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Improving the effectiveness of anomaly detection in bridges through a deep learning method based on the coherence of signals

Bono F. M.[a], Radicioni L.[a], Benedetti L.[a], Cazzulani G.[a], Meregalli S.[a], Cinquemani S.[a], and Belloli M.[a]

[a]Politecnico di Milano, Milano, Italy

ABSTRACT

In recent years, real-time monitoring of health conditions for massive structures, such as bridges and buildings, has grown in interest. Some of the key factors are the possibility to estimate continuously the health condition, as well as a reduction in the personnel involved in visual inspections and operative costs. However, while dealing with such structures, it is extremely rare to observe anomaly conditions, and when those are met is in general too late. Consequently, the structural health monitoring problem must be tackled as an unsupervised one. The idea exploited in this research is to transform the intrinsically unsupervised problem into a supervised one. Considering a structure equipped with N sensors, which measure static or quasi-static quantities (distance, inclinations, temperatures, etc.), it could be helpful to evaluate if the relations among sensors change over time. This involves the training of N models, each of them able to estimate the quantity measured by a sensor, by using the other N-1 measurements. In this way, an ensemble of models representing the system is built (iterative model). This approach allows us to compare the expected measurement of every sensor with the real one. The difference between the two can be addressed as a symptom of modifications in the structure with respect to the nominal condition. This approach is tested on a real case, i.e. the Candia bridge in Italy.

Keywords: Structural Health Monitoring, Bridge, Neural networks, regressions, damage identification, localisation

1. INTRODUCTION

Bridges improve accessibility, employment, travel conditions and social cohesion, contributing to overall national growth. Such structures are currently threatened by ageing, heavier traffic flow, and hazardous events. To date, the primary tool for this purpose is represented by visual inspections. Inherently subjective and qualitative, the validity of this practice as the only diagnostic tool is increasingly the subject of debate.[1,2] In this context, infrastructural monitoring through sensors, able to provide real-time quantitative information on the state of health of a structure, emerges as the ideal ally. The ultimate aim of this process - called Structural Health Monitoring - is the provision of information to the infrastructure managers to support them in the decision-making process. First and foremost, such a system has to perform damage identification. This problem can be framed as a hierarchical structure, organised according to the following levels:

- Detection: the method gives a qualitative indication that damage might be present in the structure.
- Localisation: the method gives information about the probable position of the damage.
- Classification: the method gives information about the type of damage
- Assessment: the method gives an estimate of the extent of the damage
- Prediction: the method provides information about the safety of the structure

Further author information: Francesco Morgan Bono: E-mail: francescomorgan.bono@polimi.it

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While many studies successfully address the issue of damage detection, dealing with the localisation problem is way more complicated. However, information about the position of possible damage is extremely valuable since it provides the infrastructure managers with an indication regarding the area where to intervene. This work contributes to this topic by proposing a methodology for damage localisation based on artificial neural networks (ANNs). In particular, an iterative algorithm is designed and trained, which recognizes possible anomalous measurements coming from one of the sensors by exploiting the signals provided by the other nodes of the monitoring system. This algorithm relies on the idea of creating N (being N the number of sensors) relationships between the different sensors, where the response of a single sensor is estimated by taking as input the other N-1 sensors. The technique is tested on a real case study, the Candia bridge. Part of a recent collaboration between Politecnico di Milano and Regione Lombardia, it has been endowed with a permanent monitoring system which included tiltmeters on the piers.[3] The Candia bridge is a historical multi-span masonry arch bridge built in the 19$^{\text{th}}$ century over the Sesia river, northern Italy. The popularity of this structural archetype in the Italian context[4] increases the value of this research, whose findings could help improve the maintenance and safety of a consistent portion of the national infrastructural heritage. Moreover, this kind of bridge is among the most sensitive ones to climate change. It is in fact widely recognised in the literature that the main threat of collapse for these structures is represented by flood-induced scour action exerted by the river on the piers.[5] Unfortunately, direct methods for scour monitoring, based on underwater equipment, are expensive. Being able to evaluate structural safety by exploiting cheaper sensors (i.e. tiltmeters installed on the piers), the herein-presented technique provides a valuable contribution to scientific knowledge on the subject.

