerometer. The vibrations are then analyzed using EDM (Engineering Data Management) software to determine the natural frequencies of cracked composite structure. Fig. 1 shows the cracked composite beam with acceleration sensor and Fig. 2 shows impact hammer test on cracked composite beam. Table 1 shows the results of first three natural frequencies of cracked composite beams. The data in Table 1 is used to train the Random Forest algorithm. Fig. 3 shows the frequency response spectrum of cracked composite beam with crack at 50 mm from fixed end.

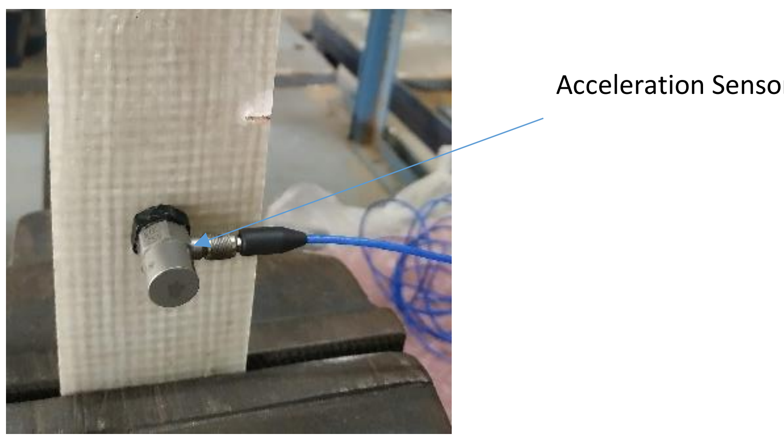

Fig. 1 Cracked composite beam with acceleration sensor

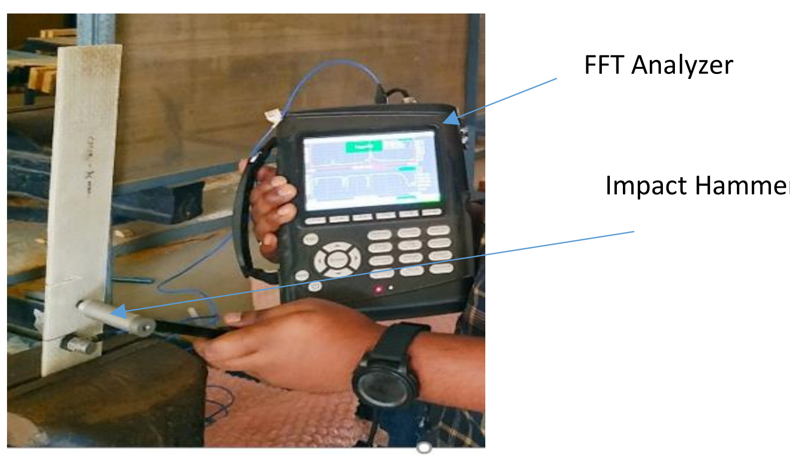

Fig. 2 Impact hammer test on cracked composite beam

Table 1. First three natural frequencies of cracked composite beam

Crack Location from Fixed End (mm)	Crack Size (mm)	First mode (Hz)	Second mode (Hz)	Third mode (Hz)
50	5	20.315	135.94	169.47
50	10	20.254	133.03	168.09
50	15	20.055	129.71	165.75
50	20	19.513	129.12	162.38
100	5	20.754	130.08	169.55
100	10	20.627	129.61	168.36
100	15	20.418	128.81	166.35
100	20	20.122	127.62	163.48
150	5	20.785	129.76	169.71
150	10	20.737	128.47	168.92
150	15	20.655	126.39	167.52
150	20	20.535	123.55	165.46
200	5	20.802	129.9	169.9
200	10	20.793	128.97	169.51
200	15	20.776	127.44	168.77
200	20	20.749	125.25	167.66
250	5	20.81	130.19	170.03
250	10	20.817	130.04	169.97
250	15	20.824	129.77	169.78
250	20	20.782	129.12	162.38

