

Article

Archetypal Use of Artificial Intelligence for Bridge Structural Monitoring

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Abstract: Structural monitoring is a research topic that is receiving more and more attention, especially in light of the fact that a large part of our infrastructural heritage was built in the Sixties and is aging and approaching the end of its design working life. The detection of damage is usually performed through artificial intelligence techniques. In contrast, tools for the localization and the estimation of the extent of the damage are limited, mainly due to the complete datasets of damages needed for training the system. The proposed approach consists in numerically generating datasets of damaged structures on the basis of random variables representing the actions and the possible damages. Neural networks were trained to perform the main structural monitoring tasks: damage detection, localization, and estimation. The artificial intelligence tool interpreted the measurements on a real structure. To simulate real measurements more accurately, noise was added to the synthetic dataset. The results indicate that the accuracy of the measurement devices plays a relevant role in the quality of the monitoring.

Keywords: structural health monitoring; damage detection; damage localization; hybrid approach; neural network

1. Introduction

Modern society makes large use of civil infrastructures. Hydroelectric power generation presupposes that dams are built along mountain valleys to store water. River and valleys are crossed by bridges and viaducts, tunnels are built under mountains. Any engineered product, in particular a structure such as a dam or a bridge, has a finite design working life. This means that after a certain amount of time (e.g., half a century), large maintenance works are required, otherwise, the structural safety reduces to unacceptable levels and the infrastructure must be destroyed or abandoned [1]. Large efforts have been made by researchers to understand the phenomena that occur on the infrastructures and the ageing processes acting on the structures, which reduce their bearing capacity [2]. After decades of tests and a larger and solid knowledge base, modern structural design philosophies account for the variability of the loads, the environmental effects on the structure, and the possibility of accidental phenomena (such as earthquakes or fire) and impose strict prescription in construction works to avoid the need of large maintenance works during the expected working life.

Nevertheless, it must be remembered that the larger part of the actual infrastructural heritage was built in the Sixties, and it has had more than fifty years of service. Such structures suffer from two major problems. First, it must be considered that loading and environmental scenarios not accounted for during the design phase could have occurred, thus, the infrastructures can have experienced a quicker ageing process. In fact, this results in costly maintenance or in abandonment before the end of the design working life. Second, the infrastructures cannot be replaced in an economical manner since

service inconveniences and high construction costs must be considered before planning the demolition and the subsequent reconstruction [3]. Therefore, to lengthen the working period, a structural health monitoring (SHM) framework must be implemented to detect the location and the extent of damage on structures [3,4].

Briefly, SHM can be implemented through non-destructive or destructive techniques. The former presupposes that continuous or discrete measurements are carried out during a time period and modification of the trends are interpreted as the evolution of the damage. The latter implies that samples of material (concrete, steel, reinforcement bars) are taken from the structure and tested in laboratories to determine the residual mechanical properties (uniaxial compression strength in concrete, tensile strength in steel) [5]. The resulting information is implemented in numerical finite element (FE) models of the structure, and the structural safety is assessed. Destructive investigations are also required when there is the possibility that components buried in the structure, e.g., post-tensioned tendons, are damaged. Referring to non-destructive methods, many approaches have been formulated, mainly based on the study of the evolution of the dynamical properties (vibration frequencies and damping) of the structure [6,7]. Details on the possible analysis techniques and their pros and cons can be found in the specific literature (see, e.g., [7–9]).

As reported by Farrar and Worden [3], machine learning is a useful tool in SHM as it can provide interesting insights into the following five hierarchical points: (i) detection of the damage, (ii) localization of the damage, (iii) classification of the type of damage, (iv) evaluation of the extent of the damage, and (v) prediction about the residual safety of the structure. Supervised and unsupervised learning approaches can be implemented into a machine learning framework. Referring to the former, it is mandatory that data from every conceivable damage situation should be available. In this sense, all the five points previously enumerated can be implemented into an artificial intelligence framework. In contrast, unsupervised learning can only be adopted for the detection of damage and, sometimes, for the localization of the damage.