2. EXPERIMENTAL SET UP

The monitoring system installed on the Candia bridge acquires continuous data and it can be divided into two parts: structural and hydraulic. The first records the transversal rotation of the piers through MEMS tiltmeters and the environmental factors (like temperature and humidity). The second foresees the acquisition of the river level through a hydrometer, the quantification of the detritus stacks at the pier base through cameras, and the measurement, during the overflow event, of the variation in the river bed level through an echo sounder. The aims of the sensors network are:

- Check in real-time (during the overflow event) the variations in the transversal rotation of the piers due to the scouring action on the foundation and detect (in the long period) eventually irreversible rotations.
- Control the hydro-metric level, as an indicator of the hydraulic events.
- Supervise the stack of rubble at the upriver side of the bridge with the target of the (i) document and characterize the annual process of plant transportation, (ii) identify the need for maintenance, (iii) highlight the critical stack during the overflow event signed by the hydrometer.
- Monitor in real-time, during the overflow event, the level of the river bed as an indicator of the erosion of bridge foundations.

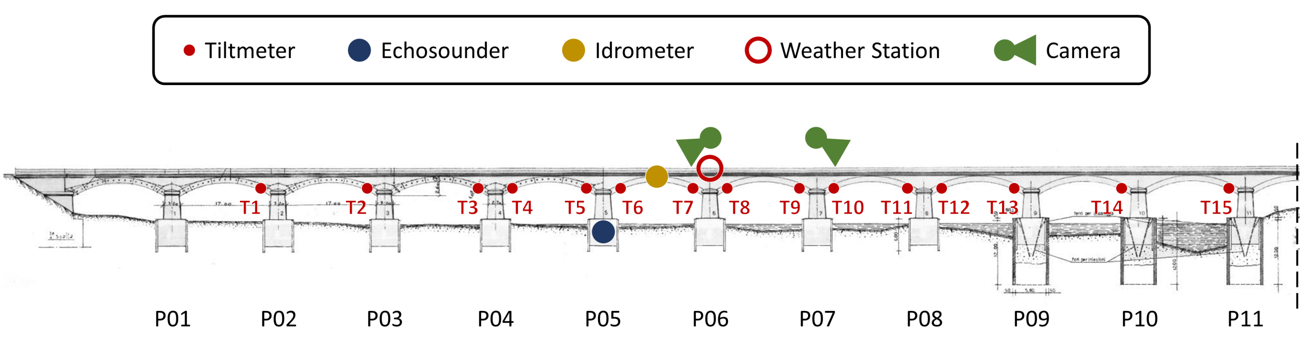

Figure 1. Candia Bridge - Monitoring System

Figure 1 shows the continuous monitoring system (quasi-static) installed on the Candia bridge, composed of (i) fifteen MEMS tiltmeters, (ii) a weather station, (iii) a hydrometer, (iv) an echosounder and (v) two cameras. The tiltmeters are placed on the arches skewback and they measure the transversal rotation of the pier, positive if upriver. These sensors are located only on the piers placed on the river bed. T2 and T14 also perform a temperature reading. A strengthening intervention was made on the river bed in 2003, it is noticed that the piers located in correspondence with the working site are more subjected to the scouring action. On these pxxiers are installed two tiltmeters, placed on the arch skewback converging on the pier, to better describe this phenomenon.

2.1 Dataset acquisition

The dataset available for this research consists of the measurements acquired from all the sensors summarised in table 1. The temperatures in correspondence of channels 23 and 24 are extracted from tiltmeters 2 and 14. Temperatures in channels 26 and 27 refer instead to the internal and external temperatures measured by the weather station. The acquisition time spans from December 2020 to December 2021. All the signals have been acquired with a frequency of 1 Hz. To make the models more robust against random noise and reduce the storage space, data have been averaged on an hourly basis - so that every channel counts one value per hour.

3. STATIC MONITORING THROUGH ONE-INPUT REGRESSIVE MODELS

The study of the static SHM can be implemented as an analysis of the deviations of a quantity, called *damage index* or *feature*, with respect to a nominal condition representing a health status. In this case, the damage index is the modulus of the residual error between a measured quantity and the output of a regressive model. This regressive model is meant to estimate the measured quantity using as input another sensor of the network. In this section, the regressive model is developed with a *linear* or *elliptical* fitting, and its input is an environmental variable (such as temperatures) or a sensor's reading acquired at the same time instant of the quantity to be estimated (static model). It is assumed and observed that these quantities vary in a bounded interval and once a sufficiently high database is available it is possible to set a threshold that defines a domain in which these quantities vary. In this way, if the future data will fall inside these intervals, the structure can be classified as healthy. On the contrary, an alarm is sent if the data fall outside that interval.

