



**HAL**  
open science

# Ambient vibration prediction of a cable-stayed bridge by Artificial Neural Network

Melissa de Iuliis, Cecilia Rinaldi, Francesco Potenza, Vincenzo Gattulli,  
Thibaud Toullier, Jean Dumoulin

## ► To cite this version:

Melissa de Iuliis, Cecilia Rinaldi, Francesco Potenza, Vincenzo Gattulli, Thibaud Toullier, et al.. Ambient vibration prediction of a cable-stayed bridge by Artificial Neural Network. Data Driven Methods for Civil Structural Health Monitoring and Resilience, CRC Press, pp.1-16, 2023, 9781003306924. 10.1201/9781003306924 . hal-04302882

**HAL Id: hal-04302882**

**<https://inria.hal.science/hal-04302882v1>**

Submitted on 23 Nov 2023

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# 1 Ambient vibration prediction of a cable-stayed bridge by 2 Artificial Neural Network

3 Melissa De Iuliis<sup>1</sup>, Cecilia Rinaldi<sup>1</sup>, Francesco Potenza<sup>2</sup>, Vincenzo Gattulli<sup>1</sup>, Thibaud Toullier<sup>3</sup>, Jean  
4 Dumoulin<sup>3</sup>

5 <sup>1</sup>Department of Structural and Geotechnical Engineering, University of Rome, via Eudossiana 19, Rome 00167, Italy;  
6 Email: [melissa.deiuliis@uniroma1.it](mailto:melissa.deiuliis@uniroma1.it), [cecilia.rinaldi@uniroma1.it](mailto:cecilia.rinaldi@uniroma1.it), [vincenzo.gattulli@uniroma1.it](mailto:vincenzo.gattulli@uniroma1.it)

7 <sup>2</sup>Department of Engineering and Geology, University of Chieti-Pescara, viale Pindaro, 42 65127 Pescara, Italy; Email:  
8 [francesco.potenza@unich.it](mailto:francesco.potenza@unich.it)

9 <sup>3</sup>Université Gustave Eiffel, Inria, COSYS-SII, I4S Teram, F-44344 Bouguenais, France; Email: [thibaud.toullier@univ-](mailto:thibaud.toullier@univ-eiffel.fr)  
10 [eiffel.fr](mailto:jean.dumoulin@univ-eiffel.fr), [jean.dumoulin@univ-eiffel.fr](mailto:jean.dumoulin@univ-eiffel.fr)

11

12

## Abstract

13 Large-scale civil infrastructures play a vital role in society as they ensure smooth transportation and improve  
14 the quality of people's daily life. However, they are exposed to several and continuous external dynamic  
15 actions such as wind loads, vehicular loads, and environmental changes. Interaction assessment between  
16 external actions and civil structures is become more challenging due to the rapid development of transportation.  
17 Data-driven models have lately emerged as a viable alternative to traditional model-based techniques. They  
18 provide different advantages: timely damage detection, structural behaviors prediction and suggestions for  
19 optimal maintenance strategies. The chapter aims to describe the advantages and the characteristics of data-  
20 driven techniques to predict the dynamic behavior of civil structures through Artificial Neural Network (ANN).  
21 The applicability and effectiveness of the proposed approach are supported by the results achieved processing  
22 the measurements coming from a monitoring system installed on a cable-stayed bridge (Tabarly, Nantes).  
23 Accelerations recorded by a network of sixteen mono-axial accelerometers and Nantes Airport weather data  
24 acquired with the observation platform of the METAR (MEteorological Terminal Aviation Routine Weather  
25 Report) Station Network have been used as training to predict the structural response and to statistically  
26 characterize the behavior through a Nonlinear AutoRegressive (NAR) prediction network. The performance  
27 has been evaluated through statistical analysis of the error between the measured and predicted values also  
28 related to both environmental conditions and number of the signals. The results show that the forecast network  
29 could be useful to detect the trigger of anomalies, hidden in the dynamic response of the bridge, at a low  
30 computational cost.

31 **Keywords:** Data-driven approaches, Nonlinear AutoRegressive network, Structural Health Monitoring, Civil  
32 Infrastructures, Accelerometric Sensors

## 33 **1 Introduction**

34 Engineering structures and infrastructures, such as bridges, gradually suffer from aging because of different  
35 loads and environmental conditions. Proper and periodic assessment operations are paramount for structural  
36 safety to prevent the effects of environmental hazards, reduce maintenance costs, and to improve the level of  
37 safety of bridges. Therefore, structural identification has become an increasingly intensive research topic for  
38 Structural Health Monitoring (SHM), damage evaluation, and safety assessment of existing engineering  
39 structures. [1-7]. A significant number of studies of SHM systems focusing on damage detection of bridges  
40 can be found in the literature [8, 9]. For instance, Dutta and Talukdar [10] proposed a modal-based approach  
41 in finite element framework for damage detection of complex structures like bridges. Magalhães et al. [8]  
42 presented a statistically-based damage detection ability through short-term vibration monitoring data sets. Liu  
43 et al. [11] evaluated the structural performance of existing bridges using a strain-based monitoring system and  
44 a condition assessment of structural components. A strain-based monitoring system was integrated into a  
45 structural performance assessment of a steel girder bridge by Orcesi and Frangopol [12], who used the  
46 monitoring data to carry out a structural reliability analysis of critical sections. A load rating of a bridge was  
47 evaluated through diagnostic load testing based on a strain-based SHM system by Phares et al. [13].