The comparison between statistical patterns of recorded data provides information about the structural condition [10,11], provided that a calibration phase on an undamaged structure is performed [12]. Pattern recognition of extracted features has been found effective for detecting damages: various artificial intelligence techniques have been proposed, e.g., autoregressive models [13], artificial neural networks [14], or support vector machines [15]. Novelty detection or anomaly detection methods have been also largely adopted; some examples are provided in [16–19].

A recent review paper on the emerging artificial intelligence methods applied in structural engineering was written by Salehi and Burgueno [20]; it concluded that the use of artificial intelligence in feature extraction is a powerful tool in SHM [21].

The current approaches reveal that large datasets are needed to monitor a structure. In particular, to detect a damage, structural information from when the damage was not present is required. This reflects that the knowledge of at least one previous state of the system is needed to check for a change in structural behavior, which can be interpreted through the approaches previously illustrated. Obviously, this is not always possible since, usually, monitoring starts after the appearance of a defect on a structure. This evidence suggests two major problems. On one side, to encompass all the possible types of damage (location, type, and extent), a consistent amount of information related to a large number of monitored structures is required. On the other, adopting unsupervised learning approaches requires long time records on a single structure. The present paper proposes a hybrid approach that helps to address these problems. The method allows for numerical modeling to simulate all the possible damage configurations on a structure and for supervised learning to interpret the records of sensors on a structure. Exploiting just a small part of the power of machine learning algorithms, in the present paper, shallow neural networks (NN) [22] are adopted as learning machines for the analysis. To be implemented in a real case, the fact that the measurements can be affected by errors must be included in the analysis. Thus, random errors are included in the analysis.

2. Methods

The current investigation involved, first, the generation of a synthetic dataset in which all the parameters are known and, then, the training of learning tools to determine whether a structure is damaged and where the damage is located.

2.1. Generation of the Synthetic Dataset

The numerical evaluation of displacements and vibration frequencies of undamaged and damaged structural members onto which a moving load is acting was first performed. Such data served as information for the training of neural networks devoted to the identification and the localization of the damage. To this aim, a simple supported beam served as the reference structure for the test. The choice of this scheme was based on the fact that this type of support was largely adopted in historical bridge building and because of its inherent low damage tolerance as a statically determinate structure. The beam was 30 m long, had a rectangular cross section ($0.4 \text{ m} \times 1.5 \text{ m}$), and was constituted by a material having elastic modulus E_0 and density equal to 30 GPa and 2500 kg/m^3 , respectively. A moving load, namely P , whose position was identified through the variable x_p , acted on the beam. The magnitude of the load was not constant across the performed simulations: A uniform distribution between 50 kN and 100 kN was attributed to P to simulate a real scenario of heterogeneous traffic.

A set of 30k simulations with moving load were performed using Matlab (MathWorks, Natick, MA, USA) coupled to OpenSees solver [23]. A first subset of 10k simulations, namely Subset A, related to an undamaged beam: In each simulation, the position and the magnitude of the load were randomly modified. In the second subset of 10k simulations, Subset B, the damage was inserted. To this purpose, the beam was split into 20 parts (elements) of equal length (1.5 m each). For beams with stronger flexural resistance mechanisms, the parameter that rules the behavior of the system is the flexural inertia, which is the product between the inertia moment around the flexural axis and the elastic modulus of the material composing the cross section. Obviously, for elements made of materials with different mechanical properties, such as reinforced concrete, it is possible to determine equivalent inertia and elastic modulus values. Thus, the reduction of the cross section of the material, for example, due to corrosion, can be simulated with a reduction of either the moment of inertia or the elastic modulus [24]. A Lemaitre-Chaboche model [25] was adopted to simulate the damage. The damage model is herein intended as a reduction of the elastic modulus of the cross section. The elastic modulus of the damaged element is

$$E_d = (1 - d) E_0, \quad (1)$$

where d is the damage parameter ($d = 0$ for undamaged, $d = 1$ for complete damage). For $d = 1$, a mechanism forms and, thus, the equilibrium cannot be guaranteed. The possible range of the damage parameter was set at $[0;0.2]$. Larger values are out of the scope of the present analysis since our interest is in incipient damage rather than on already evolved damage. For each simulation, the damaged element and the damage magnitude (parameter d) were randomly identified. The adopted approach encompasses all the possible damages that can occur on reinforced concrete elements and concrete elements with pretensioned tendons, which represent the major structural types of road bridge infrastructures.

