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Neural Network for damage detection of R/C Buildings

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Abstract
Engineering structures play a crucial role in advancing modern societies, and it is imperative to monitor their condition to ensure safety and longevity. There are various methods available for assessing the integrity of these structures, with a prominent one being damage detection. This approach focuses on identifying deviations in specific structural behavior characteristics and utilizes numerical models to simulate different damage scenarios. However, the effectiveness of this approach is limited due to discrepancies between analytical models and actual structures. This study introduces an enhanced approach for detecting structural damage, with the primary goal of identifying damaged components within a structure. It harnesses neural networks to predict which elements have sustained damage, followed by a model refinement process that utilizes an optimization algorithm. This process is crucial for accurately determining the stiffness parameters of the damaged elements, thereby bridging the gap between theoretical models and real-world structural behaviors. The integration of neural network predictions with targeted optimization algorithms represents a significant advancement in the practical application of damage detection techniques in the field of engineering structures.
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I. INTRODUCTION

Engineering structures such as bridges, buildings, roads, railways, and tunnels are essential and prevalent in contemporary societies, cutting across cultural, geographical, and economic boundaries. The assurance of their safety, cost-efficiency, and durability hinges on proper management and upkeep. A crucial aspect of this management is health monitoring, which enables early identification and observation of structural wear and tear [1]. The comprehensive data collected from monitoring must be transformed into practical knowledge. This assists in formulating and implementing maintenance plans, improving safety, validating theories, reducing uncertainties, and broadening the knowledge and consciousness about the monitored structure.

The assessment of structures' current conditions can be carried out using various techniques, with on-site manual inspections and vibration-based Structural Health Monitoring (SHM) being the most common in real-world applications [2–4]. On-site manual inspections typically consist of visually and physically examining structural elements to detect visible damage or anomalies. While this method provides significant insights into the structure's state, its dependability and accuracy are limited by human interpretation and the potential for error. Furthermore, these inspections are scheduled at fixed intervals, which may miss the ongoing and instantaneous progression of structural deterioration. On the other hand, vibration based SHM systems offer constant monitoring of the structure's behavior and response by using sensors and data collection technologies [5, 6]. These systems gather and scrutinize data, employing advanced processing techniques to derive crucial information reflecting the structure’s condition. Consequently, vibration based SHM systems offer a more thorough and unbiased assessment, promoting proactive maintenance approaches and enabling timely actions to maintain structural integrity and safety.

A multitude of research efforts have aimed to link alterations in structural conditions with changes in natural frequencies, utilizing extensive measurement data. While many of these studies have shown that natural frequency can reflect structural stiffness, it alone does not suffice for a direct assessment of structural health. Typically, natural frequency is used more as a contributing factor or characteristic within a system designed for an indirect evaluation of structural integrity. This method facilitates the assessment of structural conditions through an indirect yet revealing analysis based on dynamic response parameters. In vibration-based Structural Health Monitoring (SHM), there is growing interest in damage detection techniques for their capability to localize and quantify damage severity. These techniques primarily depend on differences in structural responses between damaged and intact states to detect damage. Various response parameters, like acceleration and displacement, are utilized to identify the structure's behavioral traits. While dynamic characteristics such as natural frequency and mode shape are often used in these analysis processes, many studies focus on natural frequencies as a key indicator for structural integrity assessment. Conventional methods in this field typically involve the creation of specific damage indices, intended to highlight frequency changes due to damage. Nevertheless, these traditional approaches frequently encounter challenges in creating an index that accurately reflects both the extent and location of damage through numerical methods. Moreover, as these methods are largely simulation-based, their practical applicability may be limited due to potential discrepancies in accurately mirroring the real-life conditions and responses of structures.

This research combines practical aspects of previously mentioned damage detection methods for real-life structures. A Finite Element (FE) model was constructed to extract the dynamic characteristics of a structure with damage. Subsequent structural analysis simulations were conducted across various damage scenarios within the structural elements. Artificial intelligence algorithms were then trained with this simulated data, particularly focusing on the dynamic behavior of the damaged model, to identify different potential damage states in the targeted structure. The developed Neural Network model is capable of pinpointing damaged elements in the structure by observing reductions in the stiffness properties of these elements. To determine which stiffness parameters (E, Iy) were altered in a specific element, a model updating process using a particle swarm optimization algorithm was adopted. This particle swarm optimization facilitated a more nuanced and detailed method for model refinement. As a result, the methodology crafted in this study is applicable to actual scenarios, especially when a finite element model (FEM) of a structure is accessible. The primary objective of this methodology is to closely estimate the real values of structural parameters, thereby narrowing the discrepancy between theoretical models and their practical counterparts. This approach enhances the accuracy and relevance of the FEM in mirroring actual structural conditions.

