

Artificial Neural Networks for Identifying minor Damage on Jacket Platforms

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ABSTRACT

In the field of structural engineering, neural networks are utilized to detect damage in offshore jacket platforms using a combination of modal analysis results. By analyzing the shape of natural frequencies and utilizing information from five modal results, damage identification indices are developed. This study investigates Structural Health Monitoring (SHM) strategies utilizing mode shape analysis and neural networks to detect failures within a multi-story structure. Various failure scenarios, including corrosion-induced damage and collisions, were analyzed across 52 structural members, with induced damage ranging from 0% to 20%. Results reveal the critical importance of floor levels: the fourth floor exhibited heightened accuracy in failure detection, particularly in columns and wind braces, crucial for corrosion protection. Notably, secondary beams consistently displayed higher precision in identifying failures compared to main beams. The neural network performance peaked at a mean squared error of 0.039206, validating its efficiency in detecting and allocating damage across different structural elements. Subsequent scenarios involving two members of the fourth floor demonstrated the adaptability of the approach in addressing diverse failure rates. This research underscores the efficacy of combining mode shape analysis and neural networks for robust SHM. It emphasizes the significance of floor levels and specific structural elements in enhancing failure detection accuracy, offering valuable insights for proactive maintenance and structural integrity preservation.

1. Introduction

Monitoring the health of structures and identifying damage early on is a crucial and essential task. One of the newer methods for identifying damage in structures is using dynamic responses of systems, which is a non-destructive and cost-effective approach. The failure to repair damage can lead to the spread and eventual collapse of the structure. Therefore, it is crucial to detect the location and extent of damage in the structure in order to take the necessary steps to prevent further damage and increase the structure's lifespan. One method that utilizes the changes in dynamic characteristics of the structure is based on changes in mode shapes. [1] [2]

Structures in the industrial sector require regular monitoring to maintain their condition and gather

information on their status. This is particularly important for marine structures, which are constantly exposed to environmental forces and can accumulate damage over time. Offshore jacket structures are a prevalent type of marine structure in shallow and medium depths and play a key role in the oil and gas industry and as infrastructure for offshore wind turbines. [1] [2]

Identifying potential damage in jacket structures is vital for safety but can be challenging due to the difficulty of conducting maintenance tests under harsh environmental conditions. Therefore, developing robust and effective methods for identifying structural damage is crucial in avoiding failure. Artificial Intelligence (AI) techniques, such as machine learning and artificial neural networks (ANN), have been used to select features for condition assessment of

mechanical systems. Machine learning is particularly useful as it can learn from large, multi-faceted uncertainties in data. ANNs are a type of algorithm used in machine learning to model data and have been used as a novel approach in structural health monitoring. [1] [2]

There are two main types of ANNs: shallow neural networks and deep neural networks. There are also two types of mechanical system data sets: artificial data sets, which can be generated manually using machining devices or virtual models, and real data sets, which are generated according to a data-driven algorithm. Data-driven methods have been shown to be effective in detecting mechanical damage and many data-driven methods are based on AI algorithms.

The way in which a material reacts to certain forces can indicate if there is any structural damage present, as was observed by rotima [1] in his research.

In addition to identifying damage through analyzing how a material responds to dynamic forces, many researchers are also exploring methods for identifying damage by making updates to a material's finite element model.

Li [2] proposed a method for updating a material's model that combines cross-modal analysis with a Guyan reduction scheme.

Weber [3] suggests that, in order to prevent measurement errors from leading to inaccurate results, nonlinear model updates should be made on a regular basis when assessing damage to a material.

Link[4] evaluated the effectiveness of two different techniques for updating a material's model.

Reynders[5] suggested using an OMAX approach to address issues that arise when trying to identify the status of a material.

Xia [6]proposed an infrastructure method that involves extracting dynamic plasticity matrices from the natural vibration modes of the overall structure, and then updating these matrices directly using current model updating techniques.

Fang [7]developed a modification to a finite element model updating method that uses response surfaces to identify damage.

Xu [8]suggested using a probabilistic approach to detect damage.

Simoen [9]researchers studied the use of model updates to assess damage, taking into account uncertainty in the process.

Waeytens [10]suggested using a Bayesian method to enhance the updating technique.

