CRACK DETECTION IN CANTILEVER LIKE STRUCTURES USING DEEP LEARNING

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ABSTRACT:

Over the decades, damage detection in structures has been given prior attention, and therefore, different new techniques are being implemented to detect the damage. Detecting cracks is vital in monitoring structural health and ensuring structural safety. If cracks develop and continue to propagate, it causes the failure of the structure. Early detection allows taking precautious measures to prevent damage and failure. This paper presents a Neural network-based model to detect defects in the form of a transverse crack in cantilever structures. The cantilever beams of two grades of Aluminium alloys, viz. Al 6061 and Al 6013 are considered for analysis purposes with the crack position at fixed intervals from the fixed end to the free end at varying crack depths. The frequencies of both damaged and undamaged beams are obtained by performing modal analysis in ANSYS. Crack prediction is done using the Artificial Neural Network(ANN) tool in MATLAB. The input parameters to the ANN tool are relative natural frequencies, and the output parameters are relative crack depth and relative crack location in dimensionless forms. The experimentation is performed using Al 6101, and it was found that the developed neural network-based model can predict the location and depth of the crack near par with the actual results.

INTRODUCTION:

Cantilever structures can be found in various civil, ocean, and aviation engineering, and they can be exposed to known and unknown cyclic loads, which may result in fatigue cracks. All structures are prone to damage, which may be due to over-stressing, extreme environmental conditions, or any other accident. A crack in a component may grow during service and may lead to component failure once they grow further than a critical limit. A crack can degrade performance and shorten the lifetime of a structure, and even worse, sometimes, it can also cause catastrophic failures. It is desirable to investigate the crack that appeared in the structure in its early stage to protect the structure from probable catastrophic failures. There are various Non-destructive techniques (NDTs) available to detect the crack in the components. They are efficient but have specific, time-consuming, expensive, and laborious drawbacks.

A crack in a structural member would affect the vibration response by reducing the component's natural frequency. The local damage also affects the mode shapes of the vibration of the component. The change in vibration can be used to detect the existence of a crack location and depth in the structural member. Thus, Vibration-Based Inspection (VBI) can be a potential method for crack detection. In the past couple of decades, vibrational analysis has gained popularity for detecting cracks in their initial stages. The location and severity of crack can be defined by the differences between the dynamic structural characteristics of the damaged and intact structures. The advantage of this method is that minor changes in the physical properties of a structure due to the damage result in detectable variations in modal parameters like natural frequencies, mode shapes, and modal damping. The primary insufficiency of this method is how to extract the essential features from the vibration response to damage detection. The vibration-based structural damage detection is a relatively new research topic, and the approach has several classifications. The model-based methods reveal the damage locations and severities by comparing data obtained during the experiments and with a mathematical model of the structure since structural damages cause changes in the dynamic characteristics. The methodology can include neural networks, genetic algorithms, and wavelet analysis. The ANN was trained to predict the location and depth from the beam's natural frequencies in [1,2]. The feasibility of using frequency changes for damage detection is limited since significant damage may cause minimal changes in natural frequencies [4,24].

Artificial Neural Network (ANN) is the novel structure of the information processing system. It comprises many highly interconnected processing elements (neurons) working parallel to solve typical applications through a learning process. Neural networks can be used to recognise patterns and detect trends too complex to be noticed by humans or other computer techniques. Although various non-destructive techniques are available to identify cracks present in a system, the response of the techniques is frail in terms of accuracy and time for computation for a complex system. The use of ANN, with its parallel computing and pattern recognition capabilities, is suitable for designing an intelligent system for damage assessment in cracked structures with higher accuracy and faster computational time.

METHODOLOGY

Modal analysis is the study of the dynamic properties of structures under vibrational excitation. The modal analysis aims to find the shapes & frequencies at which the structure will amplify the effect of load. Modes are intrinsic properties of the structure and are defined by the structure's material properties and boundary conditions. Each mode is defined by natural frequencies, modal damping, and a mode shape.

A beam is considered, as shown in Fig. 6.1. The geometry is created using CATIA v5 R21 software and is shown in Fig. 6.2. Cracks at different positions of different depths are considered on the cantilever beam, starting from the fixed end up until the free end. ANSYS modal module is selected, and the geometry of the beam with different crack lengths and severities is imported into ANSYS Design Modeller. This beam consideration can comprehend for similar slender beams, irrespective of the cross-section and length, as we have considered the relative values of the severities and positions of the crack, i.e., the depth and length ratios, respectively. Four different Aluminium grade alloy materials, viz Al 6061, Al 6013, Al 5052, and Al 5024, are used in this work, thus increasing the scope for collecting many data samples for further analysis.

The beam modelled in Catia VR 5 is converted into IGES(.igs) format and this IGES file is imported into the Design Modeller of Modal solver in ANSYS. After importing the geometry into Design Modeller, open Model and then in the geometry branch of the tree, assign the material whose properties are to be considered for analysis.

After assigning the materials to the geometry, meshing is done. Meshing is an important process of analysis, and it should be performed on the entire beam, including the crack. Meshing is the process of dividing the created model into a number of divisions or elements, which consists of nodes. By applying the meshing process, we can determine the efficiency and effectiveness of any analysis. Under mesh sizing, the mesh was set to fine mesh and under mesh methods, elements are set to Quadrilateral to achieve accurate and precise results. A mesh element of size 3mm is used for fine meshing.

In the ANSYS Modal module, open the model section, click on construction geometry and select the path option. Further, specify the starting and ending points for the generation of the path as (0,0,0) and (0,0,1500), respectively.

