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Damage Detection of Truss Bridges Using Artificial Neural Network Considering the Effect of Non-Structural Elements

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Abstract:
Identifying structural damages has been a crucial research topic in civil engineering over the past few decades. Numerical modeling methods are of particular interest for damage detection because they provide more information. The accuracy of modeling results can be impacted by errors in modeling the mass of non-structural elements. This study is focused on assessing the effects of the mass of non-structural components on the detection of current damages. An integrated neural network approach was used to study a truss bridge as a widely used structure. It was possible to detect damaged members with high accuracy using the artificial neural network trained with the results of the finite element model. According to the results, the introduced method accurately detects damage despite modeling errors associated with non-structural elements' mass.

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1. Introduction

Structures are subject to deterioration throughout their lifespan. Damage to structures can be defined as any change in the material or geometric characteristics of the structure that reduces its performance. It is possible to assess structural conditions and detect potential failures of components early through structural health monitoring, which is an effective method for increasing structure reliability and resilience. Once the damage has been identified, the main goal is to repair it.

A structural response-based damage detection method falls into two categories: static identification methods and dynamic identification methods. Static identification methods determine the changes in structural parameters by measuring the strain or displacement response under certain static loads. Alternatively, dynamic identification methods use a structure's dynamic characteristics, determined by its reaction to some excitation force, to detect damage. The vibration-based structural damage identification field has received extensive research attention in recent decades [1-6].

Natural frequencies and mode shapes are of particular interest among dynamic characteristics for model updating since they are easily interpreted. Using the difference between two mode shapes to detect damage, Wolff and Richardson [7] introduced the modal assurance criterion (MAC) to estimate their correlation. Pandey et al. [8] used modal curvature to locate damage in cases where MAC failed. An accurate damage index was developed by Kim and Stubbs [9] based on modal strain energy. Salawu [10] provides a comprehensive overview of methods for detecting structural damage through frequency changes. The response function method was developed by Lin and Ewin [11] to update mass and stiffness matrices using the real part of the Frequency Response Function (FRF). Using a pseudolinear sensitivity equation, Shadan et al. correlated the changes in FRFs to changes in structural parameters [12]. It utilizes a quasi-linear sensitivity equation to reduce the negative impacts of incomplete measurement data. Additionally, the method was experimentally validated with free-free beam tests [13].

Artificial Neural Networks (ANNs) are most commonly used to identify damage [1, 4, 14-16]. A pattern recognition technique can be used to predict structural damages. When it comes to structural systems, for instance, a precisely trained neural network can identify the occurrence, location, and severity of damage. There are several damage detection methods that rely on identifying certain modal parameters in structural systems to extract features. Natural frequencies and mode shapes are among the most commonly used parametric characteristics. According to Mehrjoo et al. [17],

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modal characteristics were extracted from acceleration response and used as damage-sensitive features in an ANN-based damage detection system on a simple truss bridge and the Louisville Bridge truss. To identify and localize damage, an ANN with a single hidden layer was used. Each neuron's value indicates the percentage of damage. Using a numerical model in conjunction with an ANN (with five input neurons and five output neurons), Yuen and Lam [18] detected damage based on the modal parameters of a simple five-story structure. Based on the FRFs of the structure, Fallahian et al. [4] developed a new pattern recognition-based damage detection method. As an authoritative feature extraction method, principal component analysis (PCA) is employed to reduce the dimension of the measured FRF data. Then, they used deep neural networks and sparse coding trained with the extracted patterns to detect damage. Using the PCA and ensemble couple sparse coding methods, Vahedi et al. [1] proposed an algorithm for damage identification in structures with flexible bases.