Altun,şık [11]proposed an automated method for updating model parameters which accounts for the effects of multiple cracks

Pedram [12]used power spectral density in the context of updated damage models.

Nozari [13] studied how environmental vibration measurements affect model updating and failure analysis.

Lu [14]proposed using a sensitivity-based finite element model updating method to identify local defects in axially functionally graded beams.

Behmanesh [15]suggested a method to reduce the impact of modeling errors when updating a material's model. Pérez[16] proposed a technique for identifying damage by using damage submatrices.

Haeri [17] proposed a new method for structural health monitoring (SHM) of offshore jacket platforms.

Overall, identifying damage in a structure is a reverse problem that requires determining structural parameters based on the structure's response. Artificial neural networks (ANNs) have been used in a variety of applications because they can solve inverse problems that cannot be expressed using mathematical equations. Guo[18]utilized a back-propagation network to study the updating model of a suspended dome. They developed a method to improve the accuracy of the back-propagation network.

Mangalathu [19] proposed a multiparameter fragility methodology using an artificial neural network to create fragility curves specific to bridges without classifying bridges into categories.

Wang et al. [20] developed an Artificial Neural Network (ANN) to enhance the computational efficiency of structural collapse calculation.

Artificial neural networks can also be used for damage identification. Adams.[21] was the first to demonstrate the use of back propagation (BP) neural networks for damage detection in the 1970s.

Later, Tsou [22]used the absolute eigenvalues of a spring-mass system in neural networks and demonstrated the effectiveness of using neural networks for injury detection.

Sahin [23]applied neural networks to locate the damage position by analyzing changes in frequency and mode shape.

Lee [24]used back propagation neural networks to assess the difference between the model's behavior before and after structural damage in terms of parameter error in the model.

Pathirage [25]suggested a method that uses an autoencoder framework to support deep neural networks for damage identification.

Tan[26]proposed a vibration-based method for predicting damage and its location, using only the first vibration mode.

Ye [27]used artificial neural networks (ANNs) to analyze a large amount of training data (damage cases) to establish the relationship between the amount of training data and the accuracy of damage location.

Padil [28] suggested using non-probabilistic artificial neural networks (ANNs) to handle uncertainty in vibration-based damage detection.

Artificial neural networks (ANNs) have also been used in other research areas such as [29][30][31].

Structural health monitoring (SHM) methods can be used to identify damage in structures, but they are often

applied to onshore structures such as bridges and buildings, and the overall modal results of the structure are used as indicators of damage. Obtaining overall modal results from partially submerged offshore structures is difficult due to a limited range of sensor measurements. Therefore, it is desirable to predict structural damage based on sparse sensor measurements. This paper presents a method for detecting damage in offshore steel platforms.

Research breakthroughs introduce several innovations. Among them are a 3D model of a steel platform enabling thorough assessment of potential failures. Additionally, there's a technique capable of pinpointing failure extent and location, even at low levels like 5%, distinguishing itself from methods that merely note a component's failure. This approach is adaptable, applicable to similar steel platforms, and accompanied by a straightforward algorithm for easy development and implementation.

The proposed damage identification index and artificial neural network (ANN) method for damage identification are discussed in Section 2, and the process for recognizing damage in offshore structures is described in Section 3. The proposed method is used to recognize damage on a jacket platform with actual damage, and the research is concluded in the last section.

2. Material and methods

2.1. Damage Identification Index

For an n-dimensional arrangement collected of mass, spring, and damper, the dynamic behavior of the arrangement can be uttered as[32]:

$$M\ddot{x}(t) + C\dot{x} + Kx(t) = f(t) = B_1 u(t) \quad 1$$

Where $x(t)$ is the displacement at incessant time t ; M , C , and K are the mass, damping, and stiffness matrices, individually; $f(t)$ is the external force. The output vector $y(t)$ can be defined as[32]:

$$y(t) = C_a \ddot{x}(t) + C_v \dot{x} + C_d x(t) \quad 2$$

Where C_a , C_v , and C_d are the output matrices of acceleration, velocity, and displacement, $y(t)$ can be further expressed as[32]:

$$y(t) = Cs(t) + Du(t) \quad 3$$

Where $S(t) = \begin{pmatrix} x(t) \\ \dot{x} \end{pmatrix}$, $C = [C_d - C_a M^{-1} \quad C_v - C_a M^{-1} C_1]$

Is the production matrix, $D = C_a M^{-1} B_1$ is the direct transmission matrix. Equations (2) and (3) are rewritten to show the discrete-time state model as [32]:

$$S_{k+1} = A S_k + B u_k \quad 4$$

$$Y_k = C S_k + D u_k \quad 5$$

Where A is the discrete state matrix; B is the discrete input matrix; $s_k = s(kdt)$ is the discrete-time state vector; dt is the time interval; k is an integer.