48 Although many studies have been conducted on SHM systems to predict the behavior of engineering structures,  
49 traditional techniques are mostly based on dynamical models of the structure. The performance of conventional  
50 approaches strictly depends on the accuracy of the analytical and numerical dynamical models that are, in most  
51 cases, very challenging to derive [14, 15]. Furthermore, the development of such models and the definition of  
52 the parameters required to represent the behavior of structures may be time-consuming and computationally  
53 intensive. With the recent development in computer technology for communication, data acquisition, signal  
54 processing and analysis, an alternative solution to structural identification can be data-driven models [16].  
55 Unlike the traditional physics-based SHM models, data-driven models exploit patterns arising from spatial and  
56 temporal correlations in measurements and offer bottom-up solutions that include damage detection, remaining  
57 life estimation and also structural control [17, 18]. In addition, data-driven techniques require a training dataset  
58 comprising measurements that represent baseline conditions of a bridge [19]. Consequently, data-driven  
59 models have recently drawn considerable attention in civil engineering community. Artificial Neural Networks

60 (ANN) are amongst the most common machine learning techniques employed for structural system  
61 identification and model updating [20]. Barai and Pandey [21] presented an ANN based approach for damage  
62 identification in steel bridges. A model updating scheme with an adaptive neural network was proposed by  
63 Chang et al. [22] for structural health assessment methodologies and control strategies. In their work, the model  
64 updating, and network training were repeated until achieving a good agreement between the calculated and  
65 measured modal responses of the bridge. In Fang et al. [23], ANNs were employed to study the identification  
66 of structural damage in beams. A cantilever beam was divided into a given number of elements, and the damage  
67 was associated with loss of stiffness in one or more elements. Bakhary et al. [24] detected simulated damage  
68 in a numerical steel portal frame model through ANNs accounting also for uncertainties derived from the  
69 model and the measured vibration data. A methodological framework for predicting the dynamic responses of  
70 the vehicle-bridge interaction system using ANNs was illustrated by Li et al. [25]. Further, de Oliveira Dias  
71 Prudente dos Santos et al. [26] presented a Neural Network (NN) to simulate and predict the structural behavior  
72 of a bridge using the air temperature as an input to the network. Taking into account the changes of the  
73 environmental conditions (e.g., climate, traffic load, and degradation mechanisms) is paramount in the  
74 structural health monitoring process and development of fault detection methods. Yun-Lai and Wahab [27]  
75 employed an auto-associative neural network combined with transmissibility to identify damage location in a  
76 ten-floor structure. Furthermore, in their study the effect of noise on natural frequencies was evaluated. A back  
77 propagation algorithm in ANN was used to apply the change of static properties (i.e., strains and  
78 displacements) for damage detection in a cantilever beam [28]. Cascardi et al. [29] employed artificial neural  
79 networks to estimate the strength of FRP-confined concrete showing that the proposed model could provide a  
80 good agreement with measurements. A novel data-driven measurement approach to predict traffic-induced and  
81 thermal response of bridges was presented by Kromanis and Kripakaran [19]. In their work, prediction error  
82 signals are created and then interpreted with anomaly detection techniques. [Wang et al. \[30\] developed a long  
83 short-term memory \(LSTM\) approach for condition assessment of bridges to provide an early warning protocol  
84 through the analysis of the time-series measured data of deflection and temperature.](#)

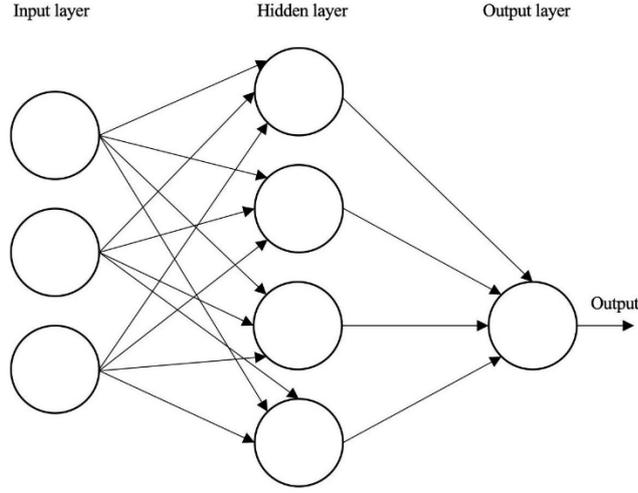
85 Among different types of recurrent neural networks, time delays neural networks (TDNN) [31, 32], layer  
86 recurrent networks [31], and Nonlinear AutoRegressive (NAR) networks [33, 34] have been widely used in  
87 time series forecasting. TDNN is a straightforward dynamic network consisting of a feed-forward network

88 with a tapped delay line at the input layer. NAR is a dynamic recurrent network with feedback connections  
89 including different layers of the network. In [35] hybrid approaches on time series data using ARMA with  
90 TDNN or ARMA with NAR are compared and results presented showed that NAR trends to perform well in  
91 providing more precise result for multi-step ahead prediction [35].

92 In the framing of the research field presented above, this study is concerned with investigation and  
93 implementation of ANNs for dynamic behavior prediction of bridges. A SHM system, installed in a cable-  
94 stayed bridge (Tabarly, Nantes, France) is used as a case study to demonstrate and verify the method. First,  
95 accelerations recorded by sixteen sensors and the Nantes airport METAR (MEteorological Terminal Aviation  
96 Routine Weather Report) weather measurements station data are used as training to predict the structural  
97 response and to statistically characterize the behavior through a Nonlinear AutoRegressive (NAR) prediction  
98 network. Statistical analysis of the error between measured and predicted values is performed. It is shown that  
99 the proposed network could constitute a useful tool to detect the presence of anomalies in the dynamic response  
100 of a bridge at a reasonable computational cost. The chapter is organized as follows: Section 2 briefly introduces  
101 ANNs and their underlying computational methodologies. Section 3 describes the geometrical and structural  
102 features of the cable-stayed bridge used as case study. Furthermore, the characteristics of a vibration based  
103 SHM system installed on the bridge are illustrated. Section 4 discusses the results obtained by the application  
104 of the data-driven approach. Finally, conclusions and future developments are drawn.

## 105 **2 Artificial Neural Network (ANNs): basic principles**

106 Artificial Neural Networks (ANNs) have been developed to model complex relationships where explicit  
107 formulae are difficult to carry out [22]. ANNs are defined as nonlinear nonparametric systems consisting of  
108 three main components: architecture, learning algorithm, and activation functions. Multi-layered feed-forward  
109 neural networks are most widely used network models in structural engineering applications. A typical neural  
110 network comprises an input layer, an output layer, and one or more hidden layers of neurons (computational  
111 units) that are interconnected through weighted connections. Figure 1 schematizes the architecture of a neural  
112 network along with the layers (i.e., input and output layers) and neuron numbers [36, 37].



