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An approach based on convolutional autoencoder for detecting damage location in a mechanical system

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ABSTRACT

In the field of structural health monitoring, the adoption of intelligent systems able to automatically detect changes in a structure are evidently attractive. A change in the baseline configuration can be an early predictor of a structural defect that has to be monitored before it reaches critical conditions. When there is no prior knowledge on the system, deep learning models such as Autoencoders could effectively detect a change and enhance the capability to determine the damage location. In this paper a deep learning approach is applied to a test rig consisting of a small building model composed by four floors connected by bending springs. Modifications of the system are simulated by changing stiffness of the spring. This algorithm is compared with traditional approach based on modal parameters by carrying out experimental tests to validate the hypothesis.

Keywords: Structural Health Monitoring, Fault detection, Neural Networks, Convolutional autoencoder

1. INTRODUCTION

In the last years, Structural Health Monitoring (SHM) of civil infrastructures, i.e. buildings and bridges, has become a trending topic.[1,2] SHM refers to the implementation of monitoring strategies to detect structural damages using dynamic response measurements, feature extraction algorithms and statistical analysis of the extracted features to asses the current state of the system.[3] Indeed, structures are subjected to many environmental factors that may affect their integrity. Most often visual inspections are used to locate the damage. However, in some cases, they may not be feasible and in general, due to their nature, are nowadays considered inaccurate and poorly reliable as well as very time-consuming.[4] Among all techniques implemented in SHM, vibration-based one provide an automatic and more reliable way to assess the health of a structure.[5–8] The basic idea relies on the change of measured vibration responses due to changes of the structural properties as function of the damage. In this framework, due to the large amount of data available, deep learning seems to be a powerful for damage detection. Indeed, deep learning is able to discover meaningful features in large datasets using multiple processing layers.[9] Most deep-learning models for damage detection are trained on both the healthy and the damaged states of the structure.[10] This can be a huge limitations, since it is not usually possible to acquire data from damaged states of the system. Convolutional autoencoders (CAEs) seems to be able to overcome this limitation, providing an algorithm able to detect damages based only on raw vibration data of the healthy structure.[10–12]

This paper proposes an unsupervised deep-learning algorithm for structural monitoring trained with vibration data acquired from the structure only in the healthy state. The algorithm, based on CAE, was tested on a four-storeys building and accelerations data coming from accelerometers placed one on each floor. The objective is to provide a general algorithm able to detect damages for different structures, i.e. buildings or bridges.

This paper is organized as follow: the description and the mathematical model of the tested structure are reported in Section **??**, the experimental campaign is presented in Section 3 while the algorithm in Section 4, the results are discussed in 5, finally the last section is devoted to the conclusion and future trends.

2. SYSTEM DESCRIPTION

The system, shown in Figure 1, is a multi-storey building composed of five aluminum plates, connected by steel laminas, respectively modelling the storeys and the pillars of the building and whose data are reported in Table 1.[13]

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Table 1: Data of the system.

Storey	
Area	$200 \times 200\ mm^2$
Thickness	$20\ mm$
Mass	$2.26\ kg$
Pillars	
Area	$0.5 \times 50\ mm^2$
Thickness	negligible
Mass	negligible

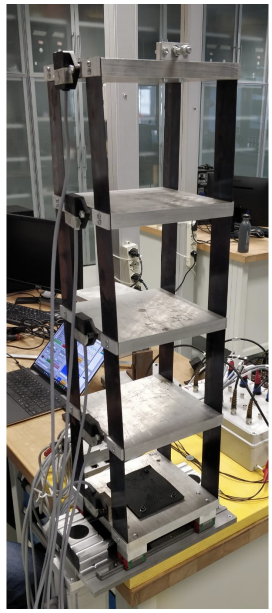


Figure 1: A photo of the real system.

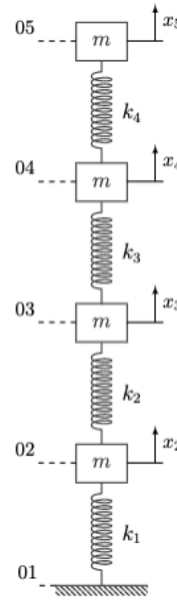


Figure 2: Lumped mass model of the system.

2.1 Mathematical model

Being the mass of each storey much larger than the mass of the laminas, the system can be modelled through a lumped mass approach. Given that, the dynamic model consists of a series of masses connected by springs, as shown in Figure 2.