The third subset of data (Subset C, 10k entries) was represented by five simulations in which the load P was located at different positions along the length of the damaged element once a damage was assigned. In detail, for each entry of the dataset, the damaged element and the damage magnitude were randomly identified, and the structure was solved for the load P at $1/5$, $2/5$, $3/5$, and $4/5$ of the beam length. An additional extra simulation accounting for the beam with just a gravity load was performed, and this condition is subsequently referred to as unloaded.

The structure was modeled as planar and discretized with 21 nodes and 20 beam-elements with 6 degrees-of-freedom each (3 for each end). The cross section and material properties were associated to the elements. The mass of the beam was attributed to each node considering its tributary length.

The mass associated to the moving load was not considered at this stage. Figure 1 illustrates the beam with its discretization.

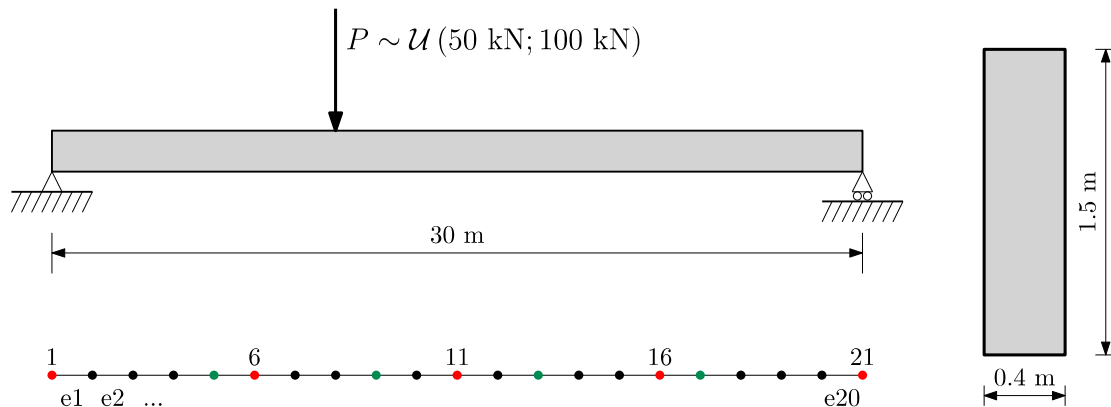


Figure 1. Sketch of the reference beam structure. The bottom scheme illustrates the discretization. Red nodes refer to the location of the inclinometers; green nodes refer to the location of the load P in the third simulations subset (Subset C).

An eigenvalue analysis was performed to determine the vibration modes, while a static analysis served for the vertical displacements. For each simulation, the frequencies associated to the first three vibration modes, namely f_1 , f_2 , and f_3 , and the rotations at the beam ends, at midspan, and at quarter lengths were recorded (red points in Figure 1). The choice of measuring the rotations instead of the displacements follows the fact that on real structures inclinometers can be installed more easily than can displacement sensors. The presence (or not) of the damage, the position and the magnitude of the moving load, the location and the intensity (d) of the damage, and the recorded frequencies and rotation constitute the synthetic dataset.

2.2. Supervised Learning

To simulate the instrumental and post-process accuracy in real measurements, a white noise was applied to the data recorded in the simulations. It is supposed that the accuracy related to the frequency estimation differs from the accuracy in the measured rotations. In detail, a_{freq} is the half amplitude of the accuracy applied to each frequency and a_{rot} is the half amplitude of the accuracy applied to each measured rotation. The modified frequencies and rotations are, respectively,

$$\begin{aligned} f_i^n &= f_i + \text{rnd}(-a_{freq}; +a_{freq}) & i &= 1, 2, 3 \\ \varphi^n &= \varphi + \text{rnd}(-a_{rot}; +a_{rot}) & i &= 1, 2, 3 \end{aligned} \quad (2)$$

where f_i is a vibration frequency and φ a rotation, $\text{rnd}(l; u)$ is a random number generator in the range $[l; u]$.