To overcome the challenges of conventional structural damage detection methods, there has been an increasing emphasis on incorporating Artificial Intelligence (AI) technologies. AI provides data-driven techniques to identify complex patterns, especially in situations where deterministic solutions are not viable. The effectiveness of AI-driven approaches largely depends on the quality of training data. Progress in data creation and processing technologies has significantly enhanced AI's utility in various fields. In structural damage detection, several neural network architectures have been utilized. Deep Neural Networks (DNNs) [7–9], forming the core architecture for neural networks, enable the examination of relationships between inputs and outputs through a feed-forward process, particularly useful when these relationships are relatively clear-cut. Recurrent Neural Networks (RNNs) [10, 11], known for their ability to incorporate previous information into current processing, are effective in managing sequential data like time series, making them ideal for analyzing structural dynamic responses. Convolutional Neural Networks (CNNs) [12–14], designed mainly for processing spatial data such as images, are adept at extracting spatial characteristics from data sets and have applications extending beyond image analysis, including improved data feature extraction for various analyses. As for training methods, there are supervised learning techniques, where networks are trained using labeled data sets to establish input-output relationships, and unsupervised learning approaches [15–17], which discover patterns in unlabeled data. While supervised learning can achieve high predictive accuracy due to clear labels, unsupervised methods are beneficial in situations where labeling is impractical or for discovering new features, such as in real-world structural conditions.

II. TRAINING PROCEDURE AND CASE STUDY

An advanced methodology for detecting structural damage was devised, starting with the creation of a foundational model. This model was crucial for dataset generation, where two critical parameters, the Elastic Modulus (E) and the Moment of Inertia (Iy), were systematically altered, reducing them to a minimum of 30% of their original values. The neural network was trained with this dataset, using the model's natural frequencies as inputs and targeting the stiffness of each element for outputs. This setup established a predictive model correlating frequency changes with potential structural damage. The model underwent a testing phase to assess its capability in estimating stiffness values from new data. The optimization process is intricately aligned with the structure's dynamic properties, ensuring a focused and effective enhancement of the model.

For the machine learning model, a dataset was generated using a structural model simulating a two-story building. This model, characterized by the elastic properties of its elements, was simulated with the OpenSeespy framework [19]. The dataset creation involved multiple modal analyses, each with randomized changes in stiffness properties (E, Iy) of different elements. The dataset was formed by varying stiffness parameters of one, two, or three elements, decreasing their values. This led to 10,860 unique models, all variations of the base model. The dataset, depicted in Figure 1, was split into training, validation, and test sets, allocated as 70% for training, 20% for validation, and 10% for testing. This split ensured a balanced representation of different damage scenarios across all subsets.

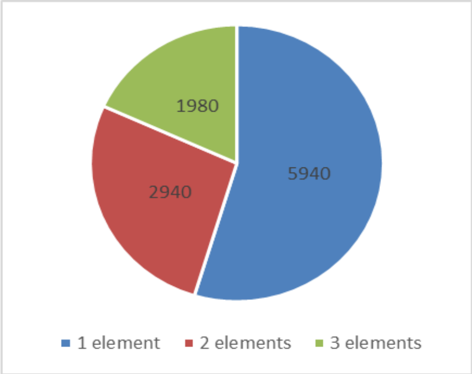

Figure 1: Components of dataset

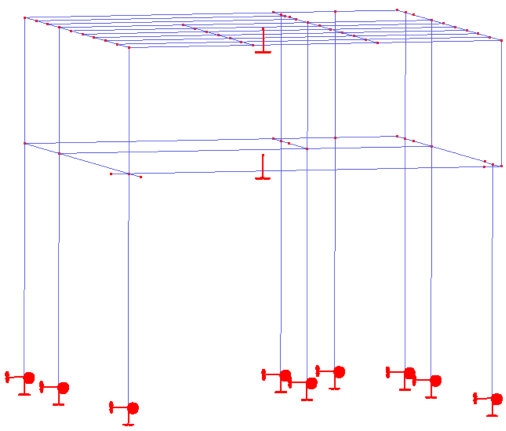

Figure 2: Reference Finite Element Model

In this study, the balance between the network's learning capacity and computational efficiency is a key focus. The number of nodes in the network is critical; more nodes enhance the network's ability to discern complex patterns, but too many can cause overfitting or increase computational burden. Setting the right maximum epoch count is crucial to avoid underfitting or overfitting, with this study opting for 15,000 epochs. Early stopping is implemented if validation accuracy doesn't improve, ensuring efficiency. The batch size, which impacts the amount of data processed in each epoch, and the learning rate, crucial for weight adjustment, were carefully considered. Due to RAM constraints, a smaller batch size was used, while a constant learning rate was maintained for steady progress. The study leveraged the TensorFlow library for developing the neural network, striking a balance between learning depth and computational practicality.