Four degrees of freedom are considered, the absolute horizontal displacements of the storey, grouped in the following vector:

$$\underline{x} = [x_1\ x_2\ x_3\ x_4]^T \tag{1}$$

The mass matrix of the model is diagonal:

$$[M] = \begin{bmatrix} m & 0 & 0 & 0 \\ 0 & m & 0 & 0 \\ 0 & 0 & m & 0 \\ 0 & 0 & 0 & m \end{bmatrix} \tag{2}$$

To compute the stiffness matrix, a clamped-clamped beam with one of the extremities subjected to a transversal displacement was considered.[14] The stiffness value of the equivalent spring can be derived as:

$$k_{eq} = 4 \cdot k = 4 \cdot \frac{12EJ}{L^3} \tag{3}$$

Moreover, the effect of the weight of each storey on the transversal stiffness is taken into account through the term $T = m \cdot g/L$.[15] In the end, the stiffness matrix:

$$[K] = \begin{bmatrix} 2k_{eq} - 7T & -k_{eq} + 3T & 0 & 0 \\ -k_{eq} + 3T & 2k_{eq} - 5T & -k_{eq} + 2T & 0 \\ 0 & -k_{eq} + 2T & 2k_{eq} - 3T & -k_{eq} + T \\ 0 & 0 & -k_{eq} + T & k_{eq} - T \end{bmatrix} \tag{4}$$

Rayleigh's damping model has been considered for the structure. So, the resulting damping matrix is written as:

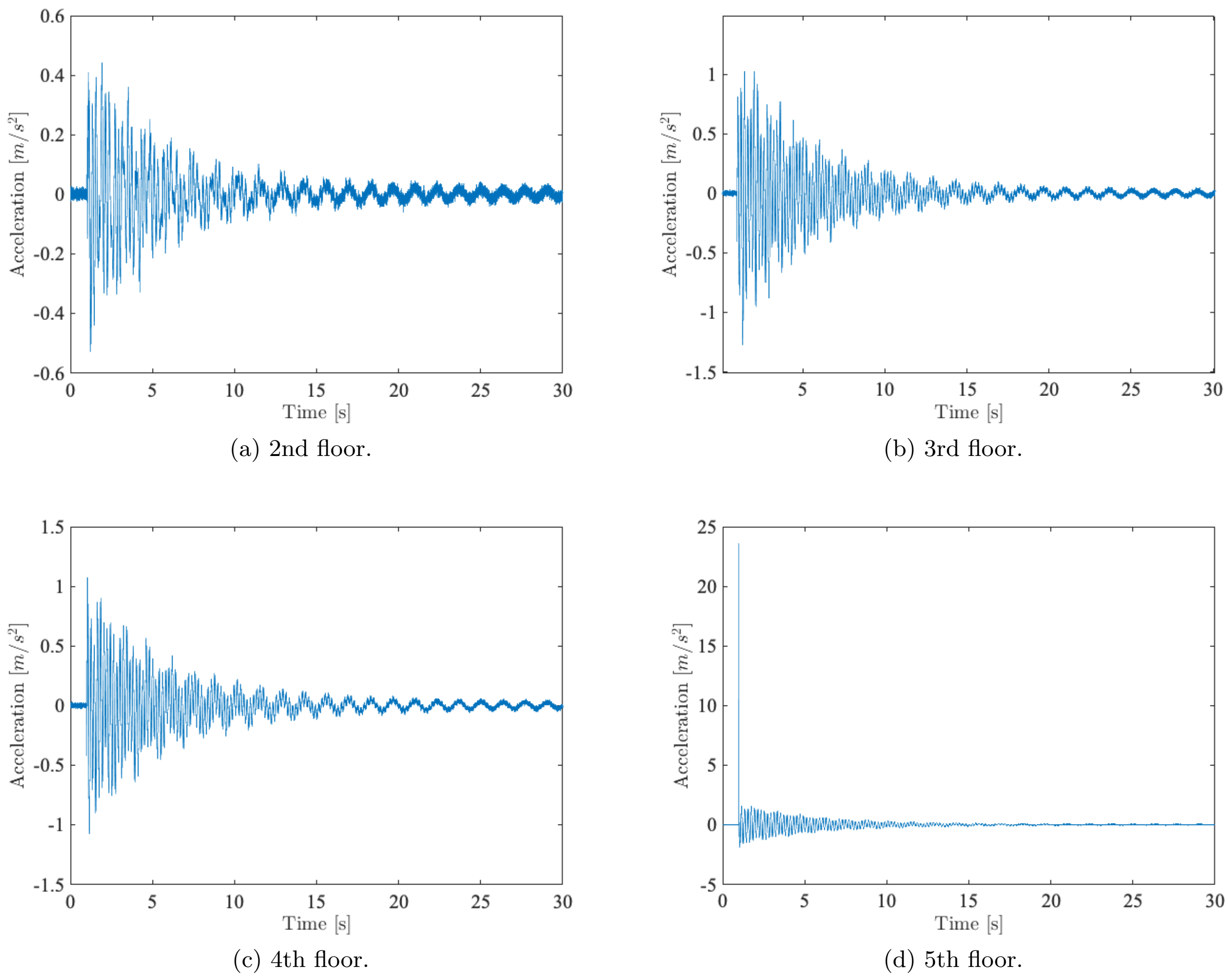
$$[C] = \alpha[M] + \beta[K] \tag{5}$$

where the coefficients $\alpha = 0.03$ and $\beta = 0.0028$ have been computed through least square minimization, considering the analysis of the experimental responses of the system in terms of modal damping and natural frequencies. Given these matrices, the equations of motion of the system can be derived solving the following second-order ordinary differential equations (ODEs):

$$[M]\ \underline{\ddot{x}} + [C]\ \underline{\dot{x}} + [K]\ \underline{x} = \underline{0} \tag{6}$$

3. EXPERIMENTAL CAMPAIGN

The aim of the experimental campaign conducted on the real system was the acquisition of raw data for both "healthy" and "damaged" structure. In both cases, four accelerometers were adopted, one for each storey. The structure was excited by an impact hammer and the transversal vibrations were acquired. In total, for the "healthy" structure, 1000 records of 50 seconds each were recorded. An example of the response is shown in Figure3. After an averaging procedure, the Frequency Response Function has been evaluated for each accelerom-