The obtained datasets served for the supervised learning of the neural networks (NN). The current investigation involved the training of three different neural networks to solve different problems in damage identification. The number of hidden neurons reflects the size of the input and output dataset [26], avoiding an excessive number of hidden units. The three considered networks were:

- Step 1: understanding whether the system is damaged or not. To this aim, a two-layers feed forward neural network-based classifier with 10 sigmoid hidden neurons and a softmax output neuron was built. Subset A and Subset B were used to train the neural network. In detail, the datasets were merged and shuffled. A two-variables state vector with values $\{-1; +1\}$ identifies if the system is undamaged (-1) or damaged ($+1$). The supervised learning consisted in splitting the entire dataset (20k entries) into three groups: 14k served for training, 3k for validation, and 3k for testing. The Levenberg–Marquardt with Bayesian regularization algorithm was adopted to train the neural network [27].

- Step 2: identifying the location of the damage. To this aim, a two-layers feed forward neural network with 16 sigmoid hidden neurons and a linear output network was built. Subset C, only, was used to train the network. In detail, the subset was offset in such a way that the contribution of the imposed strains (due, for example, to thermal effects) was compensated for: The measured rotations when load P acts are subtracted from the rotations in the unloaded case. The input training dataset consisted of 7k entries, while the output consisted of a vector containing the location of the midpoint of the damaged element. The supervised training was validated and tested with the remaining 3k entries (1.5k for validation and 1.5k for testing). The Levenberg–Marquardt with Bayesian regularization algorithm was adopted to train the neural network.
- Step 3: identifying the magnitude of the damage. To this aim, a neural network similar to the one adopted for Step 2 was built and trained. The offset Subset C was split into three groups and the training consisted of fitting the output, i.e., the magnitude of the damage, with the measured inputs (frequencies and rotations).

Figure 2 summarizes the subsets and the performed analyses. The shallow neural networks were built and trained in a MATLAB environment adopting the built-in functions. To highlight the effects of the accuracy of the inputs, various half amplitudes, i.e., a_{freq} and a_{rot} , were tested. In detail, the term related to the vibration frequencies ranged between 0.001 Hz and 1 Hz, while the term related to the measured inclination ranged between 0.001° and 1° .

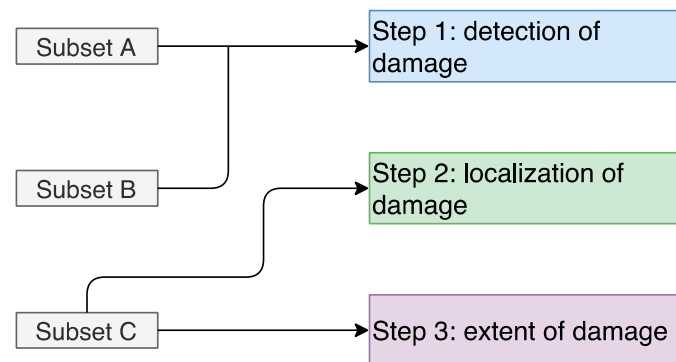


Figure 2. Scheme of the datasets adopted for the training of the neural networks for each step of the structural monitoring.

3. Results

The analyses showed a large variety of trends and dependencies on the accuracy of the estimated frequencies and measured rotations. The proposed parametric analysis only relates to the testing dataset of each neural network training process.

Referring to the identification of the presence of damage, the quality of the classification between damaged and undamaged was measured through the misclassification error. Figure 3 plots the confusion matrix for $a_{freq} = 0.01$ Hz and $a_{rot} = 0.1^\circ$. The testing dataset was constituted by 1455 undamaged and 1545 damaged beams, for a total of 3000 structures. In the green cells, the number of true positives (the NN predicts damage on a structure that is really damaged) and true negatives (the NN predicts no damage on a structure that is really undamaged) are reported. The red cells highlight the false positives (the NN predicts damage on a structure that, on the contrary, is undamaged) and false negatives (the NN predicts no damage on a structure that, on the contrary, is damaged). The misclassification error, i.e., the percentage of false values (199) with the respect to the number of tested cases (3000), was 6.63% and is reported in red in the bottom-right cell. The misclassification error was adopted as an indicator of the performance of the capacity of the system to identify whether the beam is damaged.