The long-term monitoring of the Candia bridge is carried out by evaluating the quasi-static quantities acquired by the sensor networks, i.e. the rotation of the structure read by the MEMS inclinometers. In particular, the variations of these measures are analyzed with respect to the first data available by the system, called *installation offset*: the data of the first two weeks are analyzed to detect a stable period, and their mean value is calculated and it will be subtracted to all the new measurements. This preliminary step is useful to verify the correctness of the mounting.

The next step is to find the correlations between the quasi-static sensors themselves and the environmental variables to check if it is possible to build an input base model: the target is to foresee one signal trend using the time history of another one. The results of this phase give information to develop a regressive model to describe

Channels	**Sensors**	**measurement unit**
1-15	Tiltmeters	rad
16	Hydrometer	m
23,24	Temperatures	$\circ$C
25	Atmospheric pressure	bar
26,27	Temperatures	$\circ$C
28,29	Humidity	%
30	Wind speed	Km/h
31	Wind direction	$\circ$
32	Rain rate	mm/h

Table 1. Channels, sensors and measurement units of the acquisition system mounted on Candia bridge

the bridge behaviour. This kind of strategy was adopted among others by Wang et Al.[6] on signals coming from strain gauges installed on a bridge. In that paper, multivariate linear regression was introduced to model the system alongside principal component analysis.

The characterization of the model is divided into two parts: training and testing. During the first, the coefficients of the regression fitting are calculated while, in the second, the modulus of the residual error between the simulated and real measurement is derived to define the threshold for the damage identification. These two phases require data from at least one year of acquisition to correctly consider the variations of the operational and environmental conditions. The approach used to build this regressive model is a type of unsupervised learning: this means that, during the training and test phase, the data come from an undamaged structure. The model validation is performed through the false positive (FPD) and negative (FND) damage tests: the first fed into the model data from the healthy structure. In contrast, the second simulates dummy damages to check if the developed model is able to correctly classify them through the comparison with the damage threshold defined in the test phase, as done by Fugate et al.[7] The correlation between the acquired signals is evaluated with the Pearson's coefficient (1) using a data set of measures from Candia bridge that covers from January 2021 to September 2021.

$$\rho(A,B) = \frac{1}{N-1}\sum_{k=1}^{N}\left(\frac{A_i-\mu_A}{\sigma_A}\right)\left(\frac{B_i-\mu_B}{\sigma_B}\right) = \frac{cov(A,B)}{\sigma_A\sigma_B} \tag{1}$$

Due to a malfunction of the weather station starting in October 2021, the external temperature is considered equal to the one read by sensor T2 for the next months. Pearson's coefficient shows that the majority of the tiltmeters have a high correlation with respect to the temperature while the other environmental quantities seem to have an independent behaviour. The correlation among the tiltmeters themselves is used to see if it is possible to relate their trend with their position on the bridge, table 2 resumes the clusters defined by Pearson's coefficient higher than 0.75. The sensors mounted on the right springer of not consecutive arches are contained in cluster C1, C3 has the tiltmeters on pier P05 while sensors T9 and T11 behave in an independent way with respect to all the others. Their relationship is not perfectly linear, as it can be seen in Figure 2 and Figure 3, and it is also pointed out looking at the R^2 calculated during the building of the regressive model, table 3. But since their deviation from the regression curve is in a bounded interval they can be used for the aims of this type of monitoring model. The damage index threshold can be set by considering these data as nominal. Only when a new measure produces a residual which falls over that threshold, the measurement must be flagged as an anomaly, and then the system should deliver a warning.