The equation (4) presents a clear representation of a deterministic model, in which the input and output can be accurately determined. When taking into account the presence of noise, it is possible to demonstrate a combination of a discrete-time state-space model that encompasses both determinism and stochasticity[32].

$$S_{k+1} = A S_k + B u_k + w_k \quad 6$$

$$y_k = C S_k + D u_k + v_k \quad 7$$

Where w_k is the process noise produced by modeling error; v_k is the measurement noise caused by sensor error.

2.2. Damage ID Process

Artificial Neural Networks (ANNs) are highly proficient in identifying and understanding complex nonlinear relationships between multiple inputs and outputs. The fundamental design of a neuron is illustrated in Figure 1.

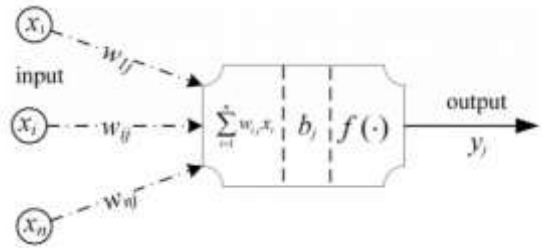


Figure 1: Schematic of the basic structure of a neuron. [31]

In Figure 1, x_n is the n th input signal, w_{nj} is the joining weight, b_j is the threshold value of the i th neuron, and y_j is the output signal of the i th neuron. The neuron output signal y_j is calculated by the activation function as follows:

$$y_i = f(\sum_{i=1}^n (w_{ij} x_i) - b_j) \quad 8$$

In a structural health monitoring (SHM) process, the system signals can serve as indicators of damage and the output signals can be the damage sustained by mechanical components. In this study, damage is applied to specific members to create distinct categories of damage. The damage inflicted on each member is the reduction of its cross-sectional area, simulating the corrosion commonly found on oil platforms in the Persian Gulf. The level of failure is determined based on specific intervals established for each member. The research aims to detect failure at levels 1 to 4 using this criterion. The BP neural network used is a multi-layer feed-forward network, and its basic structure is depicted in Figure 2.

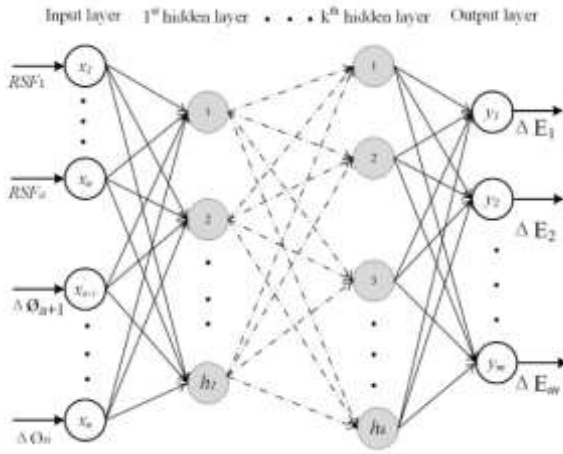


Figure 2: Structure of the BP network.[31]

The amount of nerve cell (n, m) and the hidden layer (k) are resolute based on the engineering tricky of attention. In our situation, the total number of injured elements and the total number of injury indices are known. The total number of units in the i th hidden layer (x_i) is determined by the following function:

$$X_i = N - 1 \quad 9$$

The initial values of the joining weights (w_{ij}) and thresholds (b_j) are set arbitrarily between -1 and +1. The training process involves repeatedly adjusting the w_{ij} and b_j based on the difference between the network's output and the desired output until the error falls within a certain threshold. One of the key features of Artificial Neural Networks (ANNs) is their ability to learn and adapt to problems through training. After sufficient training, the network can then solve similar problems it has not encountered before. This ability allows us to use the trained network to identify the primary damage based on the measurement results.