Output Class	Undam	1445 48.2%	189 6.3%	88.4% 11.6%
	Dam	10 0.3%	1356 45.2%	99.3% 0.7%
		99.3% 0.7%	87.8% 12.2%	93.4% 6.6%
		Undam	Dam	
		Target Class		

Figure 3. Example of a confusion matrix for $a_{freq} = 0.01$ Hz and $a_{rot} = 0.1^\circ$. Dam and Undam refer to the damaged and undamaged structure, respectively. The percentages in the grey cells can be interpreted as “precision”, “specificity”, and so forth (check [28] for each single term).

The misclassification error was evaluated for various accuracies of the vibration frequencies and rotations. Figure 4 depicts a contour plot of the error for the considered ranges of variables. Contour lines, which identify an equal amount of error, parallel to one axis denote that the variable represented in the axis does not influence the performance of the classification. That is, for precise rotation measurements or for definite vibration frequencies estimation, the influence of the accuracy of the other data is negligible, as the contour lines are parallel to the X and Y axes, respectively.

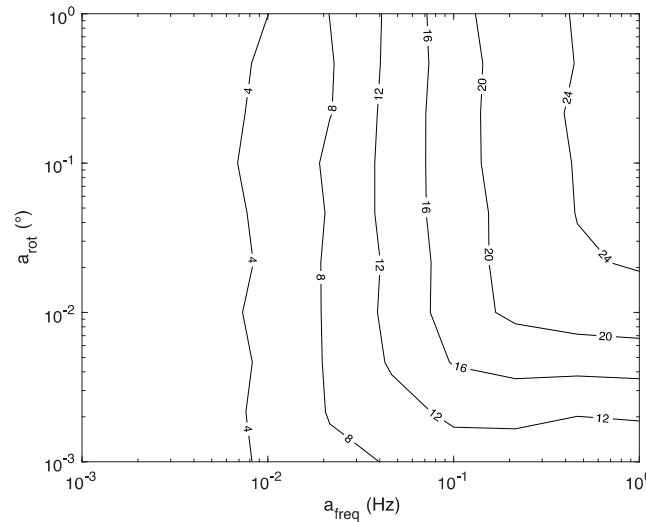


Figure 4. Misclassification error (in percentage) as a function of the accuracy in the estimation of the vibration frequency and in the measure of the rotation on log-log axes.

Referring to Step 2 and Step 3 simulations, the root-mean-squared error (RMSE) is the parameter that describes the precision in the location of the damage and its magnitude. The RMSE is defined as

$$RMSE = \frac{1}{N} \sum_{i=1}^N (O_i - T_i)^2, \quad (3)$$

where N is the number of testing entries (3k for the present case), T is the target value, and O is the output value from the trained neural network. Figure 5 illustrates the regression plot related to $a_{freq} = 0.001$ Hz

and $a_{rot} = 0.001^\circ$. Each circle corresponds to a couple $(T;O)_i$. The dashed red line relates to the perfect fitting, i.e., the output equals the target. The squared error tends to reduce for damage located at the midspan (target).