113

114

Figure 1. Artificial Neural Network architecture (adapted from [36])

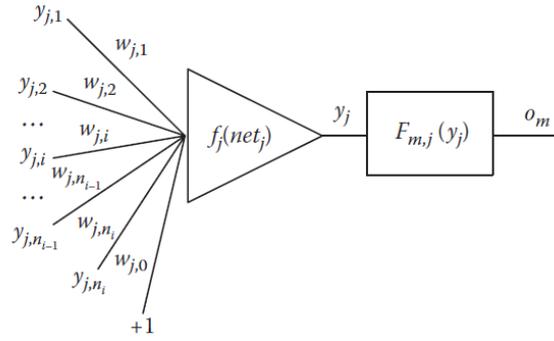
115

Let consider a neuron  $j$  with  $n_i$  inputs, as illustrated in Figure 2. If neuron  $j$  is in the first layer, all its inputs would be connected to the inputs of the network. If connections across layers are allowed, its inputs can be connected to outputs of other neurons or to network inputs. Node  $y$  can have two indices ( $y_{j,i}$ ) as the  $i$ -th input of neuron  $j$  or it can be implemented as  $y_j$  to define the output of neuron  $j$  (with one index).

116

117

118



119

120

Figure 2. Connection of a neuron  $j$  with the rest of the network (extracted from [38])

121

The output node of neuron  $j$  is computed as:

122

$$y_j = f_j(net_j) \quad (1)$$

123

where  $f_j$  is the activation function of neuron  $j$  and net value  $net_j$  is the sum of weighted input nodes of neuron

124

$j$ :

125

$$net_j = \sum_{i=1}^n w_{j,i} y_{j,i} + w_{j,0} \quad (2)$$

126

where  $y_{j,i}$  is the  $i$ -th input node of neuron  $j$ , weighted by  $w_{j,i}$ , and  $w_{j,0}$  is the bias weight of neuron  $j$ .

127 Activation functions are linear and non-linear components of neural networks. They are responsible for  
 128 mapping between input and target values. The S-shaped sigmoidal functions such as tangent-sigmoid and  
 129 logistic-sigmoid functions are widely used as activation functions as their non-linear mapping ability within  
 130 the hidden layer of the network. Usually, output layer contains linear activation functions such as step and  
 131 purelin functions [36]. The activation function in Neural Networks takes the input  $y_{j,i}$  multiplied by its weight  
 132  $w_{j,i}$ . Bias allows to shift the activation function by adding a constant to the input and it has the effect of shifting  
 133 the activation function by a constant amount ( $w_{j,0}$ ). A complex nonlinear relationship between the output node  
 134  $y_j$  of a hidden neuron  $j$  and network output  $o_m$  can be defined:

$$135 \quad o_m = F_{m,j}(y_j) \quad (3)$$

136 where  $o_m$  is the  $m$ -th output of the network. The complexity of the mentioned nonlinear function  $F_{m,j}(y_j)$   
 137 depends on the number of neurons between neuron  $j$  and network output  $m$ .

## 138 2.1 Training Algorithms

139 The training of a network is performed to adjust the weight connections between the considered neurons.  
 140 During the training process the input data is given to the network and the estimated output of the network is  
 141 computed by using the current value set of weight coefficients and it is compared with the desired output.  
 142 Then, the error between the estimated and desired output of the network is calculated and it is used to adjust  
 143 the weight coefficients (initially set based on Nguyen-Widrow initialization method [39, 40]). In Neural  
 144 Network, the learning algorithm is the component of training process which makes neural networks learn from  
 145 data lags. Learning algorithms of neural networks are basically back propagation algorithms that use error  
 146 functions derivatives as gradients. To evaluate the training process for all training patterns and network  
 147 outputs, the Sum Square Error (SSE) is implemented as:

$$148 \quad E(x, w) = \frac{1}{2} \sum_{p=1}^P \sum_{m=1}^M e_{p,m}^2 \quad (4)$$

149 where  $p$  is the index of patterns ranging from 1 to  $P$  (i.e., number of patterns),  $m$  is the index of outputs ranging  
 150 from 1 to  $M$  (i.e., number of outputs),  $x$  is the input vector,  $w$  is the weight vector, and  $e_{p,m}$  is the training error  
 151 at output  $m$  when applying pattern  $p$ , and it is defined as:

$$152 \quad e_{p,m} = d_{p,m} - o_{p,m} \quad (5)$$

153 where  $d$  is the desired output vector and  $o$  is the output vector from the model.

154 A suitable algorithm for training small- and medium-sized problem in the artificial neural-networks field is  
155 Levenberg-Marquardt backpropagation which provides a numerical solution to the problem of minimizing a  
156 nonlinear function which, in this case, is the error function  $E$ . This function uses the Jacobian for calculations,  
157 which assumes that performance is a mean or sum of squared errors. Therefore, networks trained with this  
158 function must use either the MSE (Mean Squared Error) or SSE (Sum Square Error) performance function.

159 The Levenberg–Marquardt algorithm combines two algorithms for the training process: around the area with  
160 complex curvature, it shifts to the steepest descent algorithm; when the local curvature becomes suitable for a  
161 quadratic approximation it converts to the Gauss–Newton algorithm, which can significantly accelerate  
162 convergence [38, 41].

163 The prediction performance of a network strictly depends on the network parameters, training process, and  
164 quality of the training data set. Generally, extensive parametric studies performed on different networks are  
165 necessary to get the best performance. Further details on ANNs as well as their implementation steps are  
166 provided in [42-47].

## 167 2.2 Neural network time-series prediction

168 Dynamic neural networks are generally employed to forecast future values of a time series  $y(t)$  only from past  
169 values of the actual time series. Time series prediction using neural network approach is non-parametric,  
170 therefore it is not necessary to know any information about the process that generates the signal [33, 48, 49].

171 This form of prediction is known as Nonlinear AutoRegressive (NAR) model. The NAR network is a feed  
172 forward neural network with three layers, namely input, hidden, and output layers. The NAR neural network  
173 is trained in a series-parallel configuration. In the training phase, the true output is provided, and it is used as  
174 the input to the network. In the testing phase, the computer output is fed back to the network to estimate the  
175 next value of the output in a parallel configuration.