2.3. damage ID procedure

This research proposes a general procedure for identifying damage. The method is outlined in Figure 3, and it includes four main steps: finite element modeling, creation of training samples, training of neural networks, and prediction of structural damage. The first step involves creating detailed finite element models of offshore structures for specific projects. It is also necessary to determine the number of samples and the prediction precision (ϵ) in this step. In the second step, training samples are produced using the updated damaged model. As previously discussed in sections 2.1 and 2.2, the normalized mode shape can serve as a damage indicator (ΔU) and the training data is obtained from the modal analysis of the finite element model. The third step involves setting up neural networks using the training data and training them with the samples.

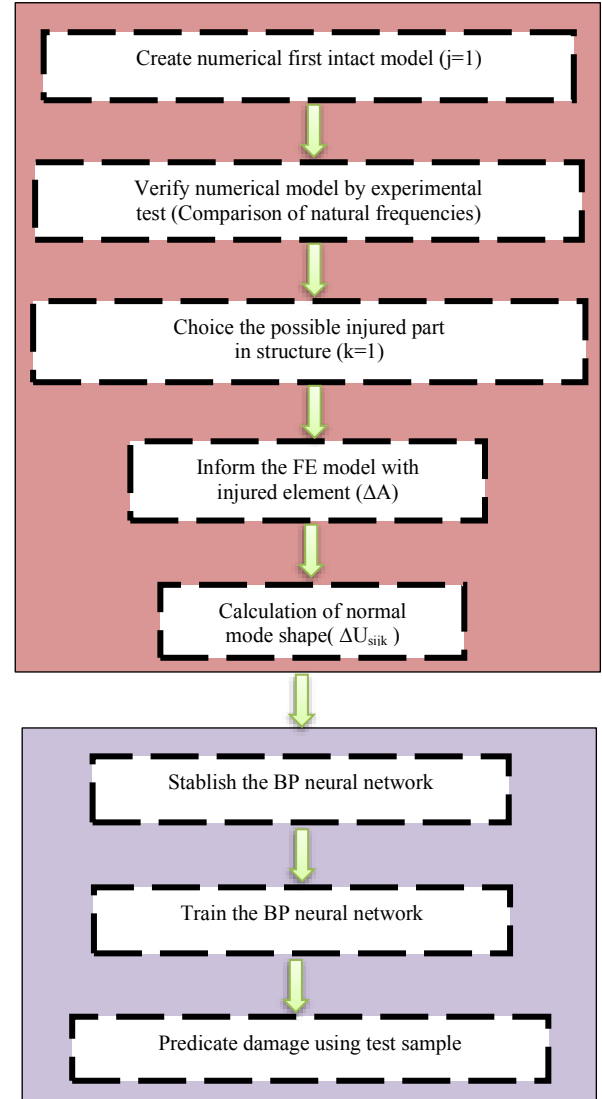


Figure 3: Analysis flowchart

2.4. Modal validation Modeling

A lab-scale model of an offshore jacket structure (referred to as the "lab-scale offshore jacket model" in this study) was used for the experimental portion of the research, as seen in Figure 4. The model was designed and set up in the Vibration and Modal Analysis Research Lab at the University of Tabriz [33]. The structure being studied is a jacket-type offshore platform model, as illustrated in Figure 4. The platform model is a welded-steel space frame with four main legs, reinforced with horizontal and diagonal members. All members are made of steel pipes, except for the top deck which is a steel plate. The following table lists the essential geometrical and material properties of the frame structure: Young's modulus (E) is a constant equal to 2.07×10^{11} Pa for all members. The main legs of the first story of the model have a diameter of 18mm with a pipe thickness of 2.5mm. The main legs of the other three stories of the model have a diameter of 14mm with a pipe thickness of 2.5mm. All the

horizontal braces have a diameter of 10mm(thickness of 2mm). All the diagonal braces in the vertical plane have a diameter of 8mm (thickness of 1.5mm). All the diagonal braces in horizontal planes are solid bars with a diameter of 10mm. The deck is a steel plate of 20mm thickness.