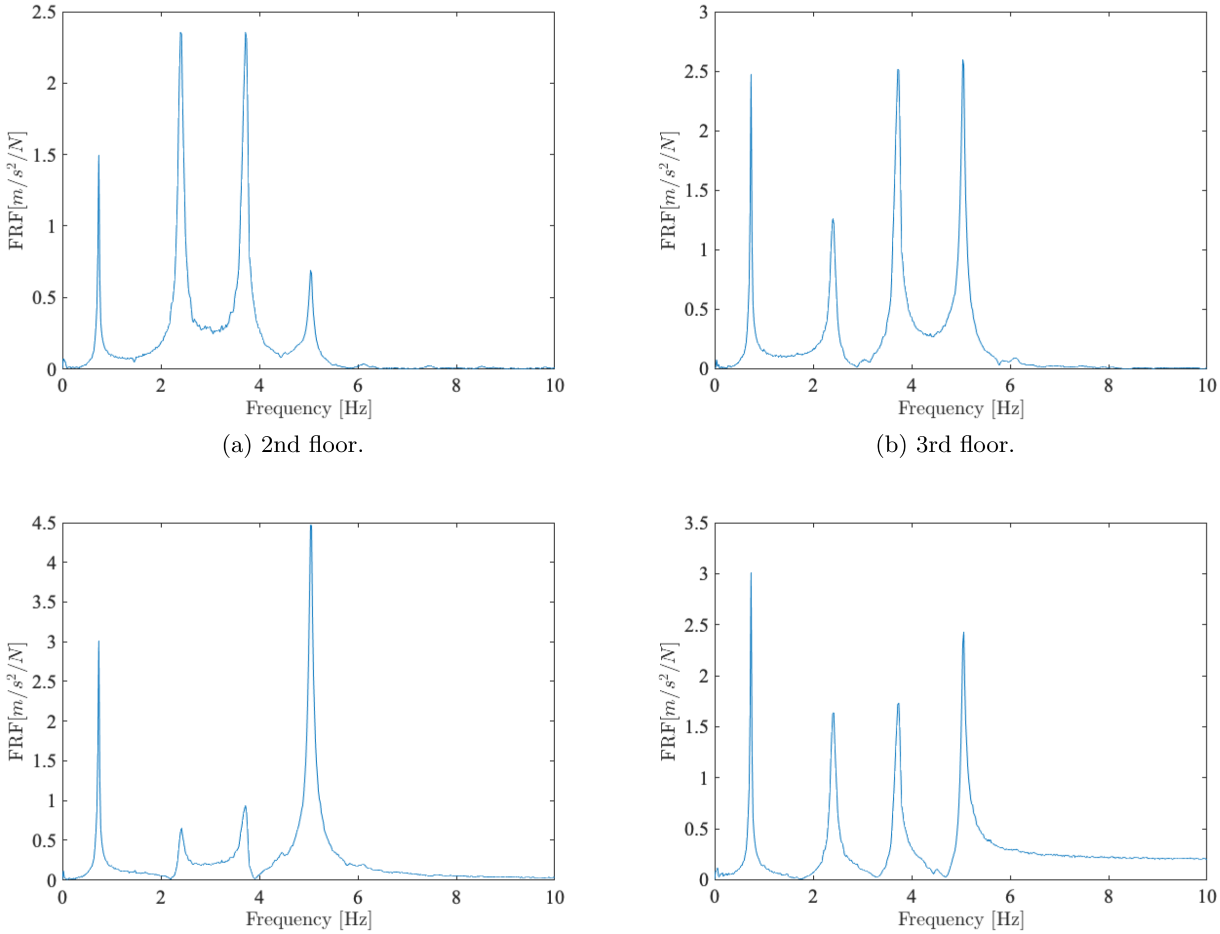


(a) 2nd floor. (b) 3rd floor.

(c) 4th floor. (d) 5th floor.

Figure 3: Acceleration of each floor with input applied on 5th floor.

eter. An example is reported in Figure 4, where the structure was excited by an input force on the 5th floor. Moreover, natural frequencies and mode shapes were extrapolated by means of the Experimental Modal Analysis (EMA).[16,17] In particular, the natural frequencies of the system are reported both for the numerical and the experimental model in Table 2.



(a) 2nd floor. (b) 3rd floor.

(c) 4th floor. (d) 5th floor.

Figure 4: FRFs evaluated for each accelerometer, one for each floor, with input applied on 5th floor.

Table 2: Natural frequencies for both the numerical and the experimental model.

Mode	Numerical model [Hz]	Experimental model [Hz]
1	0.79	0.75
2	2.51	2.41
3	3.88	3.74
4	5.01	5.04

Typical internal structural damages are not determined by a loss of material but by a change of geometry or material properties which affect one or many elements in the stiffness matrix.[18] For this reason, the "damaged" time histories were acquired changing only the stiffness value. In particular, six different sets of laminas were use to decrease, in the range of $10-60\%$, the stiffness of the spring connecting two subsequent floors. In total, 240 time histories of 50 seconds each were acquired: 10 per each combination of entity of the damage (type of lamina) and its position.

4. NETWORK ARCHITECTURE

The basic idea behind this work was to implement a convolutional autoencoder able to detect anomalies on the basis of the error of reconstruction of the input sample to the autoencoder. Autoencoders are unsupervised learning algorithms which, after several transformation and data compression, aim to reconstruct the input at the output with least distortion. This technique is widely used in remove noise, compressing and visualizing high dimensional data.[19] Convolutional Neural Networks (CNNs), on which Convolutional Autoencoders (CAEs) are based, is a class of Artificial Neural Networks (ANNs) whose algorithms are based on convolution operations. This leads to many advantages: (i) each neuron is no longer connected to all neurons of the previous layer, but only to a smaller portion, reducing parameters and speed up convergence; (ii) dimension reduction allows to remove trivial features while retaining useful information.[20]

4.1 Preprocessing

As already said, for the healthy structure, 1000 time histories of 50 seconds were recorded. In particular, the transversal accelerations were acquired by the four accelerometers with a sampling frequency of 100 Hz and arranged into a 4-columns matrix. Then, the entire set of time histories was normalized,[21,22] shuffled and divided into train, validation and test subsets, respectively composed by 800, 100 and 100 records.

4.2 Training and test

The train set was used for training procedure of the autoenconder model shown in Figure 5.