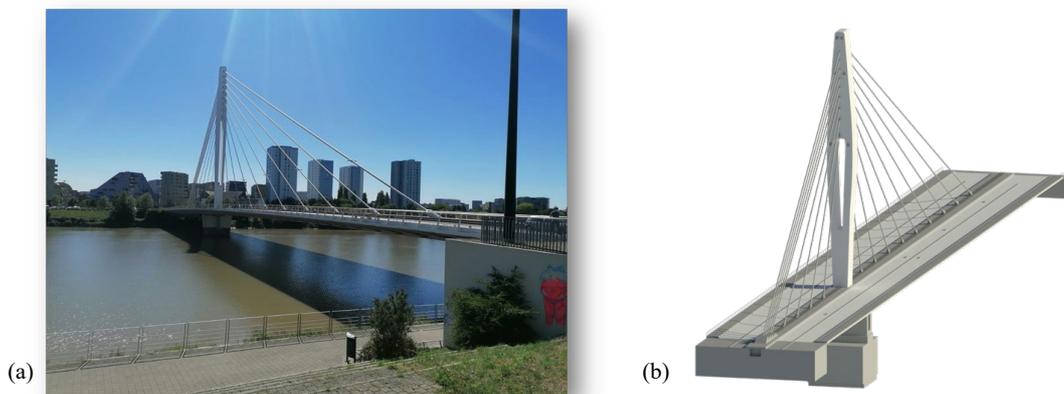
176 The NAR network consists of feedback connections, layers, and it is determined by the following equation:

$$177 \quad \hat{y}(t) = f(y(t-1) + y(t-2) + \dots + y(t-d)) \quad (6)$$

178 where  $f$  is a nonlinear function, where the future values depend only on regressed  $d$  earlier values of the output  
179 signal. Since the network performs only a one-step ahead prediction after the training in the NAR network, it  
180 is necessary to use the closed loop network to perform a multi-step ahead prediction. Subsequent time steps  
181 can be predicted in a sequence through closed loop forecasting by using the previous predictions as input.

### 182 **3 Monitoring system of a cable-stayed bridge**

183 The Éric Tabarly bridge in Nantes (France) is a 210m long cable-stayed road bridge crossing the Loire River.  
184 It is composed of a 27m wide steel deck divided into two spans by a 57m high steel pylon, being the main span  
185 143m long (Figure 3).



186

187 Figure 3. Photo (a) and BIM model (b) of the Tabarly bridge in Nantes

188 [In 2016 the instrumentation has been installed for monitoring the vibrational behavior of the bridge. That is,](#)  
189 16 single-axis accelerometers have been installed onto the bridge with 2 different acquisition zones: 8  
190 accelerometers in the deck and 8 accelerometers in the pylon. Data are acquired through a PEGASE generation  
191 2 acquisition card marketed by A3IP company under IFSTTAR (now University Gustave Eiffel) license for  
192 each of the two zones. Each acquisition card exports voltage measurements at a sampling frequency of 100  
193 Hz. Silicon Designs 2210 accelerometers, which can collect acceleration from -10G to 10G and usable with a  
194 700 Hz acquisition frequency, were used. Figure 4 depicts the locations of the accelerometers (red dots) and  
195 details of the deck and pylon. In the deck, each slot contains two single-axis accelerometers, with one along  
196 Y-direction (vertical) and one along Z-direction (horizontal-transversal). Two accelerometers along Y-  
197 direction are placed in X3 (see Figure 4a). In the pylon (see Figure 4b), three of the eight accelerometers follow

198 the Z-direction, while the others are along the X-direction. The directions of the different accelerometers along  
 199 with the sensitivities of the sensors are listed in Table 1 and Table 2.

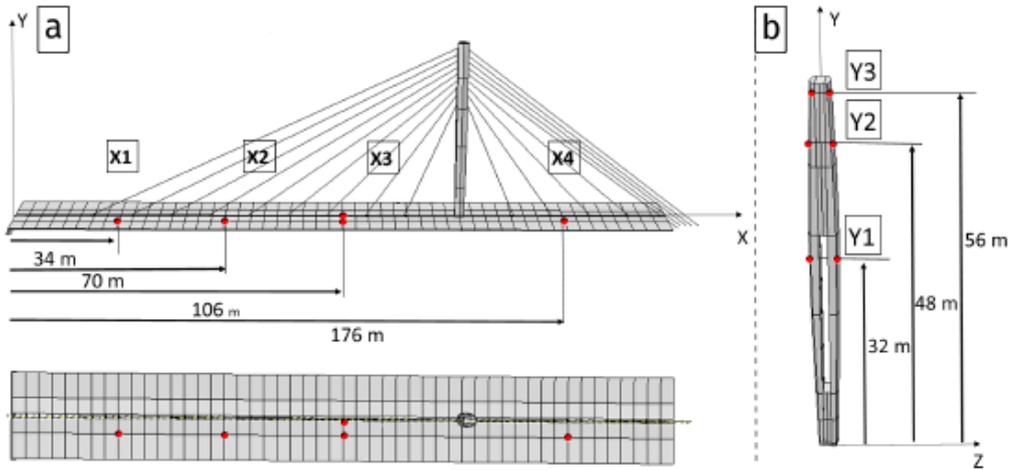


Figure 4. Layout of the accelerometric sensors placement for deck (a) and pylon (b)

Table 1. Direction and sensitivities of the deck accelerometers

| Deck     |         |               |                         |                    |
|----------|---------|---------------|-------------------------|--------------------|
| Location | Channel | Serial Number | Direction               | Sensitivity (mV/g) |
| X1       | 1       | 26188         | $\vec{Y}$               | 2009               |
|          | 2       | 26192         | $\vec{Z}$               | 2009               |
| X2       | 3       | 26187         | $-\vec{Y}$              | 2013               |
|          | 4       | 26193         | $\vec{Z}$               | 2012               |
| X3       | 5       | 26182         | $-\vec{Y}(\text{west})$ | 2004               |
|          | 6       | 26184         | $-\vec{Y}(\text{east})$ | 2012               |
| X4       | 7       | 26197         | $-\vec{Y}$              | 2010               |
|          | 8       | 26190         | $\vec{Z}$               | 2012               |