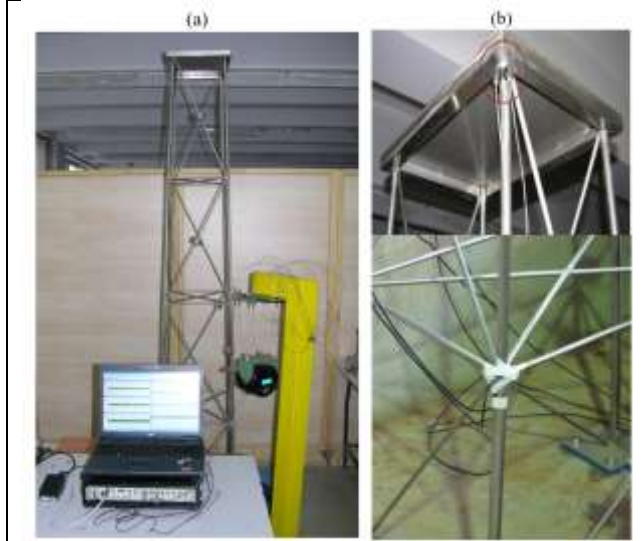


Figure 4:(a) modal testing and tested three-dimensional, (b) Installed accelerometers and sensor position

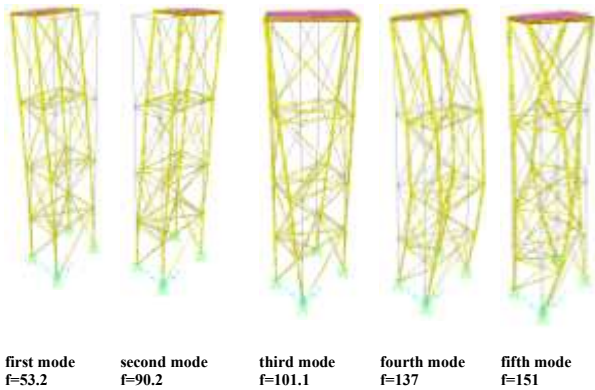


Figure 5:modal analysis results

Given the minimal distortion and linear behavior of the system, an initial 3D Finite Element (FE) model of the offshore steel jacket structure (referred to as the "FE offshore jacket model" in this article) was developed using the software SAP2000. The resulting FE offshore jacket model, in its undamaged state, is shown in Figure 6

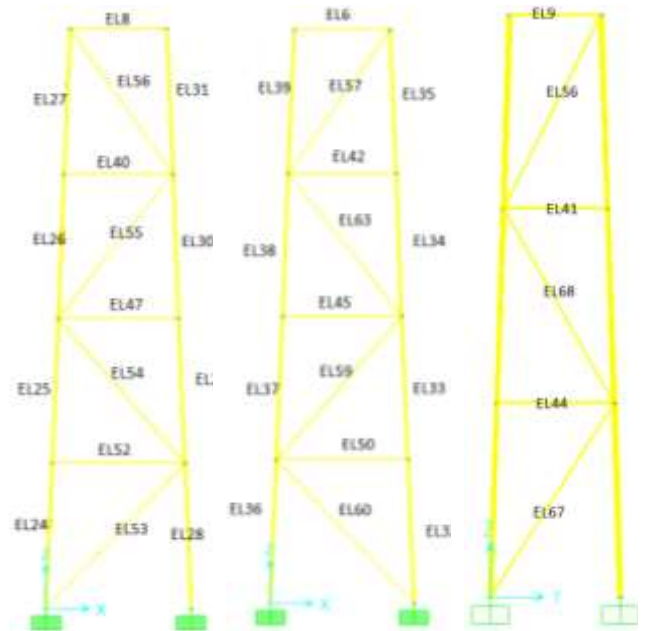


Figure 6: Naming the elements of the simulated platform

The material properties for all members are detailed in Table 1. The joint connections are assumed to be rigid. The clamp boundary condition is applied to the bottom of the structure. All model members were meshed with two-node linear beam elements (type B31) to account for transverse shear distortion. Table 2 compares the four main frequencies of the constructed numerical model with the numerical modes obtained from the laboratory model. The results have an error of less than 10%.

