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The Prediction of Natural Frequencies of Cracked Plates Using the Machine Learning Methods

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Abstract

In this study, the first to fourth natural frequencies of a cracked plate with simply supported boundary conditions are predicted using machine learning methods, namely Random Forest and Linear Regression. Initially, a dataset comprising 200 observations was generated based on experimental and theoretical data to facilitate the prediction of natural frequencies. The crack characteristics (length, depth and location) were selected as the key parameters influencing the natural frequencies. Furthermore, 80% of the data was randomly assigned for training and 20% for testing the developed models. To evaluate the performance of the proposed models, various statistical indicators were analyzed for both the training and testing datasets. The results demonstrated that both methods yield highly accurate predictions of the natural frequencies for both training and testing data. The highest correlation coefficients for the training and testing datasets were observed to be 0.999 and 0.992, respectively. Moreover, the highest root mean square error (RMSE) values for the training and testing datasets were found to be 0.43 and 2.7, respectively, indicating the high precision of the proposed models. Additionally, an assessment of the reliability and generalizability of the models revealed that the Random Forest-based model exhibited greater stability and generalization capability across all frequency modes.

Keywords: Natural Frequency, Crack, Machine Learning, Random Forest, Prediction, Correlation Coefficients

1. Introduction

The study of the effect of cracks on the behavior of structures has long been an important research topic in aerospace, mechanical, marine, and civil engineering, as cracks are common causes of structural failure, and their identification is essential to prevent catastrophic failure and maintain structural integrity. In the last two decades, extensive research has been conducted in this field, both in the form of direct and inverse studies. In the analytical studies, Ismail and Cartmell [1], Joshi et al. [2], Moradi et al. [3], and Xue et al. [4] have investigated the vibration behavior of cracked plates using classical and Mindlin theories, linear or rotational spring models, and methods such as Ritz and differential quadrature elements. Also, Raza et al. [5] evaluated the effect of porosity on the vibration characteristics of cracked functionally graded plates using the extended finite element method and higher-order shear deformation theory.

In recent years, artificial intelligence and machine learning-based approaches have also been developed for crack detection and identification. Satpute et al. [6] presented a method based on synthetic data and gradient optimization to identify five crack parameters in isotropic plates. Salgado-Ancona et al. [7] compared the performance of different machine learning algorithms for crack detection in wind turbine blades and showed that the k-nearest neighbor algorithm and decision tree perform well. Karpat et al. [8] also presented a method for early detection of gear root cracks without the need for extensive experimental data using machine learning. In addition, Avarzamani et al. [9] were able to identify several types of damage in composite structures with high accuracy using regression analysis, and Hoseintabar Marzebali [10] et al. also reported an accuracy of more than 90% in identifying bearing defects using LSTM networks.

The aim of this research is to present a distinctive machine learning-based method for modeling the effect of cracks on the natural frequencies of a plate. In this study, the first four natural frequencies of a simply supported cracked plate are accurately predicted using machine learning models and the performance of these models is comprehensively evaluated. For this purpose, 200 observations including 50 experimental data and 150 theoretical data are used, 80% of which are allocated for training and 20% for model evaluation. Considering the applicability of this method in inverse analyses and determination of crack characteristics based on natural frequencies, the development of a machine learning-based model for extracting dynamic properties of cracked structures is of particular importance.

2. Theory

2.1. Governing equations

In this part, the differential equations governing the vibrations of thick plates have been extracted. For this purpose, using Mindlin's first-order shear theory and van Karman's strain-displacement relations, the mid-plane strains of the plate are obtained in the form of relations (1).

$$\begin{aligned}
\varepsilon_x &= \frac{\partial u_0}{\partial x} + z\frac{\partial \alpha}{\partial x} + \frac{1}{2}\left(\frac{\partial w}{\partial x}\right)^2 \\
\varepsilon_y &= \frac{\partial v_0}{\partial y} + z\frac{\partial \beta}{\partial y} + \frac{1}{2}\left(\frac{\partial w}{\partial x}\right)^2 \\
\varepsilon_z &= 0 \\
\gamma_{xy} &= \frac{\partial u_0}{\partial y} + \frac{\partial v_0}{\partial x} + z\frac{\partial \alpha}{\partial y} + z\frac{\partial \beta}{\partial x} + \frac{\partial w}{\partial x}\frac{\partial w}{\partial y} \\
\gamma_{xz} &= (\frac{\partial w}{\partial x} + \alpha) \\
\gamma_{yz} &= (\frac{\partial w}{\partial y} + \beta)
\end{aligned} \tag{1}$$

Here u, v and w are the displacements along the x, y and z axes respectively. Also α and β are the rotations around the y and x axes respectively. Using the stress relations in isotropic materials, the plate strains can be calculated, and substituting them into the plate equilibrium relations, the governing equations for the plate can be obtained in the form of equations 2. $I_x = I_y = \frac{bh^3}{12}$ and ρ *is* the density of the desired plate.