Table 2. Direction and sensitivities of the pylon accelerometers

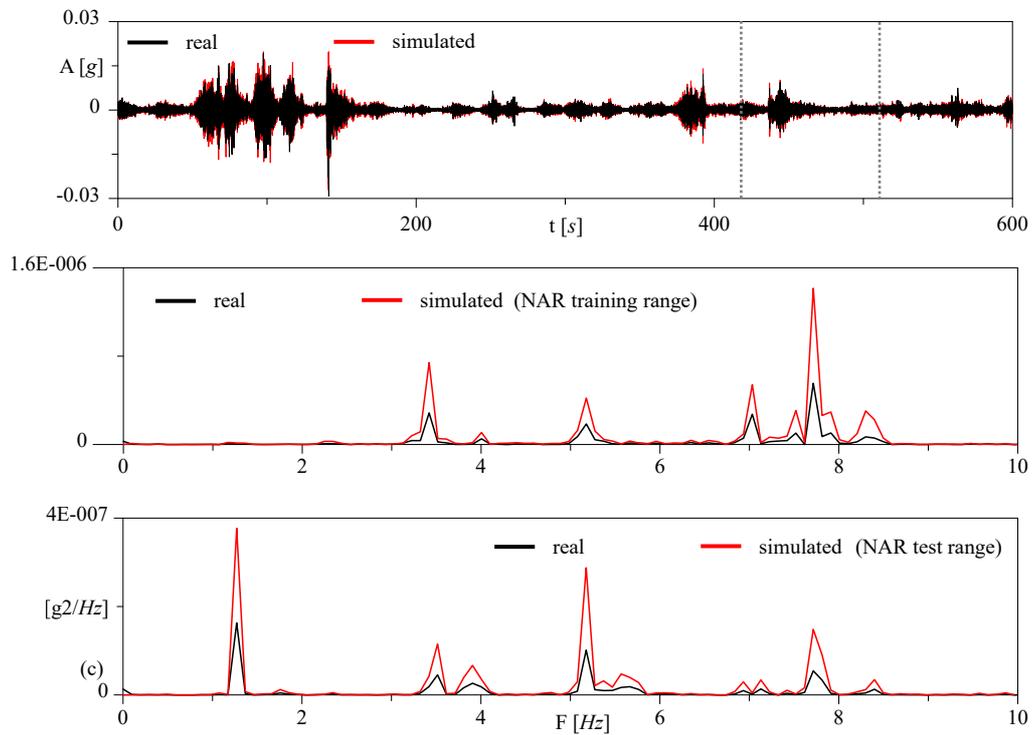
| Pylon    |         |               |            |                    |
|----------|---------|---------------|------------|--------------------|
| Location | Channel | Serial Number | Direction  | Sensitivity (mV/g) |
| Y1       | 1       | 26183         | $-\vec{X}$ | 2013               |
|          | 2       | 26189         | $-\vec{Z}$ | 2008               |
|          | 3       | 23435         | $-\vec{X}$ | 2000               |
| Y2       | 4       | 26194         | $\vec{Z}$  | 2013               |
|          | 5       | 26191         | $-\vec{X}$ | 2010               |
|          | 6       | 26185         | $-\vec{X}$ | 2008               |
| Y3       | 7       | 26186         | $\vec{Z}$  | 2008               |
|          | 8       | 26195         | $\vec{X}$  | 2009               |

206 A global schematic view of the monitoring system and its connection to a cloud database solution is presented  
207 in Figure 4. As shown, the fully system is connected to a cloud database through a 3G/UMTS modem. Due to  
208 few bandwidth limitations induced by some communication components of the first monitoring system  
209 solution, only data issued from accelerometers were feeding the database. All accelerometers were integrated  
210 in a designed cube accessory connected to the structure.

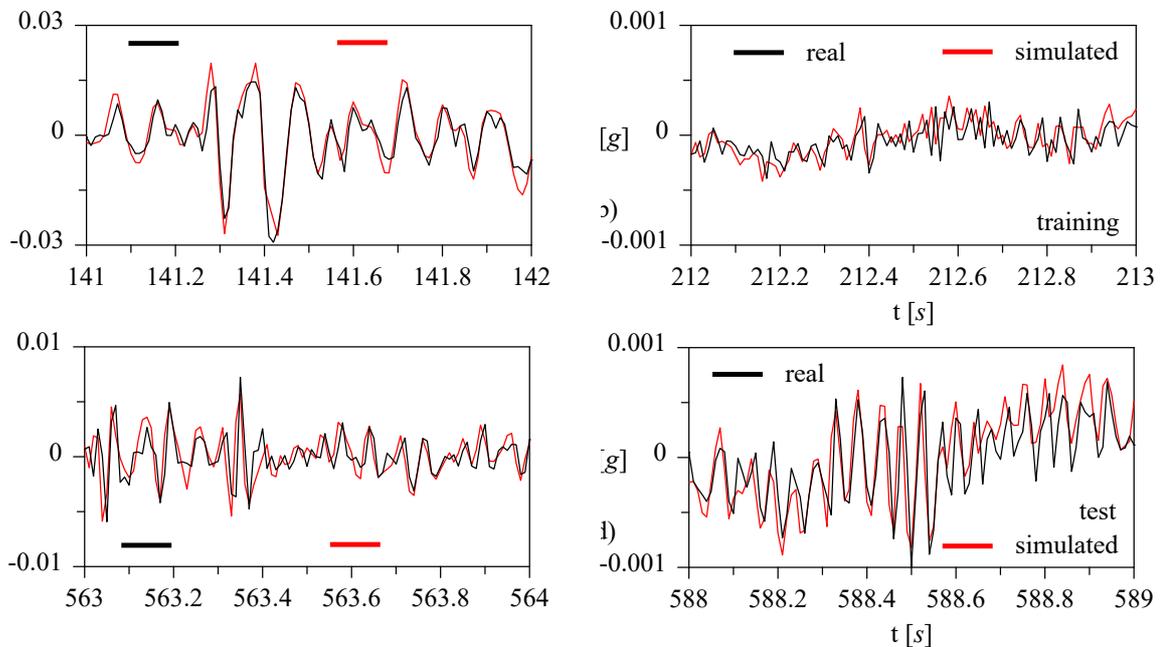
## 211 **4 Application of the NAR algorithm to the monitored data**