Table 1: Material characteristics considered in the numerical model		
No.	property	value
1	E	200 GPa
2	poisson ratio	0.3
3	density	7800 kg/m ³
4	modal damping ratio	0.01

Table 2: the first five natural frequencies			
Model no.	Natural frequencies(Hz)		Difference(%)
	Numerical Analysis	Experimental Result	
1	53.2	58.34	8.81
2	90.2	94.13	4.17
3	101.1	106.21	4.81
4	137	130.28	5.15

2.5. Failure factors

A variety of factors such as corrosion, ship impact, damage caused by severe storms and earthquakes, fire, explosions and terrorist attacks can cause damage to offshore platforms. Among these, corrosion is the most significant and ongoing issue that affects all marine platforms. It is the primary factor that alters the structural characteristics and behavior of platforms that have been in operation for an extended period.

3. Result and discussion

3.1. Damage scenario

As shown in Figure 5, the structure consists of 52 members which are located on four different floors. These members include 16 columns, 16 main beams, 4 secondary beams and 16 wind braces. The study creates damage scenarios based on two cases of damage, one where a single member is affected, another where two or more members are damaged in different ways.

3.2. Failure of a single member

The first scenario considered is the individual failure of a member, which can be caused by corrosion, ship collision or other factors. It was assumed that each of the 52 members of the structure lost between 0 and 20% of their area, one by one. In this scenario, the mode and mode shape analyses were calculated for the first five modes of the structure.

The number of mode shapes used for Structural Health Monitoring (SHM) depends on several factors, including the size and complexity of the structure, the type and location of potential damage, and the accuracy and resolution of the measurement system.

In general, a larger number of mode shapes can provide more detailed information about the structure and may improve the accuracy of damage detection. However, using too many mode shapes can increase the complexity and computational cost of the analysis, as well as the potential for noise and measurement errors [27] [28][29][30][31].

Therefore, the optimal number of mode shapes for SHM depends on a trade-off between the level of detail required and the practical limitations of the measurement and analysis system. Typically, a small number of mode shapes, such as the first 1-10, may be sufficient for most practical SHM applications. However, this number can vary depending on the specific structure and the intended purpose of the monitoring.

In general, the first few mode shapes of a structure are considered to have a greater impact on the overall behavior of the structure compared to the higher mode shapes. This is because the lower modes typically correspond to the dominant vibration patterns and have higher participation factors, meaning that more of the mass of the structure is involved in the mode shape.

The first mode shape, also known as the fundamental mode, typically has the largest amplitude and is the mode with the lowest frequency. This mode corresponds to the overall motion of the structure as a whole, and any changes in this mode shape can indicate significant damage or degradation of the structure.

For each member in the failure scenario, 20 analyses were performed, with 16 analyses used for network training and 4 analyses for testing. This resulted in a total of 1200 analyses performed in this section. The members then entered the training process for further validation, with comparisons ranging from 4 members to 16 members to reduce errors.

Error! Reference source not found.-a compares the first and second-floor braces included in a training process. As it is known, with an average error of 15%, the damaged member was identified. **Error! Reference source not found.-b** is also all the wind brace types located on the third and fourth floors. Due to the proximity to the water level and the surf zone, these members have a high probability of failure and only 5% error in identifying their location. **Error! Reference source not found.-c** shows a combination of windbreaks from different floors. The identification error rate in these classes is reported to be 30%. **Error! Reference source not found.-d** shows four columns in the same direction and on different floors. The accuracy of failure detection in these members was 90%. **Error! Reference source not found.-e** examines four sub-beams of four different floors. These sub-beams are each placed as a stiffener on one floor of the platform structure. The accuracy of detecting the failure location in this analysis was 70%. In Figure 7-a, the columns of the fourth floor have been examined, and 100% detection has been done. The fourth floor is the most important part in protecting against corrosion due to its location outside the water area. Also, in Figure 7-b, all the windbreaks of the fourth floor have entered the training process, and 100% recognition accuracy has been obtained performance diagrams for the injured neural network are obtainable in Figure 8. The performance limitation monitored is the mean squared error, which is 0.039206 at the best network.