$$\begin{aligned}
&\frac{Eh}{1-\nu^2}[u_{,xx} + \nu(v_{,xy})] + \frac{Eh}{2(1+\nu)}[u_{,yy} + v_{,xy}] = \mu\ddot{u} \\
&\frac{Eh}{1-\nu^2}[v_{,yy} + \nu(u_{,xy})] + + \frac{Eh}{2(1+\nu)}[u_{,xy} + v_{,xc}] = \mu\ddot{v} \\
&K_s Gh(\alpha_{,x} + w_{,xx}) + K_s Gh(\beta_{,y} + w_{,yy}) + \frac{Eh}{1-\nu^2}(u_{,x}w_{,xx}) = \mu\ddot{w} \\
&\frac{Eh^3}{12(1-\nu^2)}(\alpha_{,xx} + \nu\beta_{,xy}) + \frac{Eh^3}{12(1-\nu^2)}(\alpha_{,yy} + \beta_{,xy}) - K_s Gh(\alpha + w_{,x}) = I_y\ddot{\alpha} \\
&\frac{Eh^3}{12(1-\nu^2)}(\beta_{,xx} + \nu\alpha_{,xy}) + \frac{Eh^3}{12(1-\nu^2)}(\alpha_{,xy} + \beta_{,xx}) - K_s Gh(\beta + w_{,y}) = I_y\ddot{\beta}
\end{aligned} \tag{2}$$

2.2. Crack modeling

Due to the reduction in plate stiffness in the crack area, slope discontinuity is observed on both sides of the crack. Therefore, in order to calculate the additional rotation of the cracked plate, using the fracture mechanics relations and the definition of the stress intensity factor for the first crack mode (opening), the amount of this additional rotation can be calculated as equation (3).

$$\theta = \frac{12(1-\nu^2)}{E}\sigma_b \alpha_{bb} \tag{3}$$

Here, σ_b is the nominal bending stress in the direction perpendicular to the crack and α_{bb} is the bending softness coefficient, which is presented in equation (4) as a function of the crack parameters.

$$\alpha_{bb} = \frac{1}{h}\int_0^{h_c} g_b^2\, dh_c \tag{4}$$

In this relation, g_b is a dimensionless function of the relative crack depth ($\xi = \frac{h_c}{h}$) in the range ($0 \le \xi \le 0.8$), which is considered as relation (5).

$$\begin{aligned}
g_b = \sqrt{\pi\xi}(1.1202 - 1.8872\xi + 18.0143\xi^2 \\
- 87.3851\xi^3 + 241.9124\xi^4 \\
- 319.9402\xi^5 + 168.0105\xi^6)
\end{aligned} \tag{5}$$

3. Extended Abstract Preparation

The study was conducted for square PVC plates with a length and width of 0.5 *m*, a thickness of 6 *mm*, an elastic modulus of 3.7 *GPa*, a density of 1400 *Kg/m³*, and a Poisson's ratio of 0.3. The plate has a crack parallel to the square side. The boundary conditions considered for this plate are simple support boundary conditions, which are modeled using a V-shaped groove and a two-bar support as shown in Figure 1(b). After the plate is placed inside the structure, excitation is applied by a hammer impact and the plate response is collected using a sensor. After that, by performing fast Fourier transform on the force and response data of the plate, the frequency response curve of the structure is obtained and the natural frequencies of the plate vibrations are extracted. In the experiments conducted to extract data, the plate was excited with a hammer (Global test AU02) and the response was measured with a miniature accelerometer (B&K 4508) and analyzed with a signal analyzer (B&K type 3032A) to obtain the first 4 frequencies of the plate. The structure used in these experiments is shown in Figure 1.

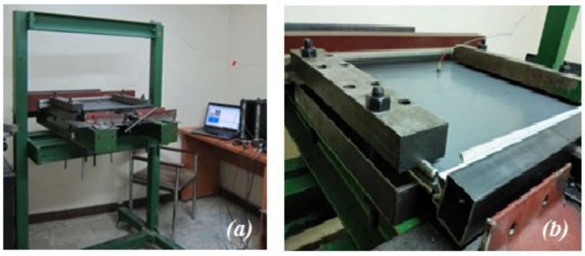


Figure 1. (a) Test structure (b) Modeling of plate boundary conditions.

A small sample of the first four natural frequencies obtained from the experimental test in comparison with the numerical results is presented in Table 1. The examination of the presented results confirms the accuracy of the numerical solution answers and the difference between the numerical and experimental results is acceptable.

Table 1. Sample of the first four natural frequencies of the plate obtained from the experimental test and numerical solution.

Natural frequencies (Hz)	hc/h=0.7 Lc/b=0.4 lc/a=0.5		
	Experimental	Numerical	Percentage of

			relative error
First	39.50	38.99	1.29
Second	95.50	97.75	2.36
Third	96.25	98.95	2.80
Forth	154.00	157.27	2.12

2.4. Machine Learning Methods

Random Forest is a machine learning method used to solve prediction and classification problems. This method achieves high accuracy and stability in results by combining multiple decision trees and using randomization concepts. In this method, the training data is randomly divided into several subsets and a decision tree is built separately for each subset. Linear regression is one of the most basic and yet most widely used statistical analysis and machine learning methods used for modeling and prediction. The basis of this method is based on the assumption that there is a linear relationship between the independent variables (inputs) and the dependent variable (output). In fact, this algorithm tries to discover the general trend of the data by drawing a suitable line or surface through them and can predict the output value based on new inputs.