212 In this study, a NAR network model is employed to predict the dynamic response of a cable-stayed bridge  
213 induced by ambient vibration through the measurements recorded by the SHM system previously described.  
214 The data-driven processing has been carried out through the Neural Network Time Series, that is a specific  
215 tool implemented in MATLAB. The accelerations elaborated by the algorithm were recorded on [July 17, 2017,](#)  
216 [at 11:00 a.m.](#) The registration has a total length of almost ten minutes, and it is composed of 59991 samples  
217 since the rate was 100 Hz. A first simulation has been performed by selecting different parameters: the training  
218 function “*trainlm*” that updates weight and bias values according to Levenberg-Marquardt optimization  
219 (among the fastest ones), and the network parameters (number of *hidden layers* and *time delay*) [38, 41].  
220 Furthermore, the neural network modeling approach requires the determination of the percentages proportion  
221 of the data which are divided into a training dataset, validation dataset, and a test dataset. More specifically,  
222 the properties of the neural network are the following: (a) a Levenberg-Marquardt backpropagation algorithm,  
223 (b) the hidden layers were equal to 10, (c) the selected number of delays was equivalent to 10, (d) the network  
224 training set ratio was equal to 70%, the validation set was equal to 15%, and the network test ratio was  
225 equivalent to 15%. The neural network’s performance results are presented in Figure 5 in terms of real (black  
226 line) and simulated (red line) acceleration time series related to location X2 (Deck) and channel 3 (Y-  
227 direction). Results show that the simulated time series is slightly higher than the real time series, resulting in  
228 a good match between them. Furthermore, a comparison between frequencies has been performed in the  
229 training dataset (the first 70% of the recorded samples) and test dataset (the last 15%) (see Figure 5b and  
230 *Figure 5c*). From the figures we observe a good agreement of the frequencies and higher amplitudes between  
231 the experimental and the simulated results by the network (red line). Figure 6 depicts different zoom (ranging

232 1 second) of the analyzed results. The ranges have been selected in areas with relatively high and small  
 233 amplitudes. Results show a better agreement for the higher amplitudes (see Figure 6a, and Figure 6c).



234  
 235 Figure 5. Time (a) and frequency (b, c) comparison between recorded and simulated acceleration trained by NAR algorithm. Training  
 236 (70%), validation (15%), test (15%). Hidden layers:10 and time delay:10



237  
 238 Figure 6. Zoom of the comparison reported in Figure 5: range of relatively high (a, c) and low (b, d) amplitudes.  
 239 A parametric analysis has been conducted by changing the *hidden layers* and *time delay* network parameters.  
 240 Specifically, the hidden layers have been set to 10 and 20, while for the time delay, six different values have

241 been chosen (i.e., 10, 20, 50, 100, 1000, and 2000). Results, listed in Table 3 and Table 4, have been compared  
 242 in terms of Standard Deviation (Std), Root-Mean-Squared-Error (RMSE), and Coefficient of Determination  
 243 (R-squared,  $R^2$ ). From the results, it can be claimed that Std show a low variability when *hidden layers* and  
 244 *time delays* are equal to 10 and to 1000 and 2000, respectively. RMSE and  $R^2$  are substantially the same in all  
 245 cases. However, it is right to highlight that while the simulations for the *time delays* 10, 20, 50 and 100 the  
 246 computation time is up to few minutes, for *time delays* 1000 and 2000 the computation time is over ten hours.

247 **Table 3. Performance of the ANN algorithm: hidden layers 10.**

| Time delay [sample] | StD real [g] | StD simulated [g] | StD Difference (%) | RMSE    | $R^2$ |
|---------------------|--------------|-------------------|--------------------|---------|-------|
| 10                  | 0.00092      | 0.00081           | 13.58              | 0.00060 | 0.57  |
| 20                  | 0.00092      | 0.00084           | 9.52               | 0.00061 | 0.56  |
| 50                  | 0.00092      | 0.00083           | 10.84              | 0.00060 | 0.57  |
| 100                 | 0.00092      | 0.00086           | 6.98               | 0.00059 | 0.59  |
| 1000                | 0.00092      | 0.00087           | 5.75               | 0.00060 | 0.58  |
| 2000                | 0.00092      | 0.00087           | 5.75               | 0.00061 | 0.56  |

248

249 **Table 4. Performance of the ANN algorithm: hidden layers 20.**

| Time delay [sample] | StD real [g] | StD simulated [g] | StD Difference (%) | RMSE    | $R^2$ |
|---------------------|--------------|-------------------|--------------------|---------|-------|
| 10                  | 0.00092      | 0.00083           | 10.84              | 0.00061 | 0.56  |
| 20                  | 0.00092      | 0.00083           | 10.84              | 0.00061 | 0.56  |
| 50                  | 0.00092      | 0.00084           | 9.52               | 0.00060 | 0.57  |
| 100                 | 0.00092      | 0.00086           | 6.98               | 0.00059 | 0.59  |
| 1000                | 0.00092      | 0.00084           | 9.52               | 0.00059 | 0.60  |
| 2000                | 0.00092      | 0.00086           | 6.98               | 0.00060 | 0.58  |

250

## 251 **Conclusions**

252 Recently, artificial neural networks have been implemented in time series forecasting applications due to their  
 253 nonlinear modeling capability. In this context, the chapter aims at evaluating the performance of an ANN in  
 254 the prediction of the dynamic response of a cable-stayed bridge induced by ambient vibration. The proposed  
 255 network was formulated to be capable of efficiently predicting relevant dynamic responses associated with the  
 256 bridge. Accelerations recorded by a SHM system installed in the Tabarly bridge (Nantes, France) has been  
 257 used as case study. Such measurements have been processed by a script generated by the Neural Time Series  
 258 tool included in the toolbox of MATLAB. The Levenberg-Marquardt solution algorithm was preferred as it is

259 found to attain faster convergence without compromising the quality of the final network. After the training of  
260 NAR, MATLAB software can predict future value of one-time step ahead. The results, even if not completely  
261 satisfactory (for example the maximum value achieved of  $R^2$  is equal to 0.60), are promising and with margins  
262 of improvement. Indeed, they could be useful as an adjunct tool to detect the trigger of possible anomalies  
263 related to the structural health.

264 Future attempts, including different variables to address missing parameters, such as temperature, that explain  
265 the predicted error, would likely attain a higher degree of accuracy. Finally, Deep Learning models for time  
266 series forecasting could be applied to improve the results.