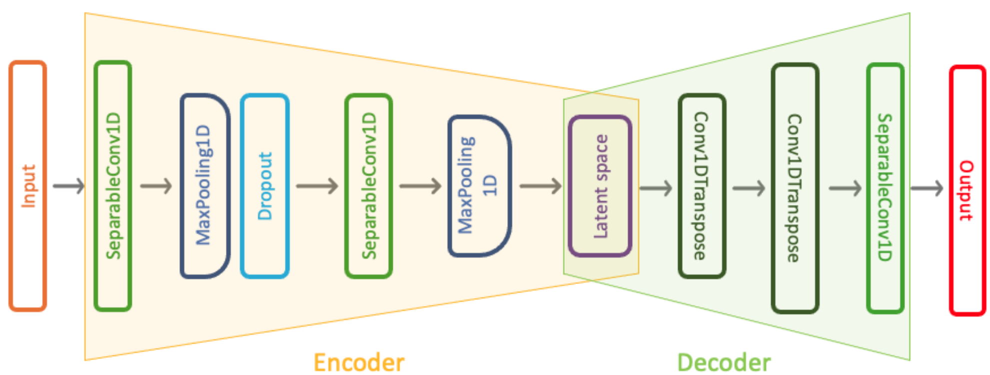
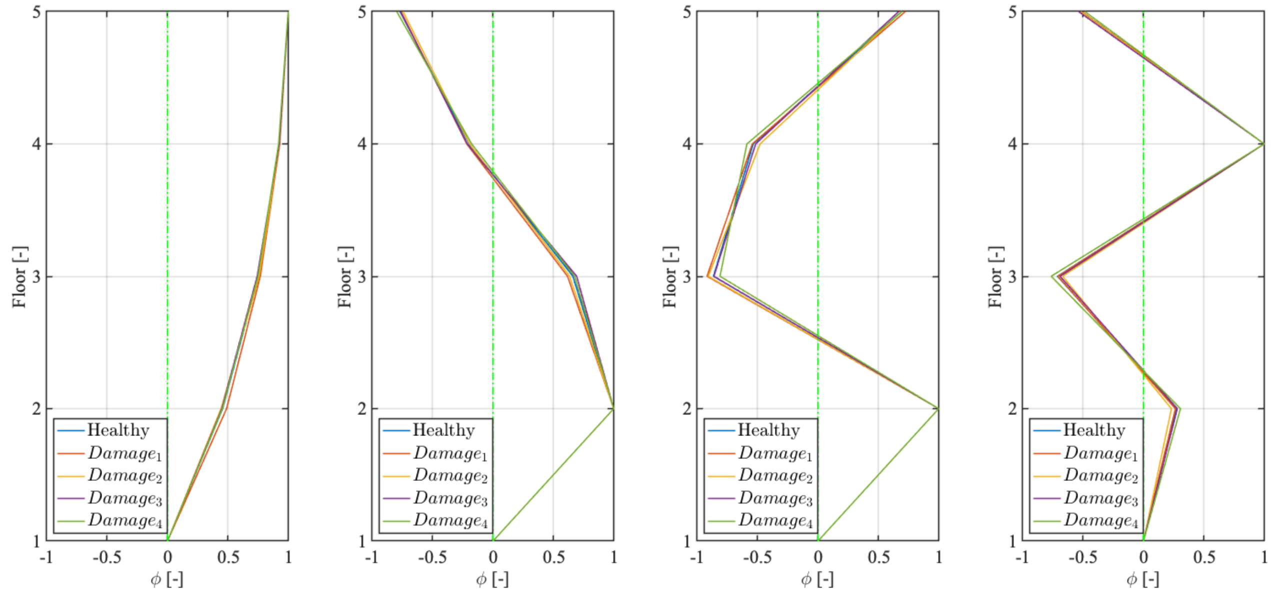


Figure 5: Autoencoder model.

In particular, 200 training epochs were considered and the Mean Squared Error (MSE) was used as loss function. Moreover, a callback setting on the validation loss was adopted. Then, the trained model was used to reconstruct the test set, and the Mean Absolute Error (MAE) was evaluated separately for each accelerometer. The maxima over all the test set were taken as thresholds, to be considered for detecting the anomalies. Indeed, the MAE loss represent the error of reconstruction done by the autoencoder. So, it is likely to assume that the greater the error of reconstruction the greater the damage is.

5. RESULTS

The 240 damaged records were firstly analyzed via EMA. However, natural frequencies and mode shapes were found to slightly change for damages of 10%, as shown in Figure 6.



(a) 1st mode. (b) 2nd mode. (c) 3rd mode. (d) 4th mode.

Figure 6: Vibration modes of structure for 10% reduction of the stiffness value and for different positions of the damage.