Non-structural components are usually not considered in finite element models for damage detection. Although non-structural components have a limited effect on the stiffness and mass of structures, they are still important. Vibration-based model updating techniques must consider this inaccuracy since the dynamic parameters of structures are influenced by stiffness and mass. Several studies have shown that non-structural components influence the dynamic behavior of structures [19-24]. Devin and Fanning [19] examine how non-loading bearing elements contribute to dynamic response. As part of this study, the ambient vibration response of a new structure was recorded at different stages of construction. As a result of the addition of non-load-bearing facades and partitions, the vibration modes changed, and the natural frequencies increased. An operational modal analysis of a reinforced concrete frame building under construction was performed by Devin and Fanning [25] and indicated that cladding panels and internal partitions significantly affected the dynamic parameters. By considering the effect of non-structural components, Jahangiri et al. [24] reported that natural frequency and damping ratio values have significantly increased during construction. Ventura et al. [26 and 27] and Turek et al. [28] studied the effect of non-structural elements on a global building response using the structural response induced by ambient vibrations. Li et al. [29] determined that a 79-story building's natural frequencies were higher than those calculated from the FE model, concluding that non-structural components contributed to this difference.

An artificial neural network and dynamic data extracted from a finite element model of a truss bridge were used in this study to detect damage in that bridge. Due to the fact that the mass of non-structural components that are not modeled affects the dynamic properties of the model, the effect of this issue has been assessed. For implementing this concept, each neuron's value indicates the percentage of damage, while the response was the structure's dynamic characteristics for each case of damage. During the training of the network, the weights of the non-structural elements were not taken into account, as is typical for updating structural models. However, this network was later used for detecting structures in real-life cases that include the mass of non-structural elements, making the process more challenging. This study evaluates the presented method by detecting damage to a 2D truss consisting of 29 elements. Since the bridge's deck floor is considered non-structural, its mass is not considered when training the neural network. The method was able to accurately identify the damaged element as well as the severity of the damage.

2. The Impact of Non-Structural Elements on the Dynamic Behavior of Bridges

The dynamic behavior of structures is determined by the stiffness and mass of elements. Static response, however, depends only on elemental stiffness. In other words, modeling structures without taking into account non-structural elements has a greater impact on their dynamic response. In a previous study, the authors found that ignoring non-structural elements led to significant changes in dynamic properties [30].

As noted by Shirazi et al. [30], the weight of the non-structural elements of a bridge, such as the deck and pavement, is added to their related elements, and its impact on its natural frequency is explored. An illustration of the effects of non-structural components on the frequency response function can be found in Figure 1. As can be seen in the graph, the extra mass added by the non-structural elements leads to much closer spacing between the lower modes. It is worth noting that a vibration-based damage detection method faces difficulties when modes are closely spaced [3].

Table 1 compares the natural frequencies of a structure with and without non-structural elements' mass to examine these changes in detail. Clearly, this weight has a great impact and cannot be ignored.

Table 1. The first ten frequencies of the structure [30]

Mode No.	With the mass of non-structural components (Hz)	Without the mass of non-structural components (Hz)	Difference percent (%)
1	6.58	16.66	59.71
2	14.96	35.95	61.75
3	28.00	63.78	63.74
4	31.37	89.89	54.37
5	45.12	120.53	57.46
6	52.47	156.71	52.44
7	71.28	158.45	64.61
8	74.46	176.41	62.27
9	84.36	208.77	60.59
10	91.16	274.12	52.12