The regressive model is built by using sensors that show a correlation coefficient higher than 0.75 as input variables. A linear regression, eq. 2 is applied to all the sensors and the evaluation of the regression goodness is done through the R^2 coefficient, eq 6, table 3, for R^2 lower than 0.75 an elliptical fitting, eq. 5 is tried to see if there is an enhancement of the situation: this choice can be useful to better describe the presence of hysteresis in the data trend. For one input the elliptical fitting gives two solutions, but the one with a lower distance with respect to the experimental data will be considered. The drawback of the elliptical regression is a loss in precision at the boundary of the input domain but the residual error does not increase significantly, figure 5The coefficients of the linear regression are calculated through a minimization of the least-squares, eq. 4 and 3 while the definition of the ellipse coefficients is performed following the steps contained in.[8]

$$Y_i = \beta_0 + \beta_1 X_i + r_i \tag{2}$$

Cluster	**Sensors**	**Counterphase**
C1	T1, T6, T13	C2
C2	T2, T3, T4, T7, T8, T12, T15	C1
C3	T5, T6	C2
C4	T10, T14	/

Table 2. Candia Bridge - Correlation between Inclinometers

Sensor	Input	R^2
T1	Temperature	0.61
T2	Temperature	0.88
T3	Temperature	0.86
T4	Temperature	0.91
T5	T6	0.49
T6	Temperature	0.73
T7	Temperature	0.75
T8	Temperature	0.47
T10	T14	0.75
T12	Temperature	0.92
T13	Temperature	0.56
T14	T10	0.75
T15	T6	0.74

Table 3. Candia Bridge - Linear Regression

$$\beta_1 = \frac{\sigma(x,y)}{\sigma^2(x)} \tag{3}$$

$$\beta_0 = \bar{y} - \beta_1 \bar{x} \tag{4}$$

$$\alpha_1 X_i^2 + \alpha_2 X_i Y_i + \alpha_3 Y_i^2 + \alpha_4 X_i + \alpha_5 Y_i + \alpha_6 + r_i = 0 \tag{5}$$

$$R^2 = \frac{\sum_i (\hat{y}_i - \bar{y})^2}{\sum_i (y_i - \bar{y})^2} \tag{6}$$

The data from one year of acquisition (2021) are divided into training and test subsets. To take into account their daily period trend it is decided to partition the data set in such a way that every six days, the first four are used for training and the last two for testing.

It is noticed with the R^2 that with Pearson's coefficient higher than 93% the linear fitting gives good results Although T3 has a satisfying linear fitting, it is observed as a hysteresis phenomenon, so the elliptical fitting is

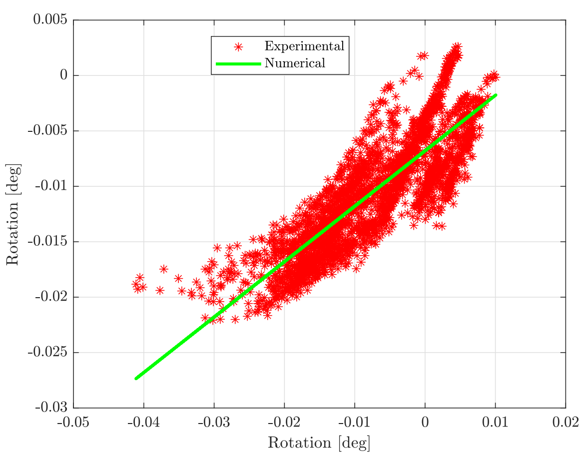

Figure 2. Candia Bridge - T10 vs. T14.

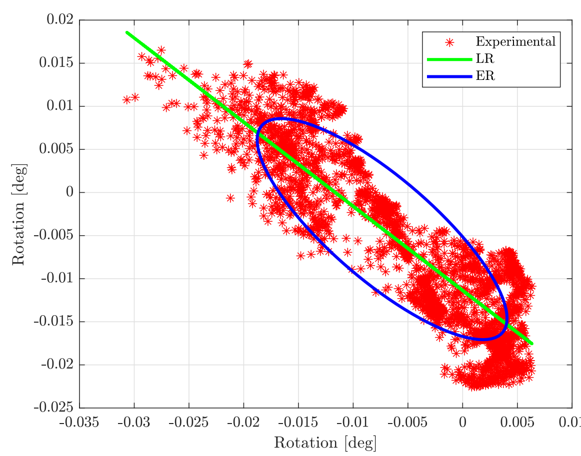

Figure 3. Candia Bridge - T6 vs. T15.