A parametric analysis was carried out to determine the most effective neural network model for predicting structural damage using stiffness values. The analysis revealed a trend where network performance generally improved with an increased number of nodes. Most configurations yielded satisfactory performance, except when the number of nodes was very low. The optimal network configuration identified for damage detection, as trained with the generated dataset, achieving an RMSE of 0.9742%.

Figure 3 presents the outcome of the network's performance on test data, indicating effective training as evidenced by the Root Mean Square Error (RMSE). This low RMSE suggests a high degree of accuracy in the network's predictions of stiffness compared to actual values, demonstrating its ability to generalize across a spectrum of stiffness degradation scenarios. Figures 5 offers a sample of a case study from the test dataset, where exemplifies the network's precision in identifying damaged elements.

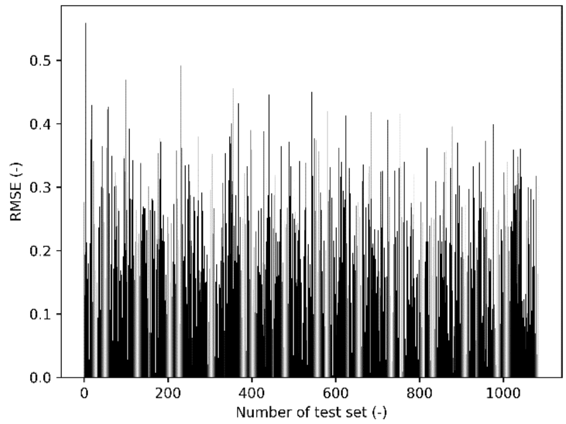

Figure 3: RMSE in test set

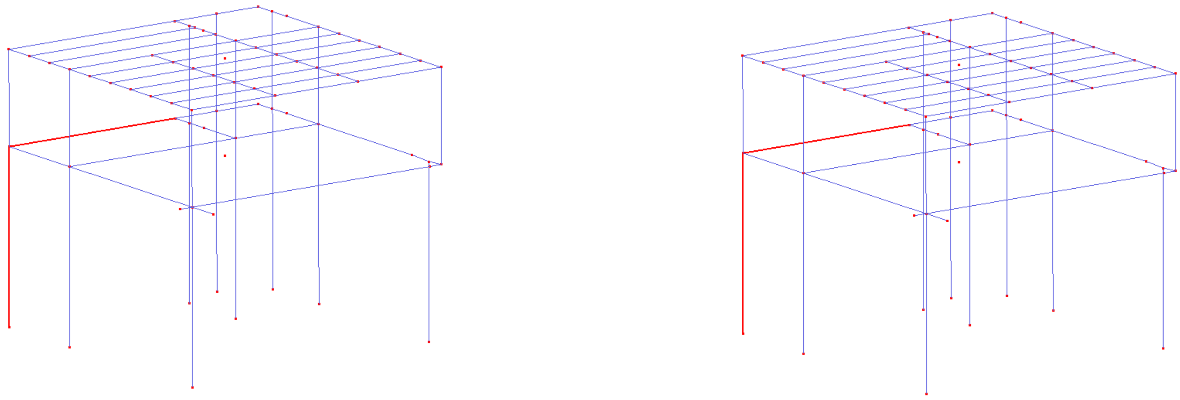

Figure 4: (Left) Ground truth damaged elements, (Right) predicted damaged elements.

III. CONCLUSION

This research applied a novel damage detection technique using a deep-learning model focused on estimating damage conditions from the modal characteristics of structures. The methodology was tested using an extensive dataset specifically created for this study. Beyond natural frequencies, dynamic characteristics like mode shape and modal energy were considered as potential input features. Future research might explore neural networks based on nonlinear structural models. This advancement aims to increase the method's precision and versatility, catering to more complex structural conditions and a wider array of damage types.

IV. FUNDING

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