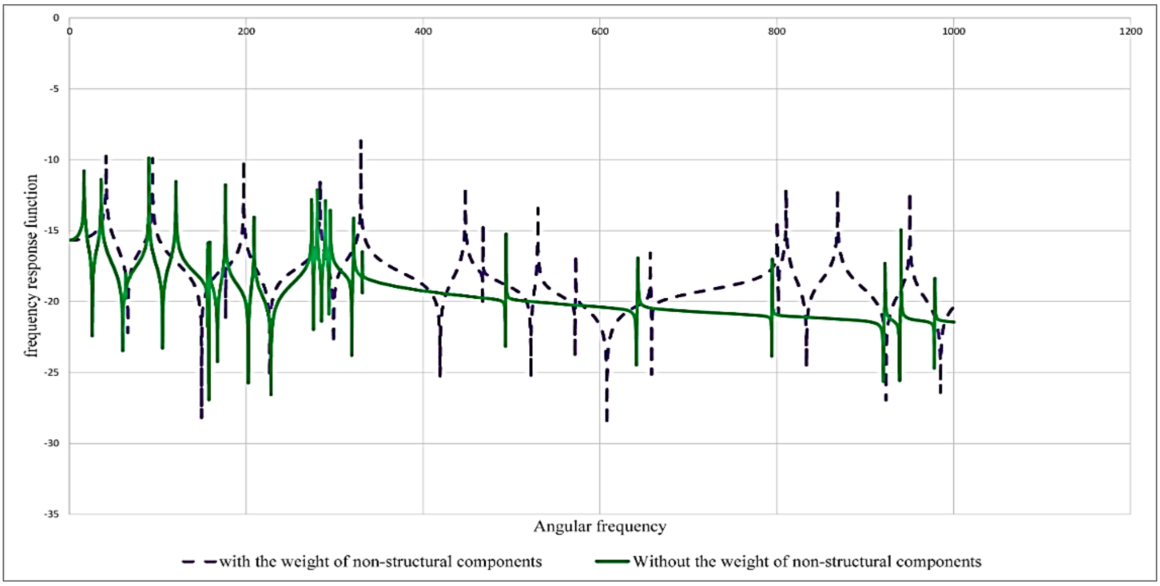


Figure 1. The changes in the frequency response function [30]

3. Artificial Neural Network (ANN)

A neural network is a paradigm for processing information inspired by the brain. ANNs can be configured and trained through the nonlinear parameterized mapping between the input and the output sets via their neurons, just as the brain has multiple neurons working together to process information. The main advantage of ANNs is that they can be applied to problems without an algorithmic solution or where it would be too complex to find an algorithmic solution. ANNs also possess other capabilities for real-time applications, such as self-adaptability, generalization, abstraction, and suitability. Recently, they have been widely used to estimate the severity and location of damage.

This study utilized an ANN method based on a back propagation learning algorithm. For a network to meet its target by minimizing the mean square error between the actual and predicted vectors, various internal weights and biases are adjusted during the network training process. Using the gradient search technique, this minimization is achieved. Even inputs that are not included in the network training can be accurately predicted by a neural network that has been appropriately trained. The Levenberg-Marquardt (LM) algorithm is considered to be one of the fastest and the most efficient training algorithms. According to Fausett [31], the back-propagation architecture is sufficient with one hidden layer for most applications; therefore, only one hidden layer is considered. In designing a neural network, it is important to determine the number of hidden layers and neurons within each hidden layer [32]. Seibi and Alawi [32] suggested that the following formula be used to calculate the number of neurons for a single hidden layer if the number of training pairs is known:

$$n = \theta \times (N_h \times (m+1) + p \times (N_h + 1)) \tag{1}$$

where n is the number of possible training pairs, θ is a constant coefficient greater than one, N_h is the number of neurons in a hidden layer that are used in the network with a hidden layer, and m and p express the number of input and output nodes, respectively.

In this study, a global vibration parameter is used as input to an ANN to predict the location and severity of the damage. The global parameter refers to a change in a structure's natural frequencies. Finite element analysis has been used to estimate the parameters based on undamaged and damaged structures' free vibration dynamic behavior. Training an ANN to establish the relationship between inputs and outputs is necessary. An FE model is used to generate a series of random damage cases during the training phase. By reducing the stiffness parameter of selected elements, damage cases are idealized.

4. Numerical Study

This study considered an asymmetric 2D truss bridge consisting of 29 elements. Figure 2 illustrates the geometry, and Table 2 lists the mechanical properties of the truss elements.