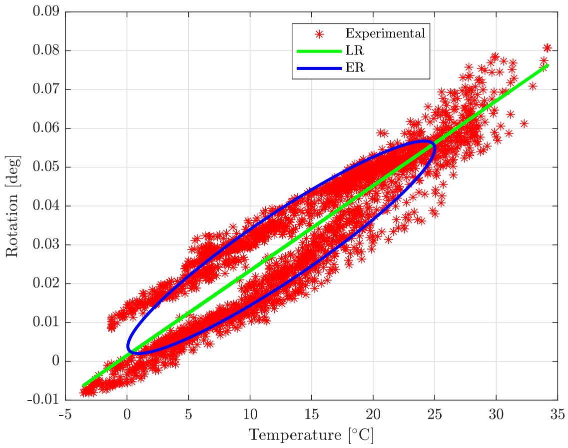

Figure 4. Candia Bridge - T3 Experimental vs. Numerical

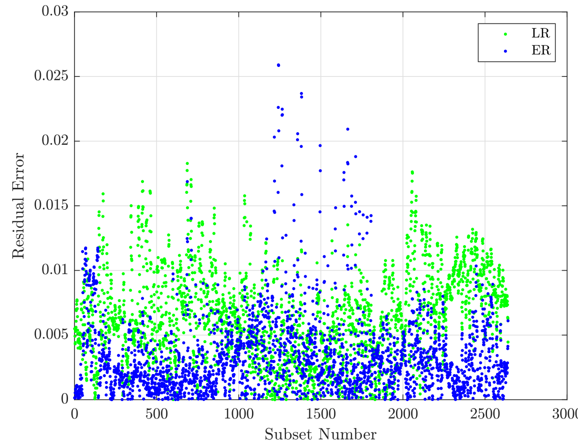

Figure 5. Candia Bridge - T3 Test Residual Error

also tried (Figure 4 - 5) The elliptical fitting is used also for the sensor T9 which seems to be uncorrelated with respect to all other variables, while T11 seems to have a random trend during the year, both strategies are not able to describe it.

After the choice of the regression type through the R^2 the test data set is used for the calculation of the damage index, the modulus of the residual error between a measured quantity and the output of a regressive model that wants to estimate it using another sensor of the network as an input. The identification of damages requires the definition of a threshold that in this case is set making the hypothesis of a normal distribution of the residual error from the test phase with a confidence interval of 95%. During this phase there will be some outliers: it can be noticed that they are concentrated in the middle and at the end of the subset number, which corresponds to the period of the year in which there are highest and lowest temperatures. Figure 6 shows the application of linear regression, while figure 8 the elliptical one. In the residual error plot, e.g. Figure 7, the x-axis is called Subset Number and it represents the mean of one hour of the time history.

4. MULTI-INPUT MACHINE LEARNING MODELLING

Although simple models such as the ones described in section 3 are easy to interpret and give a sufficiently accurate description of bridge physics, they have some intrinsic limits. For instance, the number of inputs that