3. Results

Figures 2 and 3 show the scatter plots of the results of the prediction of the first to fourth natural frequencies for the training and test data, respectively, using the random forest and linear regression methods. In these plots, the vertical axis represents the prediction results and the horizontal axis represents the actual values. The interpretation of the results is that the closer the points obtained are to the y=x line, the better the model is trained and, with its excellent performance, it has been able to make predictions with higher accuracy. In Figures 2 and 3, it can be seen that the points obtained from the prediction results of the first to fourth natural frequencies and the actual values are well centered around y=x and within a deviation range of -20% to +20% (except for the prediction graph of the fourth natural frequency using the linear regression method). This shows that the model trained using the random forest and linear regression methods is able to predict natural frequencies very close to the actual values, in other words, the models have predicted with very high accuracy. It is also seen from the results of the prediction of different frequencies that the models proposed by both prediction methods did not have outliers in their results. In other words, there is no point that is far from the best-fit line. Another result that can be seen is that for all small and large values of the actual frequencies, both models were able to predict with very high accuracy, and therefore it can be concluded that the resulting models have high generalizability. It is also seen from the comparison of the two methods that the prediction results using the random forest method are more focused on the best-fit line.

4. Conclusion

In this study, the first to fourth natural frequencies of a cracked plate were predicted using two machine learning methods including random forest and linear regression. For training and evaluation of the models, 1000 data from 200 experimental and theoretical observations were used. The plate thickness, length, depth and crack location were considered as inputs and the first to fourth natural frequencies were considered as outputs. Also, the correlation coefficient, root mean square error and average absolute error percentage were used as indicators to evaluate the performance of the models.

The results showed that the models presented in the training data had a very accurate performance; so that the correlation coefficient was reported between 0.9952 and 0.999 at all frequencies. In the experimental data, the random forest model provided the lowest mean absolute error for the first to third frequencies, and the value of this index was in the range of 0.2087 to 1.5432, which indicates the appropriate accuracy of the model. On the other hand, in the same frequencies, the linear regression model showed the lowest value of the root mean square error, and this value was obtained between 0.2819 and 0.5272.

In general, the correlation coefficient close to one in the training and testing data showed that both models have good stability. However, the closeness of the correlation coefficient values of the random forest model in different data sets indicates that this method has higher generalizability than linear regression.

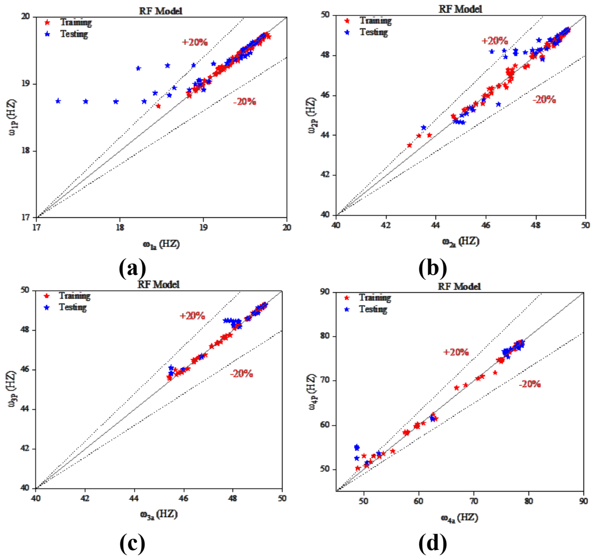
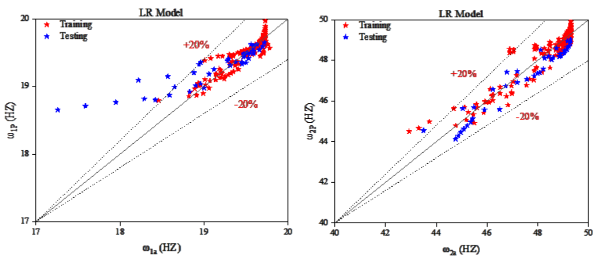
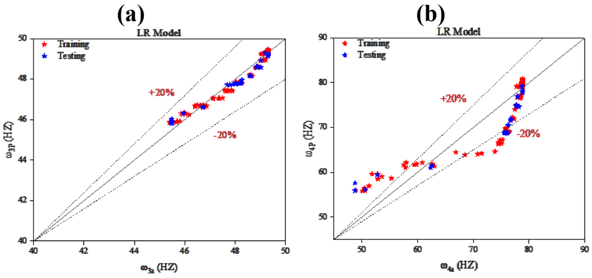


Figure 2. Scatter plot of the random forest method.



(a) (b)



(c) (d)

Figure 3. Scatter plot of the linear regression method.

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