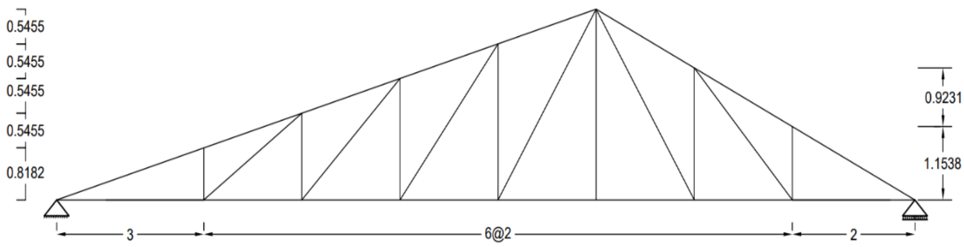


Figure 2. The asymmetric 2D truss

Table 2. The mechanical properties of the elements

Modulus of elasticity	200 GPa
Cross-sectional area	0.0018 m^2
Density	7800 kg/m^3

A database with known damage cases and their natural frequencies should be created to train the neural network. As part of this study, numerous damages were applied to each structural element (Table 3), and corresponding natural frequencies were measured. As this network is designed to identify single-element damages, only one element is damaged in the damage cases of the database. Members experienced 15-45% damage in 1% increments, and 29 natural frequencies were calculated. A total of 899 cases were obtained by considering these 31 damage increments for each element.

Using Equation 1, N_h will be 6.81, and hence, 7 neurons are considered. As a result of this architecture, the regression coefficient would be $R = 0.4856$, which is an unacceptable level of accuracy. Using the test and error procedure, 50 neurons make an accurate result, resulting in a R value of 0.99999.

4.1. Results and Discussion

The study considers non-structural components to simulate a real case. It is assumed that the bridge's deck floor is not structural. Therefore, the effect of not including this mass in finite element modeling is taken into account by adding its error to the related elements. Hence, two percent of the deck's elemental mass is assigned to its nodes as random error, distributed uniformly.

Four damage cases are presented to test the reliability of the trained network. Every damage case involves damage to one element whose severity was not taken into account in the network training process. Table 4 shows that the imposed damages are decimal numbers, in contrast to the steps involved in adding damage during database extraction.

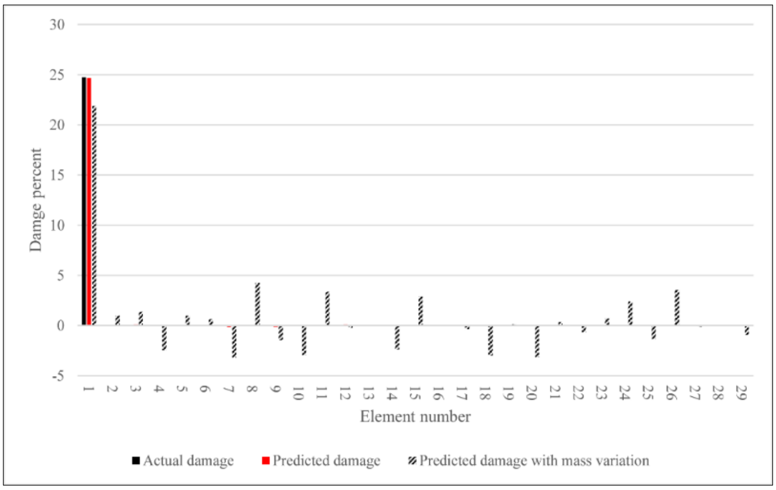
Figures 3-a to 3-d demonstrate the network's accuracy in identifying the given damage scenarios listed in Table 4. The network can locate the damaged element and evaluate the damage severity with decimal numbers despite being trained with damage patterns with integer numbers. Even when the mass error was added to the elements, the network's ability to detect damaged elements remained the same. Moreover, as part of the damage detection process, the network could identify whether the frequency variations were due to combined stiffness and mass error damage or solely to mass error.