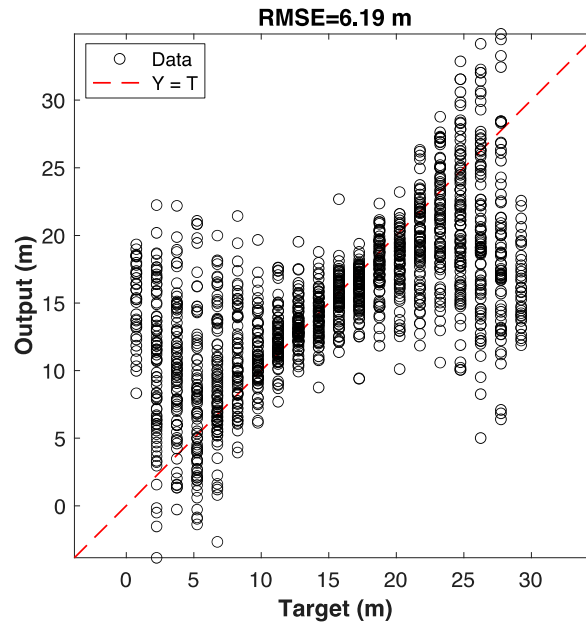


Figure 5. Regression plot related to $a_{freq} = 0.001$ Hz and $a_{rot} = 0.001^\circ$. RMSE: root-mean-squared error.

The same analysis was repeated, varying the accuracy variables in the aforementioned range. As can be seen from Equation (2), the root-mean-squared error for damage location is a quantity with a physical dimension. The parameter related to damage location is in meters, while the parameter related to damage magnitude has the same physical dimension as d , i.e., it is dimensionless. Figure 6 reports the values of the errors for damage location and damage magnitude. It can be noted that damage location largely depends on the accuracy in the measure of the rotation of the beam, while it is roughly unaffected by the accuracy in the frequency estimation. The opposite consideration can be drawn for damage magnitude.

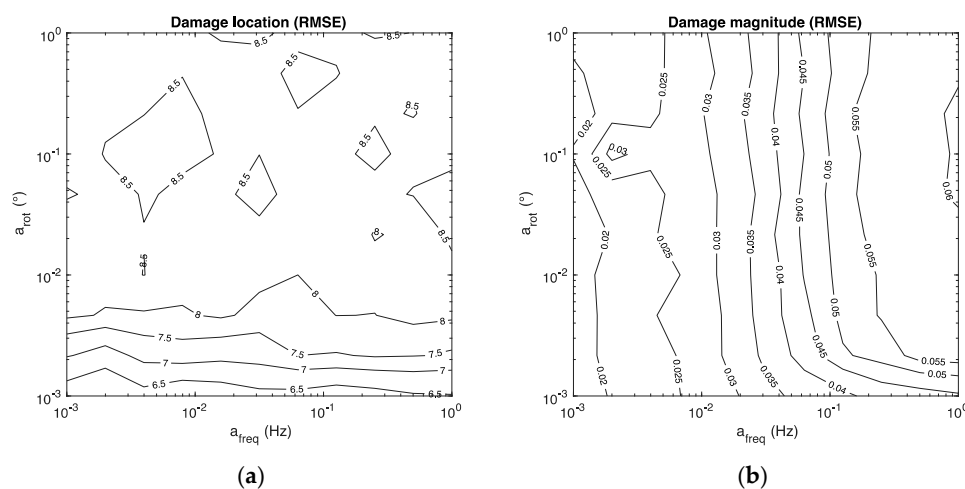


Figure 6. Root-mean-squared errors for the accuracy of the frequency in the range 0.001 Hz to 1 Hz and the accuracy of the rotation in the range 0.001° to 1° . In (a) the root-mean-squared error, in meters, related to damage location is proposed. In (b) the root-mean-squared error related to damage magnitude is reported.

It should be mentioned that considering datasets without any errors, i.e., $a_{freq} = 0$ and $a_{rot} = 0$, the misclassification error drops to 2%, the root-mean-squared errors related to damage location and magnitude are 0.47 m and 0.001, respectively.

4. Discussions and Conclusions

Tests on a simply supported beam subjected to damage provided interesting insights into the possibility of implementing a hybrid method consisting of numerical simulations and real measurements for monitoring the state of conservation of a structure. Real measures can be, for example, recorded during the motion of a vehicle over the beam.

Referring to the detection of damage, Figure 4 details the relative importance between precision in the estimation of the vibration frequencies and the accuracy in the measured inclinations. In this sense, the performed analyses highlight that the most relevant information is provided by the dynamic properties of the system, i.e., the vibration frequencies if the accuracy in their evaluation is smaller than 5×10^{-2} Hz, otherwise both static (inclination) and dynamic information are needed.