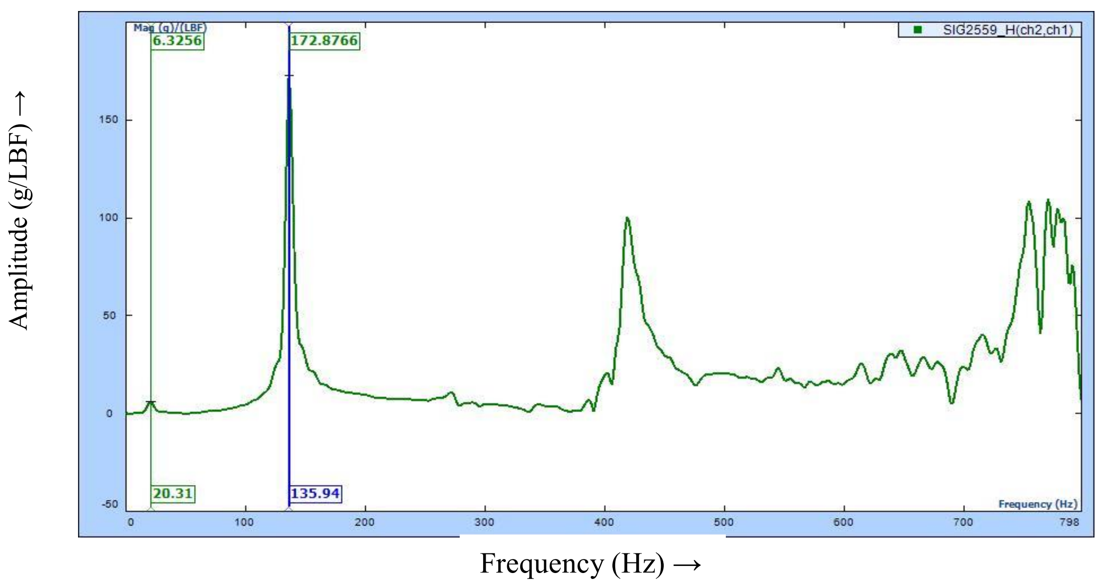

Fig. 3 Frequency response spectrum of cracked composite beam with location of crack is at 50 mm from fixed end and width of 5mm.

3. Random Forest Algorithm

In the paper Random Forest algorithm is used to detect the crack location in the cracked composite beam with the data of first three natural frequencies obtained from impact hammer test as shown in Table 1 of the previous section 2. The Random Forest technique is a machine learning algorithm used for both classification and regression tasks, it is used for regression tasks in the present paper. It is an ensemble method that combines multiple decision trees to improve the accuracy and robustness of the model. The Random Forest algorithm works by creating a set of decision trees, where each tree is trained on a random subset of the input data and a random subset of the features. The trees are created using a process called bagging, which involves randomly sampling the data with replacement and training a decision tree on each sample. During the training process, each decision tree is trained on a different subset of the input data and features, which helps to reduce overfitting and improve the generalization of the model. The final output of the Random Forest algorithm is the average prediction of all the decision trees in the ensemble.

Fig. 4 shows the Workflow of random forest regression. This dataset shown in Table 1 used to train the Random Forest technique consists of a three sets of inputs as first three natural frequencies and corresponding outputs consists of two sets of data as crack location from clamped end and crack width. The inputs are the extracted features from impact hammer test on cracked composite specimens, while the outputs are the locations of the damage in the composite structure. The data is divided into two parts, the first part is used to train the model and another part is used to validate the model. Random Forest model is trained using dataset shown in Table 1. After training the model, it is to be validated with R-squared score to check its accuracy and efficiency. This can be done by using a validation dataset that was not used during the training process. Once the model is trained and validated, it can be used to locate the damage in the composite structure. The pre-processed data is input into the model, and the output is the location of the damage in the structure. Fig. 5 shows plot between the predicted and actual values of crack location.