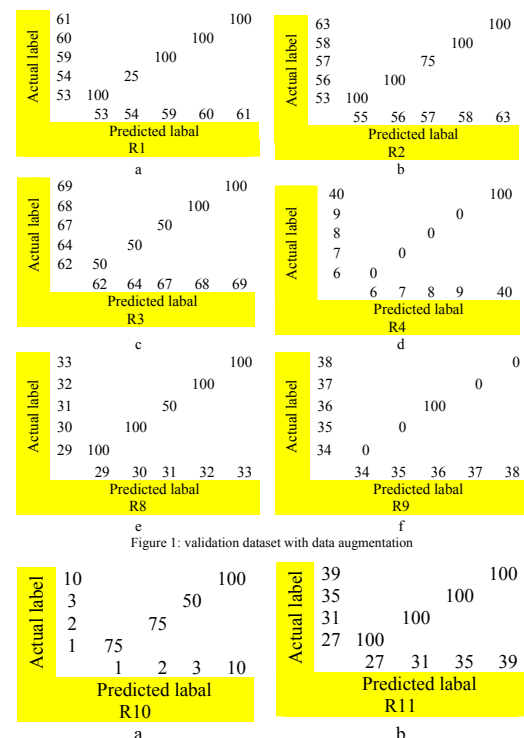


Figure 7: validation dataset with data augmentation

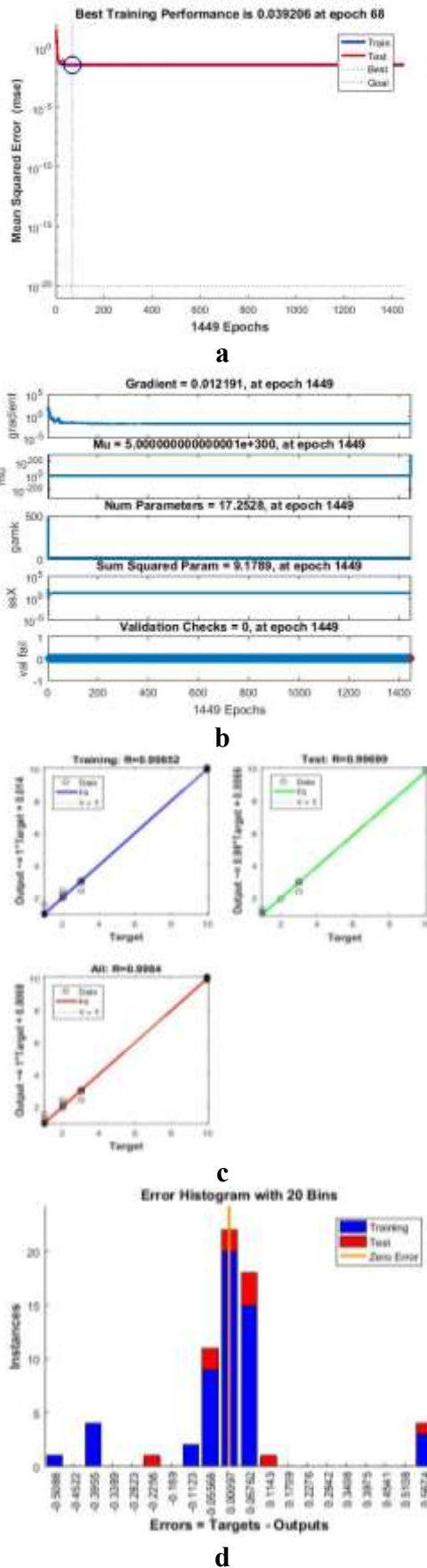


Figure 8 -Performance graph of damage localization

Figure 9 compares the effect of floor and member on failure detection accuracy. As it is apparent in the figure, the secondary beams have the most accuracy in

detecting failure, and the main beams have the least accuracy in detecting failure. Also, the difference in failure detection in different classes is not high.

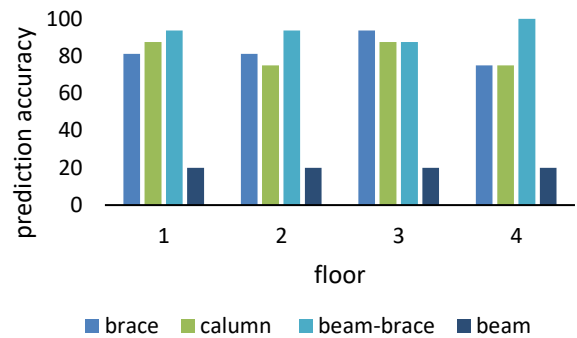


Figure 9: Comparison of average failure detection in different members

Figure 10 compares members for the fourth floor, which is very important. As it is known, the columns have the most accuracy in damage allocation, followed by wind braces. The main beams of the structure have also entered this process with very little precision.