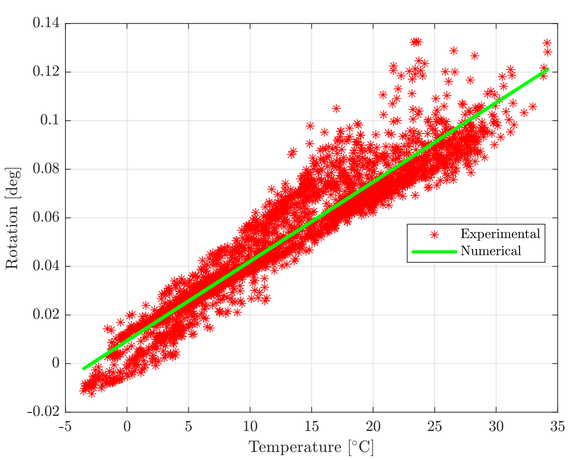

Figure 6. Candia Bridge - T4 Experimental vs. Numerical

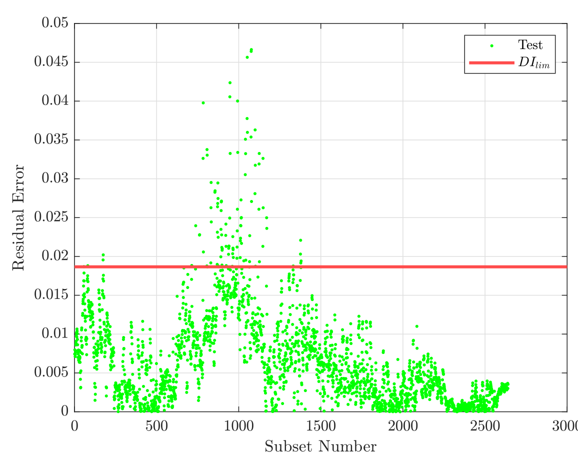

Figure 7. Candia Bridge - T4 Test Residual Error

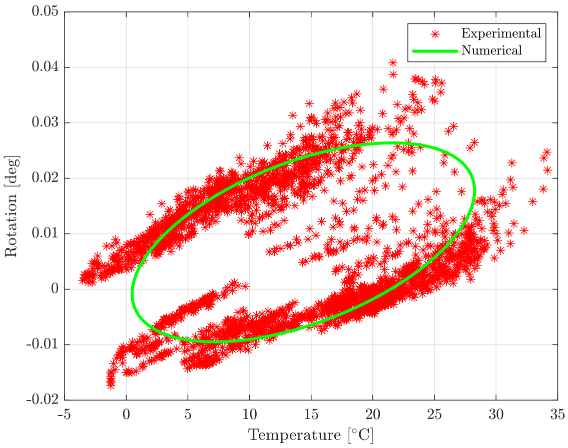

Figure 8. Candia Bridge - T9 Experimental vs. Numerical

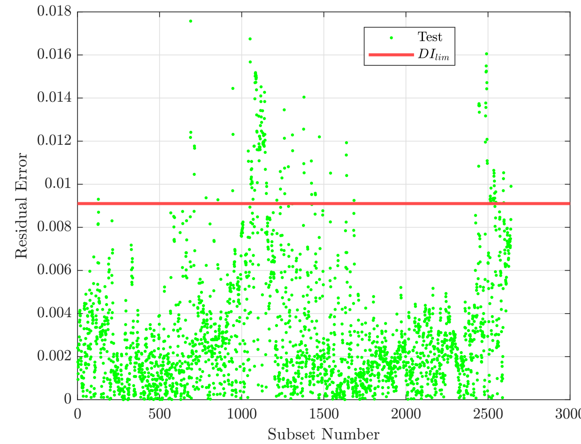

Figure 9. Candia Bridge - T9 Test Residual Error

can be introduced while keeping a representation of the laws understandable for humans is usually no more than two, so that the model can be represented in a 3D space. Besides, linear models are characterized by a limited number of parameters, having then an inadequate capability to represent the behaviour of complex systems. It can consequently be beneficial to model the system by contemplating *more inputs* and models characterized by *more parameters*. A fully *data-driven* modelling of the system is then suitable for this purpose. The problem of structural health monitoring with an *unsupervised* dataset is commonly regarded as *novelty detection* or *anomaly detection*.[9] The logic is to use the *training data* to establish the *nominal condition* of the structure. The monitoring system must be then able to identify whichever modification in the system. Before fitting whichever model into the dataset, a *baseline* must be defined, that is, the portion of the dataset corresponding to periods where the structure is regarded as healthy. Therefore, the baseline coincides with the training set for the model. In practice, given a time-series matrix $X \in \mathbb{R}^{n\times m}$, made of n measurements for m time "snapshots":

$$X = [x_1, x_2, \cdots, x_m] \tag{7}$$

and defining the training set finally consists in selecting the proper $k < m$ so that:

$$X_{\text{train}} = [x_1, x_2, \cdots, x_k] \tag{8}$$

4.1 Iterative models

The dataset collected from a structure is most of the time unsupervised, namely a dataset with no specific labels (numerical or categorical) associated with the dataset objects. Most of the unsupervised approaches rely on the detection of the dataset modifications. However, in this way, the monitoring system is only able to identify whether something has changed, without actually *localizing* where the modification took place.[10] A possible approach to overcome these limitations could be to turn the unsupervised problem into a *supervised* one. For example, some health monitoring algorithms are based on the use of environmental variables (such as temperatures) as input of a regressor, which must estimate the features extracted from the sensors. This allows the normalization of the signals with respect to the environmental effects, before applying an anomaly detection algorithm usually based on statistics.[11,12] If the physical variables measured are *static*, which means they measure low-frequency variations only, this procedure can be applied directly to the sensors' readings, without any particular feature extraction.