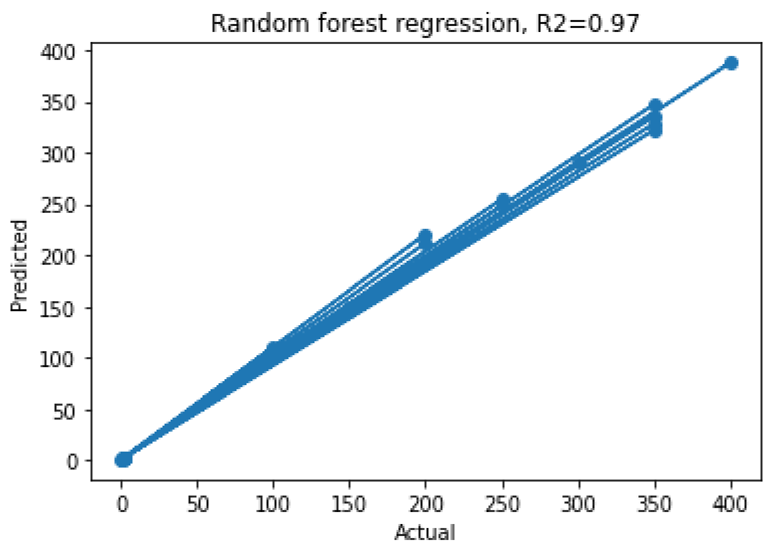

Fig. 5 Plot between the predicted and actual values of crack location

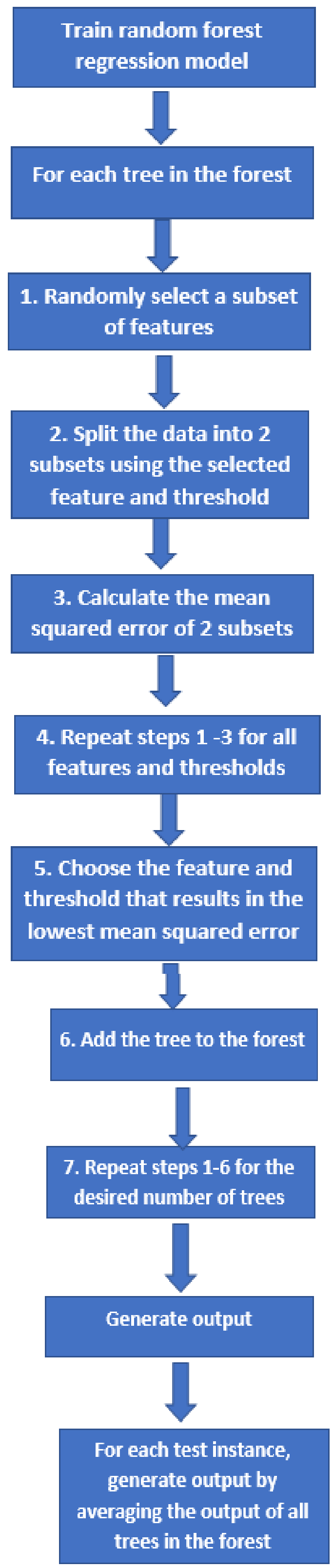

Fig. 4 Workflow of random forest regression

The performance of the model was evaluated using several metrics, including the mean absolute error (MAE), mean squared error (MSE), and coefficient of determination (R2 score). The results of the evaluation showed that the model performed exceptionally well in predicting the crack location. The MAE of the model was found to be 5.547, which suggests that the average deviation between the model's predictions and the actual crack locations was small. The MSE was 92.52, further demonstrating the model's accuracy in predicting the crack location. The model's R2 score of 0.971 indicates that the model explains 97% of the variance in the target variable, the crack location. This is an outstanding result and demonstrates the model's strong ability to accurately predict the crack location. In conclusion, the results of the performance analysis of the improvised model show that it has a mean absolute error of 5.55, a mean squared error of 92.52, and an R2 score of 0.97. This indicates a high level of accuracy in predicting the location of a crack for the three resonant frequencies as input. The results of the study demonstrate the potential of the model in accurately detecting cracks and other forms of internal damage in composite structures, such as bridges. The use of multiple non-destructive inspection results, as inputs for the model, enhances its accuracy compared to using just one inspection result.

4. Conclusions

In conclusion, the results of this research show that the ML model developed in this study is highly effective in predicting the location of cracks in a structure based on its resonant frequencies. The high level of accuracy achieved by the model makes it a valuable tool for structural engineers and other professionals in the field. Further research may be necessary to optimize the model's performance and explore its potential applications in other areas. In conclusion, the proposed method offers a reliable and efficient way to diagnose composite structures, and could lead to more accurate inspection methods based on artificial intelligence. Future research challenges include the incorporation of additional non-destructive methods and analysing parameter measurement error and the applicable range. Overall, the results of this study highlight the potential of using machine learning algorithms to diagnose composite structures and ensure their safety.

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