267

268 **Acknowledgments:** The research leading to these results has received funding by project DESDEMONA -  
269 *DEtection of Steel Defects by Enhanced MONitoring and Automated procedure for self-inspection and*  
270 *maintenance* (grant agreement number RFCS-2018\_800687) supported by EU Call RFCS-2017.

271

272

273

274

275

276

277

278

279

280

281

282

- 284 [1] Lee, J. J., and Shinozuka, M., *A vision-based system for remote sensing of bridge displacement*. Ndt  
285 & E International, 2006. **39**(5): p. 425-431.
- 286 [2] Lee, J. J., Cho, S., Shinozuka, M., Yun, C.-B., Lee, C.-G., and Lee, W.-T., *Evaluation of bridge load*  
287 *carrying capacity based on dynamic displacement measurement using real-time image processing*  
288 *techniques*. Steel Struct, 2006. **6**: p. 377-385.
- 289 [3] Ribeiro, D., Calçada, R., Ferreira, J., and Martins, T., *Non-contact measurement of the dynamic*  
290 *displacement of railway bridges using an advanced video-based system*. Engineering Structures, 2014.  
291 **75**: p. 164-180.
- 292 [4] Yu, J., Zhu, P., Xu, B., and Meng, X., *Experimental assessment of high sampling-rate robotic total*  
293 *station for monitoring bridge dynamic responses*. Measurement, 2017. **104**: p. 60-69.
- 294 [5] Gattulli, V., Cunha, A., Caetano, E., Potenza, F., Arena, A., and Di Sabatino, U., *Dynamical models*  
295 *of a suspension bridge driven by vibration data*. Smart Structures and Systems, An International  
296 Journal, 2021. **27**(2): p. 139-156.
- 297 [6] Gattulli, V., Potenza, F., and Piccirillo, G., *Multiple Tests for Dynamic Identification of a Reinforced*  
298 *Concrete Multi-Span Arch Bridge*. Buildings, 2022. **12**(6): p. 833.
- 299 [7] Domaneschi, M., Cimellaro, G., De Iuliis, M., and Marano, G., *Laboratory investigation of digital*  
300 *image correlation techniques for structural assessment*, in *Bridge Maintenance, Safety, Management,*  
301 *Life-Cycle Sustainability and Innovations*. 2021, CRC Press. p. 3260-3266.
- 302 [8] Magalhães, F., Cunha, A., and Caetano, E. *Continuous dynamic monitoring of an arch bridge: strategy*  
303 *to eliminate the environmental and operational effects and detect damages*. in *Proc. 24th International*  
304 *Conference on Noise and Vibration Engineering (ISMA2010), Leuven, Belgium*. 2010.
- 305 [9] Lee, L. S., Karbhari, V. M., and Sikorsky, C., *Structural health monitoring of CFRP strengthened*  
306 *bridge decks using ambient vibrations*. Structural Health Monitoring, 2007. **6**(3): p. 199-214.
- 307 [10] Dutta, A., and Talukdar, S., *Damage detection in bridges using accurate modal parameters*. Finite  
308 Elements in Analysis and Design, 2004. **40**(3): p. 287-304.
- 309 [11] Liu, C., DeWolf, J. T., and Kim, J.-H., *Development of a baseline for structural health monitoring for*  
310 *a curved post-tensioned concrete box-girder bridge*. Engineering Structures, 2009. **31**(12): p. 3107-  
311 3115.
- 312 [12] Orcesi, A. D., and Frangopol, D. M., *Inclusion of crawl tests and long-term health monitoring in*  
313 *bridge serviceability analysis*. Journal of Bridge Engineering, 2010. **15**(3): p. 312-326.
- 314 [13] Phares, B. M., Wipf, T. J., Klaiber, F., and Abu-Hawash, A. *Bridge load rating using physical testing*.  
315 in *Proceedings of the 2003 Mid-Continent Transportation Research Symposium, Iowa State*  
316 *University*. 2003.
- 317 [14] Gattulli, V., Lepidi, M., Potenza, F., and Di Sabatino, U., *Modal interactions in the nonlinear*  
318 *dynamics of a beam-cable-beam*. Nonlinear dynamics, 2019. **96**(4): p. 2547-2566.
- 319 [15] Gattulli, V., Lepidi, M., Potenza, F., and Di Sabatino, U., *Dynamics of masonry walls connected by a*  
320 *vibrating cable in a historic structure*. Meccanica, 2016. **51**(11): p. 2813-2826.
- 321 [16] Gattulli, V., Franchi, F., Graziosi, F., Marotta, A., Rinaldi, C., Potenza, F., and Sabatino, U. D., *Design*  
322 *and evaluation of 5G-based architecture supporting data-driven digital twins updating and matching*  
323 *in seismic monitoring*. Bulletin of Earthquake Engineering, 2022: p. 1-21.
- 324 [17] Zhao, R., Yan, R., Chen, Z., Mao, K., Wang, P., and Gao, R. X., *Deep learning and its applications*  
325 *to machine health monitoring*. Mechanical Systems and Signal Processing, 2019. **115**: p. 213-237.
- 326 [18] Di Girolamo, G. D., Smarra, F., Gattulli, V., Potenza, F., Graziosi, F., and D'Innocenzo, A., *Data-*  
327 *driven optimal predictive control of seismic induced vibrations in frame structures*. Structural Control  
328 and Health Monitoring, 2020. **27**(4): p. e2514.
- 329 [19] Kromanis, R., and Kripakaran, P., *Data-driven approaches for measurement interpretation: analysing*  
330 *integrated thermal and vehicular response in bridge structural health monitoring*. Advanced  
331 Engineering Informatics, 2017. **34**: p. 46-59.
- 332 [20] Park, H. S., An, J. H., Park, Y. J., and Oh, B. K., *Convolutional neural network-based safety evaluation*  
333 *method for structures with dynamic responses*. Expert Systems with Applications, 2020. **158**: p.  
334 113634.
- 335 [21] Barai, S., and Pandey, P., *Vibration signature analysis using artificial neural networks*. Journal of  
336 computing in civil engineering, 1995. **9**(4): p. 259-265.