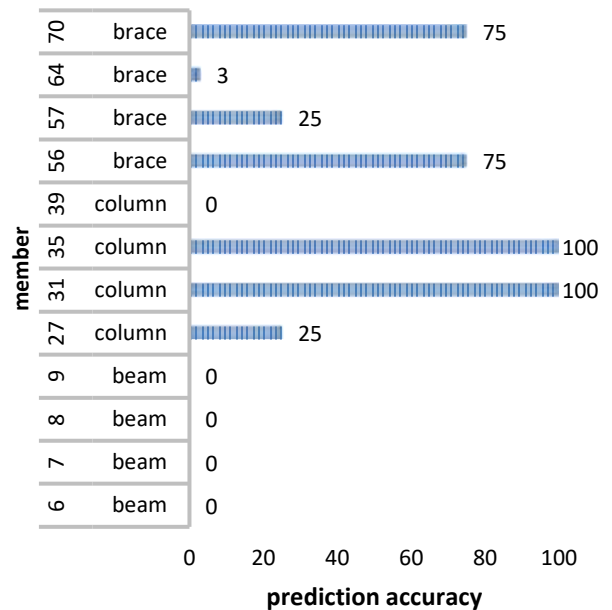


Figure 10 Comparison of all components of the fourth floor

3.3.Failure in two members at the same time

In another scenario, we create failure in two members of the fourth floor, and according to the previous section, we randomly create 20 accidental failure rates between 20% and 0% for each sample and then perform the relevant analysis. In this research, the following element numbers have been selected as samples, as shown in f and Figure 12

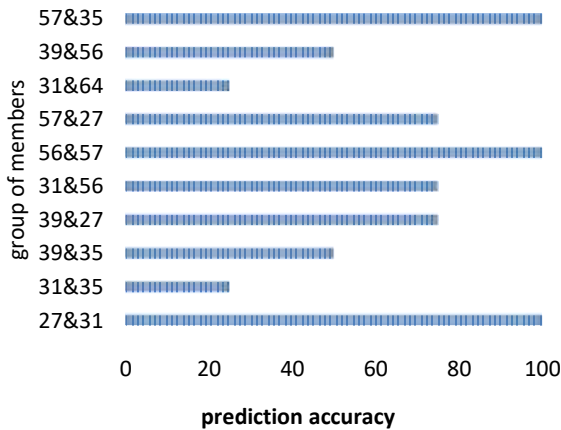


Figure 11: Comparison of average failure detection in different members-two member

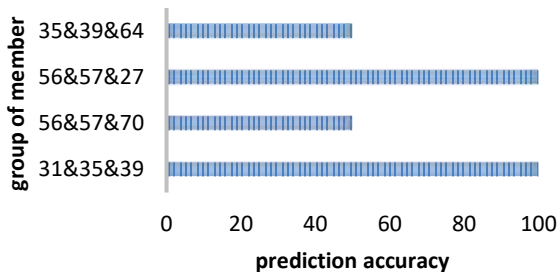


Figure 12: Comparison of average failure detection in different members-three member

4. Conclusion

This research focuses on the use of Artificial Neural Networks (ANNs) for modal-based damage identification in offshore structures. The damage identification approach is based on modal shape and utilizes AI methods and principal component analysis for feature extraction. Numerical studies were conducted on simplified prototypes of offshore structures to evaluate the proposed damage identification procedures. The study considered challenging conditions with a limited number of sensors. The research provides a damage identification process suitable for jacket-type offshore platforms. The main conclusions of this research are:

(1) A neural network-based quantitative structural damage identification method is proposed, and the case study of a jacket-type offshore platform shows that this technique can effectively identify physical damages of different components.

(2) The new method presented in this research can determine the location and approximate extent of the failure through the first five modes, which can be obtained in various ways. This method is effective in detecting local losses and can detect small and localized damages before they cause further damage, in contrast to traditional methods which can only predict complete removal of a member.

(3) The results show that the proposed method has a high accuracy for identifying failures in columns on different floors, secondary beams, and windbreaks. However, due to the small effect of main beam failures on the stiffness of the offshore structure, the method did not yield satisfactory results. It is worth noting that using structural frequency instead of modal shape and deep learning methods instead of traditional methods would be more suitable for identifying main beam failures.

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