Table 3. The first 31 cases for element 1

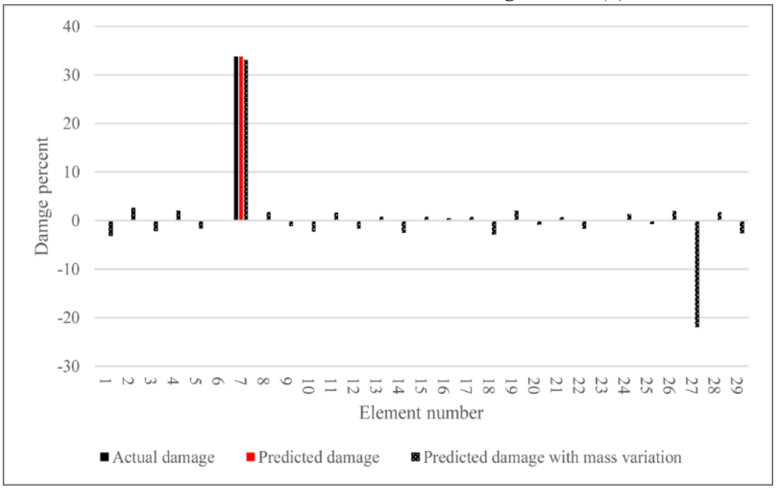
	Element no.	Damage %	Element no.	Damage %	…	Element no.	Damage %
Case 1	1	15%	2	intact	…	29	intact
Case 2	1	16%	2	intact	…	29	intact
Case 3	1	17%	2	intact	…	29	intact
.		.					.
.	1	.			…	29	.
.		.					.
Case 31	1	45%	2	intact	…	29	intact

Table 4. The damage scenarios

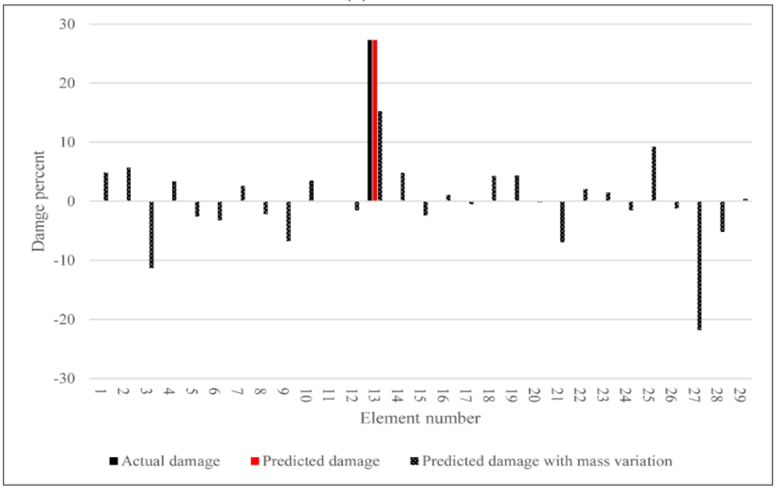
Case1		Case2		Case3		Case4	
Element number	Damage percent	Element number	Damage percent	Element number	Damage percent	Element number	Damage percent
1	24.75%	7	33.8%	13	27.3%	23	39.2%