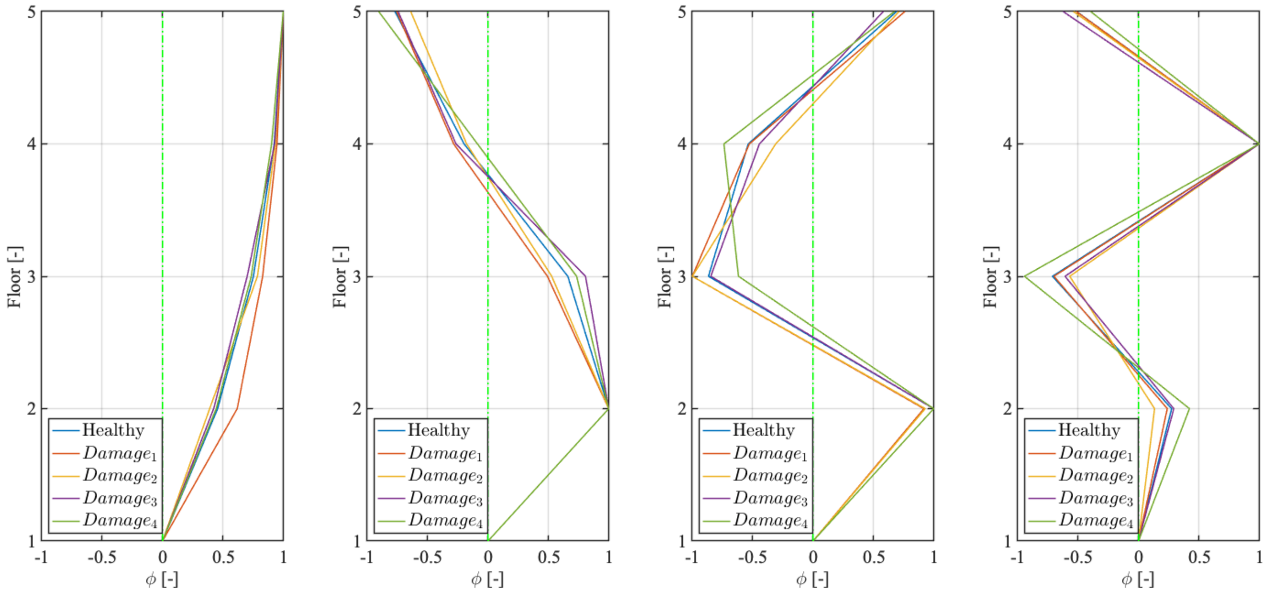
For damages of higher entity, reported in Figure 7, the differences were appreciable, but the detection of damage position was not straightforward. With this in mind, the anomalies set was preprocessed with the same scaler obtained for the training set and then fed to the autoencoder. The MAE errors for each of the anomaly record and for each channel (accelerometer) were then compared to the previously found MSE test thresholds. Each record with a loss higher than the threshold was classified as anomaly. All anomalies were detected, confirming the precision of the method for detecting the structure's damage, also for cases in which the entities of the damage are not so high. Moreover, for each anomaly detected, the channel (corresponding to the accelerometer position, i.e. the floor) with the maximum value of the MAE loss was selected as the damage position and compared with the real and known damage position. So, for each damage entity in the range $10-60\%$ and taken as reference, the following index was evaluated:

$$detection = \frac{n_d}{n_{tot}} \times 100 \tag{7}$$

where n_d is the number of anomalies with damage entity equal or higher than the reference value and whose position was correctly detected by the model, while n_{tot} is the total number of anomalies with damage entity equal or higher than the reference value. The results are reported in Table 3.

Table 3: Anomalies detection.

Damage	Detection
-10%	33.19%
-20%	40.20%
-30%	52.24%
-40%	65.11%
-50%	84.61%
-60%	100%



(a) 1st mode. (b) 2nd mode. (c) 3rd mode. (d) 4th mode.

Figure 7: Vibration modes of structure for 50% reduction of the stiffness value and for different positions of the damage.

6. CONCLUSION

The use of a convolutional autoencoder for damage detection was investigated. In particular, raw data coming from experimental acquisitions on a four-storey building were used and the error of reconstruction was taken as instrument to detect the anomalous records. The algorithm, compared to conventional vibration-bases methods, was able to detect all records with structural damages, showing good precision in the detection of their position, especially for higher damage entities. Future developments of this work will include changes in the mass of the system and the use of the model together with the NNs for detecting anomalies for more complex structures.

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