Amid possible machine learning methods for regression, *neural networks* are among the most flexible ones. The layers of neural networks can be selected and adjusted to take in input and output tensors of whichever size. It is then possible to divide the sensors mounted on the structure into groups, according to the type of physical quantity they measure (tiltmeter, strain gauges, thermometers...) or their location (1^{st} span of the bridge, 2^{nd}

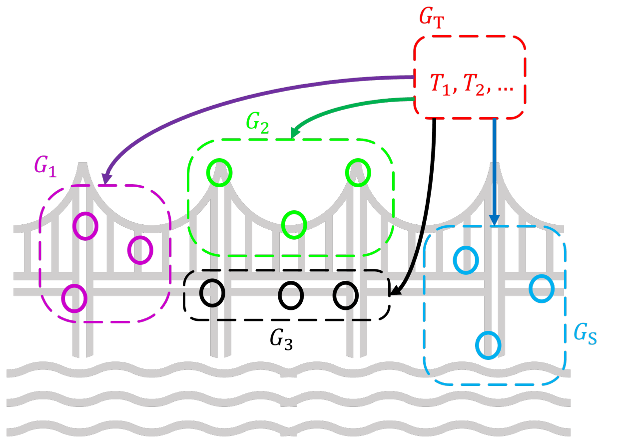

Figure 10. A model (such as a neural network) takes in input the temperature and gives an estimation of the readings of other sensors.

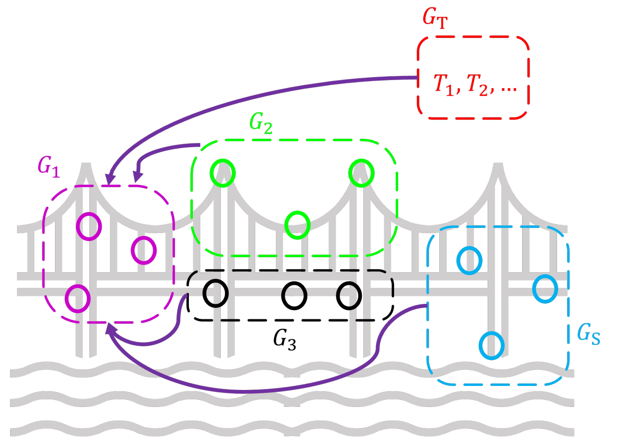

Figure 11. A model estimates the values of one group of sensors by taking in input all the other groups

span ...), and then train a neural network so that it can take one group in input to estimate the values of the sensors another group. Then, the residuals e_{ij} can be computed as:

$$e_{ij} = y_{ij} - \hat{y}_{ij} \tag{9}$$

where y_{ij} and $\hat{y}_{ij}$ refer to the measured value and the value estimated by the neural network, respectively, while the subscript i refers to the i^{th} sensor considered and j to the j^{th} timestamp. The residuals can then be used as an indicator of the structure's health condition. In this way, the *normalization of the signals with respect to the environmental effect* can just be seen as a particular case of this procedure, where the inputs of the neural network are the *temperatures* and the output a group (or more groups) of sensors, as shown in figure 10. By following this procedure, the *residuals* obtained represent all the disturbances that cannot be attributed to temperatures. However, one might also focus on one single group, and establish the effect of all the other groups of sensors (figure 11). The physical meaning of residuals is now different compared to the case where only the temperatures are used as input. Now the model takes into account the readings of sensors of different natures. Therefore, the residuals are proportional to the *level of coherence* of one group of sensors with respect to the others. By iterating the process for all groups of sensors, given G groups, every iteration consists of the training of G models, so that each of them estimates the value of one group of sensors taking into account the other $G-1$.