With reference to the localization of the damage, the precision in the measurements of the inclination of the beam represents the key aspect for the determination of the position of the damage. For accurate measurements (around 1×10^{-3} degrees), it is expected that the accuracy of the localization is around 6 m, independent from the precision in the evaluation of the vibration frequencies. The accuracy is more or less 30% of the beam length. For more rough measurements, i.e., an accuracy of about 1×10^{-2} degrees or larger, the expected precision is around 40% of the beam length. This appears to be sufficient for a rough localization of the damage and a good input for other traditional techniques, say material sampling.

Referring to the extent of the damage, the finer the evaluation of the frequencies, the more precise the amount of damage. The accuracy of inclination measurements does not undermine the estimation of the extent of the damage.

Interesting comparisons can be drawn between the results of the present investigation with those of other studies found in the literature. The obtained results are in agreement with the studies performed by Neves and colleagues [24] on a numerical model of a railway bridge subjected to damage. In their case, they found that the accuracy of the trained classification neural network is very high if the damage extends along the beam for 3.5% of the beam length, roughly similar to the case herein analyzed (5%). The results, although applied to different structures, are similar. The dependency of the results on the dynamic properties is in accordance with Rageh et al. [29], who trained a neural network using a dataset of numerical time series solutions of a damaged bridge structure.

The importance of training the artificial intelligence system with processed data is a key aspect in damaged/undamaged classification. Cury et al. [30] determined an increase of the quality of the classification process by adopting modal data, i.e., processed information rather than raw accelerations. The same results were found in the present analysis: The classification error depicted in Figure 4 shows that the accuracy of the system was sensitive to the precision of the estimated frequencies, which are processed data, rather than to the measured inclinations, which are raw measures. The importance of a full analysis of the influence of sensors precision on the accuracy of the system improved the results of Yan et al. [31], who limited their analysis to 1% and 3% noise relative amplitude.

The possibility of using computational mechanics methods for building datasets for training the artificial intelligence system aims at overcoming the problem of having sets of measures on damaged structures. This point was precisely pointed out by Cheung et al. [21], who showed that the autoregressive algorithm provides precise indication, provided that the system previously experienced damage. In civil engineering structures, this is not possible, since there is no possibility of damaging a structure without causing its destruction. An example of modelling the damage on a recoverable structural element is proposed by Shahsavari et al. [32]. Although interesting and a harbinger of suggestions, their experimental campaign is tailored for the single tested steel element, rather than to

a complete frame structure. Hence, the present approach is a tentative implementation of existing techniques for wider use of artificial intelligence for structural health monitoring.

As highlighted by Salehi and Burgueno [20], the majority of the studies focusing on the use of pattern recognition for SHM serve to detect damage. The localization of the damage and its extent are not possible since information on the evolution of the damage is not known a priori on the structure. This is the result of the fact that the structural behavior is directly dependent on damage location. In this sense, artificial intelligence can play an integrated role with structural numerical modeling.

The novelty of the proposed approach consists in the fact that the dataset that servers for training the learning algorithm comes from numerical analyses, rather than from observations on the structure. A set of damage configurations (location and extent) are modelled and the resulting structural displacements and dynamical properties are used for supervised training, in the present case, of a shallow neural network. In this sense, the use of machine learning can be enlarged to damage location and damage extent. The proposed approach was aimed at overcoming the limitations that emerged in the previous studies. Although theoretical, the approach can be applied for studying structures that are very similar (in construction engineering two structures cannot be identical since there is always human intervention in the construction process). This is the case, for example, of the overpasses of Highway A21 “Torino-Piacenza-Brescia” in the Northwest of Italy. Here, there are several overpasses that are coeval and have the same structural scheme, details, and techniques (Figure 7). The design of such infrastructures was performed by Dott. Ing. Gervaso [33]. The hybrid approach herein proposed fits well with monitoring such types of structures, for which an in-depth preliminary study and a detailed numerical modeling can be performed. The simulated structural dataset can be considered for a large number of similar real structures. Future studies on a real monitored structure are planned, as well as tests on more complex structural types, for example, portal frames.



Figure 7. Street view of one of the overpasses of the Italian Highway A21 (source Google Maps).

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