MATERIALS USED

Four different grades of Aluminium alloy are used viz. Al 6061, Al 6013, Al 5052 and Al 5024, whose properties are shown in table 6.1.

Table 6.1. Material Properties

Material	**Young's Modulus (GPa)**	**Density (g/cm^3)**	**Poisson's ratio**
Al 6061	68.9	2.7	0.3
Al 6013	69	2.8	0.33
Al 5052	69.3	2.68	0.33
Al 5024	72	2.65	0.33

Modal Analysis is performed in ANSYS software, and the natural frequencies, mode shapes, directional deformations, and total deformations for the beam are calculated. The obtained results are tabulated. Apart from the tabulated results, 3-directional graphs are plotted, using MATLAB and Sigma Plot. These act as a helpful reference for further analysis.

Further, the obtained directional deformations serve as the basis for generating MAC (Modal Assurance Criterion) values. These MAC values are generated in order to fortify the accuracy of the results while performing functions like “training”, “testing”, and “validation” in MATLAB.

The obtained MAC values are tabulated for all modes, ranging from 1 to 10. The subsequent objective of the project is to deliver a data set consisting of the aforementioned relative frequencies, relative severities, relative positions, and MAC values.

The data obtained is fed to the Artificial Neural Network tool in MATLAB software to perform the “Training” operation for 80% of the total data set obtained, while the rest 20% of it is fed to the tool for “Testing”.

The final objective is to predict the location and severity of the crack as a consequence of performing reverse-engineering using MATLAB’s Neural Network tool. In other words, if the frequency obtained through practical apparatus is fed to the program, we would have trained the tool to predict the relative position and severity of the crack on the beam.

“Validation” is performed by giving such frequency values of such cracks to get their severity and position on the beam.

The Modal Assurance Criterion (MAC) is a statistical indicator sensitive to significant differences and relatively insensitive to minor differences in the modes. Mode shapes used in the comparison can originate from a Finite Element Analysis or experimental modal analysis.

The Modal Assurance Criterion (MAC) along with the natural frequencies, is calculated as the normalized scalar product of two modal vectors, to quantify a mode-to-mode correlation between damaged and undamaged structures. The MAC value between two modes is the normalized dot product of the complex modal vector at each common node (i.e., points), as shown in Fig.6.7.

Where $\{\varphi A\}$ and $\{\varphi B\}$ are the damaged and undamaged modal vectors for the ith and jth modes, respectively, this indicator can take values from 0 (no consistent correspondence) to 1 (consistent correspondence). The MAC value will be near one if a linear relationship exits between the two complex vectors and will be near zero if they are linearly independent.

A complex vector includes both amplitude and phase, whereas a real vector is a real part only. In the above figure, it is also clear that the MAC is not sensitive to scaling, so if all mode shape components are multiplied with the same factor, the MAC will not be affected.

RESULTS

Total Deformations and Directional Deformations

In addition, Frequency responses, total deformation responses and directional deformation responses of the beam are calculated and tabulated for all the 10 modes corresponding to all the four materials considered, and the Modal Assurance Criterion values are also calculated.

3-D graphs

3-D graphs with the relative position on the X-axis, relative severity on the Y-axis, and frequencies on the Z-axis, respectively, are plotted for all the 10 modes for the four materials we have considered.

MATLAB results

Results without MAC

The final data set is imported to MATLAB for training using the ANN tool, followed by the "testing" phase. The following quantities are considered as the deciding outcomes for the trained data values to be validated accurately.

- **NMSE (Normalized Mean Square Error):**

  i. NMSE-testing = 0.209093413531037

  ii. NMSE-validation = 0.172048027898558

- **R^2 coefficient:**
    i. R^2-testing = 0.789555853510844
    ii. R^2-validation = 0.827459070019925
- **RMSE (Root Mean Square Error):**
    i. RMSE-testing = 0.078683018706796
    ii. RMSE-validation = 0.071179634285413

Results with MAC

The results obtained after the incorporation of MAC values into the frequency dataset are as follows,

- **NMSE (Normalized Mean Square Error):**
    i. NMSE-testing = 0.178123760078
    ii. NMSE-validation = 0.158367095642
- **R^2 coefficient:**
    i. R^2-testing = 0.788126700983
    ii. R^2-validation = 0.8269654281001
- **RMSE (Root Mean Square Error):**
    i. RMSE-testing = 0.07329012765
    ii. RMSE-validation = 0.0700543729981

CONCLUSIONS

The present study shows that ANN could accurately predict the responses of the relative crack position (RCL) and the relative crack depth (RCD), which are used in the health monitoring of the cantilever beam structures, as errors between the actual and the predicted responses is minor than 4.12%. It is seen that the prediction accuracy of the relative crack length is higher than that of the relative crack depth of the cantilever beam. The developed ANN model was found to predict the desired outputs convincingly. Thus, it shows that ANN modelling can be successfully used in the health monitoring of structures to predict their failure, reducing the enormous efforts being imparted and the tedious calculations involved in the monitoring process. It has been observed that the natural frequency values of the beam decrease with an increase in severity of the crack, i.e. depth of the crack.

Modal Assurance Criterion (MAC) is used to quantify a mode-to-mode correlation between damaged and undamaged structures to find a clear correlation between a change in natural frequencies and the presence of damage. The MAC values can range between 0(no consistent correspondence) and 1(consistent correspondence). It is also observed that there has been an approximate 6% increase in regression accuracy after including MAC values to train the neural network tool.