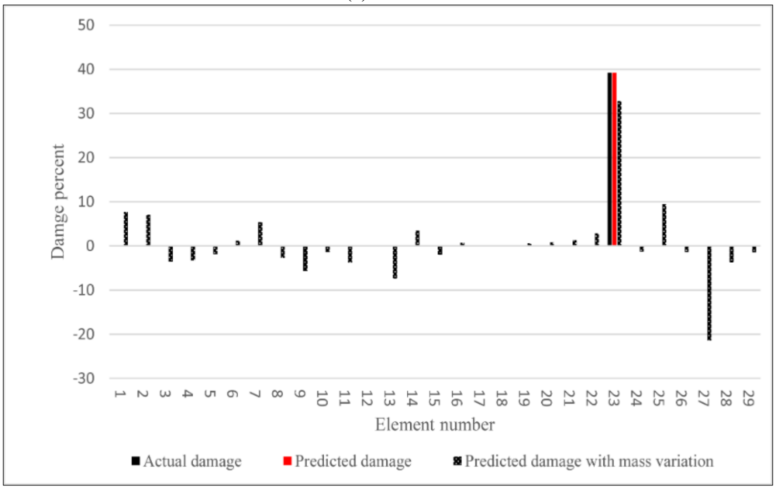
(a) case 1



(b) Case 2



(c) Case 3



(d) Case 4

Figure 3. Comparison between the predicted damage with and without mass errors

4.2. Results' Accuracy Indices

The accuracy of damage detection is evaluated using some accuracy indices in order to investigate the effect of mass error in detail. To measure the error of not detecting damaged elements, Damage Missing Error (DME) is utilized. The definition of DME is as follows:

$$DME = \frac{1}{NT}\sum_{t=1}^{NT} \varepsilon_t{}^{I}, (0 \le DME \le 1) \quad (2)$$

In the above equation, NT is the correct number of damaged elements. If the damaged element is detected, ε_t^I equals 0; otherwise, it equals 1. As a result, DME equals 0 if all the damaged elements are detected. This study considered a damaged element to be detected if the damage in an element of the structure was predicted with an error of 40%.

FAE (False Alarm Error) refers to the error caused by an element being incorrectly identified as damaged.

$$FAE = \frac{1}{NF}\sum_{P=1}^{NF} \varepsilon_P{}^{II}, (0 \le FAE \le 1) \qquad (3)$$

where NF gives the number of detected damaged elements. If an element's damage prediction is correct, ε_p^{II} equals 0; otherwise, it equals 1. The FAE value of 0 indicates that all elements detected as damaged are actually damaged. The study considered damaged elements whose prediction errors exceeded 10%.

There is a term called Mean Sizing Error (MSE) that describes the difference between damages as predicted in analytical model parameters δP_e^p and damages as observed in real structure parameters δP_e^a.

$$MSE = \frac{1}{N}\sum_{e=1}^{N}\left|\delta P_e^a - \delta P_e^p\right|, (0 \le MSE \le \infty) \qquad (4)$$

Undoubtedly, lower values in the three introduced indices indicate more accurate outcomes.

Table 5 shows the accuracy indices calculated from Equations 2 to 4 based on the results. As shown by the indices values, the network can detect the damaged element and its severity with sufficient precision. Due to the addition of mass errors, the indices are slightly higher but still acceptable. According to DME values, there are no missing damaged elements, but FAE values indicate that some elements have slight damage as a result of mass error additions.

Table 5. The values of accuracy indices

	Case1		Case2		Case3		Case4	
	Without mass	With mass variation	Without mass	With mass variation	Without mass	With mass variation	Without mass	With mass variation
DME	0	0	0	0	0	0	0	0
FAE	0	0.034483	0	0.068966	0	0.068966	0	0.034483
MSE	0.000557	0.014367	0.000197	0.003235	0.000204	0.060297	2.3E-04	0.03197679

5. Conclusions

This study aimed to determine if the mass of non-structural components affects damage detection. A truss bridge damage detection system was developed using an artificial neural network and dynamic data extracted from a finite element model. When developing the network, the weights of the non-structural elements were not taken into account. A challenge arose when this network was later used to detect structures with mass derived from non-structural elements. A numerical study is conducted using a 2D truss 29-element with the bridge deck floor as non-structural components. Despite modeling errors associated with the mass of non-structural elements, the introduced method accurately detects damage. In addition, a few accuracy indices were presented and examined to demonstrate the precision of the method.

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