- 337 [22] Chang, C., Chang, T., and Xu, Y., *Adaptive neural networks for model updating of structures*. Smart  
338 materials and structures, 2000. **9**(1): p. 59.
- 339 [23] Fang, X., Luo, H., and Tang, J., *Structural damage detection using neural network with learning rate*  
340 *improvement*. Computers & structures, 2005. **83**(25-26): p. 2150-2161.
- 341 [24] Bakhary, N., Hao, H., and Deeks, A. J., *Damage detection using artificial neural network with*  
342 *consideration of uncertainties*. Engineering Structures, 2007. **29**(11): p. 2806-2815.
- 343 [25] Li, H., Wang, T., and Wu, G. *Dynamic response prediction of vehicle-bridge interaction system using*  
344 *feedforward neural network and deep long short-term memory network*. in *Structures*. 2021. Elsevier.
- 345 [26] de Oliveira Dias Prudente dos Santos, J. P., Crémone, C., da Silveira, A. P. C., and de Oliveira Martins,  
346 L. C., *Real-time damage detection based on pattern recognition*. Structural Concrete, 2016. **17**(3): p.  
347 338-354.
- 348 [27] Yun-Lai, Z., and Wahab, M. A., *Damage detection using vibration data and dynamic transmissibility*  
349 *ensemble with auto-associative neural network*. Mechanics, 2017. **23**(5): p. 688-695.
- 350 [28] Maity, D., and Saha, A., *Damage assessment in structure from changes in static parameter using*  
351 *neural networks*. Sadhana, 2004. **29**(3): p. 315-327.
- 352 [29] Cascardi, A., Micelli, F., and Aiello, M. A., *An Artificial Neural Networks model for the prediction of*  
353 *the compressive strength of FRP-confined concrete circular columns*. Engineering Structures, 2017.  
354 **140**: p. 199-208.
- 355 [30] Wang, C., Ansari, F., Wu, B., Li, S., Morgese, M., and Zhou, J., *LSTM approach for condition*  
356 *assessment of suspension bridges based on time-series deflection and temperature data*. Advances in  
357 Structural Engineering, 2022: p. 13694332221133604.
- 358 [31] Haykin, S., and Lippmann, R., *Neural networks, a comprehensive foundation*. International journal of  
359 neural systems, 1994. **5**(4): p. 363-364.
- 360 [32] Ji, W., and Chee, K. C., *Prediction of hourly solar radiation using a novel hybrid model of ARMA and*  
361 *TDNN*. Solar Energy, 2011. **85**(5): p. 808-817.
- 362 [33] Markham, I. S., and Rakes, T. R., *The effect of sample size and variability of data on the comparative*  
363 *performance of artificial neural networks and regression*. Computers & operations research, 1998.  
364 **25**(4): p. 251-263.
- 365 [34] Chow, T., and Leung, C.-T., *Nonlinear autoregressive integrated neural network model for short-term*  
366 *load forecasting*. IEE Proceedings-Generation, Transmission and Distribution, 1996. **143**(5): p. 500-  
367 506.
- 368 [35] Benmouiza, K., and Cheknane, A., *Small-scale solar radiation forecasting using ARMA and nonlinear*  
369 *autoregressive neural network models*. Theoretical and Applied Climatology, 2016. **124**(3): p. 945-  
370 958.
- 371 [36] Bal, C., and Demir, S., *JMASM 55: MATLAB Algorithms and Source Codes of cbnet'Function for*  
372 *Univariate Time Series Modeling with Neural Networks (MATLAB)*. Journal of Modern Applied  
373 Statistical Methods, 2021. **19**(1): p. 19.
- 374 [37] Hasançebi, O., and Dumlupınar, T., *Linear and nonlinear model updating of reinforced concrete T-*  
375 *beam bridges using artificial neural networks*. Computers & Structures, 2013. **119**: p. 1-11.
- 376 [38] Yu, H., and Wilamowski, B. M., *Levenberg-marquardt training*. Industrial electronics handbook,  
377 2011. **5**(12): p. 1.
- 378 [39] Nguyen, D., and Widrow, B. *Improving the learning speed of 2-layer neural networks by choosing*  
379 *initial values of the adaptive weights*. in *1990 IJCNN international joint conference on neural*  
380 *networks*. 1990. IEEE.
- 381 [40] Pavelka, A., and Procházka, A. *Algorithms for initialization of neural network weights*. in *In*  
382 *Proceedings of the 12th annual conference, MATLAB*. 2004.
- 383 [41] Marquardt, D. W., *An algorithm for least-squares estimation of nonlinear parameters*. Journal of the  
384 society for Industrial and Applied Mathematics, 1963. **11**(2): p. 431-441.
- 385 [42] Rafiq, M., Bugmann, G., and Easterbrook, D., *Neural network design for engineering applications*.  
386 Computers & Structures, 2001. **79**(17): p. 1541-1552.
- 387 [43] Maier, H. R., and Dandy, G. C., *Neural networks for the prediction and forecasting of water resources*  
388 *variables: a review of modelling issues and applications*. Environmental modelling & software, 2000.  
389 **15**(1): p. 101-124.
- 390 [44] Hagan, M. T., Demuth, H. B., and Beale, M., *Neural network design*. 1997: PWS Publishing Co.
- 391 [45] Feng, N., Wang, F., and Qiu, Y., *Novel approach for promoting the generalization ability of neural*  
392 *networks*. International Journal of Signal Processing, 2006. **2**(2).

- 393 [46] Tang, C.-W., Chen, H.-J., and Yen, T., *Modeling confinement efficiency of reinforced concrete*  
394 *columns with rectilinear transverse steel using artificial neural networks*. *Journal of Structural*  
395 *Engineering*, 2003. **129**(6): p. 775-783.
- 396 [47] Yun, C.-B., and Bahng, E. Y., *Substructural identification using neural networks*. *Computers &*  
397 *Structures*, 2000. **77**(1): p. 41-52.
- 398 [48] Denton, J. W., *How good are neural networks for causal forecasting?* *The Journal of Business*  
399 *Forecasting*, 1995. **14**(2): p. 17.
- 400 [49] Zhang, G. P., *Time series forecasting using a hybrid ARIMA and neural network model*.  
401 *Neurocomputing*, 2003. **50**: p. 159-175.

402