The logical extension of this procedure is to consider only groups made of *one single* sensor only (leave one out strategy). If N sensors are mounted on the structure, this strategy involves the training of N neural networks, so that at every iteration the neural network estimates the value of one single sensor by taking in input the other $N-1$ ones. Eventually, a *comprehensive model* made of N neural networks is associated with the structure. For simplicity, we call this "comprehensive" model *iterative model.* It is worth mentioning that the iterative model can be made of other machine learning regressive models rather than neural networks, since the output is, in this case, a single continuous variable.[13,14] By considering the set of measurements $Y_j = [y_{1j}, \cdots, y_{nj}]$ available at the j^{th} timestamp, the iterative model can synthetically be represented by the system:

$$\hat{y}_{ij} = \hat{f}_i(X_{ij}) \quad \text{for} \quad i = 1, \cdots, n \tag{10}$$

where $X_{ij} = Y_j - \{y_{ij}\}$ represents the set of values measured by all the sensors except the i^{th} one, whereas $\hat{f}_i$ is the regressor able to estimate the value of the i^{th} sensor from X_{ij}. Finally, the residuals can be computed with equation 9. In this context, the residuals represent how distant is the value measured by a sensor from the expected one, and therefore it quantifies coherence among all sensors' readings. This approach reaches level 2 in the SHM hierarchical structure, namely the localisation of damage, but also its assessment even though to a limited degree only. With this regard, it is necessary to remark on an important aspect: the application of an iterative model to a new observation Y_{new} will produce a vector of residuals: $E_{new} = [e_{1,\text{new}}, \cdots, e_{n\text{new}}]$, which must show low values in case of healthy structure. Besides, in case of damage undergoing in correspondence of the i_{th} sensor, the residual vector E_{new} is expected to feature a "spike" in the i^{th} residual $e_{i,\text{new}}$. However, since $y_{i\text{new}}$ is an input for the other sensors, an increase in the residuals will be seen in all the other elements of the vector E_{new}. Therefore, the damage identification capability is maintained as long as the residual in the i^{th} position of E_{new} grows more than the others. However, since the method is fully data-driven, is hard to define when and how this might happen.

During the monitoring phase, some statistical considerations can be carried out on the vector of residuals E, so to define the confidence level for raising warnings.
For the case study of Candia bridge, the periods from December 2020 to December 2021, except for May 2021, are used for both training and validating the neural networks of the iterative model. Then, some tests have been carried out in the month of May.

5. MODELS COMPARISON

The two approaches considered in section 3 and 4 are evaluated by means of anomalies generated "artificially" by *doping* the values of one channel per time. The test is performed on signals acquired in May which is a central month for the dataset acquired.

5.1 One-input regressive model test

Once the model is built, its validation is performed through the false positive and false negative damage (hereafter respectively called FPD and FND). In the first, data from May 2021 are used as input while in the second one the same month is edited with an amplitude modulation of $\pm 5\%$ and $\pm 20\%$ before the compensation of the mounting offset, table 4.

The results are summarised in table 5. Almost all sensors, with the exception of T4, T8, T9 and T12 have good results in the false positive test - the FPD should not be higher than 5% by definition. One reason why T8 and T9 failed this test can be the high dispersion in the measure that, although well approximated with an ellipse, can have higher residual error. T4 and T12 have a good linear regression but since May is a month of transition between hot and cold temperatures this phenomenon can generate in the inclinometer signals with a higher dispersion that is detected. The false negative test shows that the modulation of 20% brings all the sensors, except four, in the damage state while decreasing its value at 5% the number of FND increase but still, 50% of them are still identified as damage. The worst result of the false negative test is for T11, which is known as a problematic sensor due to the high dispersion of its data similar to a cloud of points in the plane, and for T2 and T12 due to the fact that the imposed modulation is not higher enough to exit the boundary of the recorded pier rotation during the measure of 2021.

5.2 Iterative model test

An iterative model is trained onto the data from Candia bridge collected from December 2020 to December 2021, except for the month of May. The sensors considered are the ones in table 1 except for pressure, humidity, wind speed, wind rate and rain rate, namely all the features that showed no correlations with the other sensors. Moreover, information regarding the month has been added and encoded as a continuous variable from 0 (January) to 11 (December). The neural networks of the iterative model count 4 layers (a dense with 210 neurons,

ID	Month	Damage
FPD	May 2021	/
FND1	May 2021	$+5\%$
FND2	May 2021	$+20\%$
FND3	May 2021	-5%
FND4	May 2021	-20%

Table 4. Candia Bridge - False Positive and False Negative Test Data

Sensor	FPD[%]	$FND1$[%]	$FND2$[%]	$FND3$[%]	$FND4$[%]
T1	2.53	53.57	0	100	0
T2	0.89	98.66	94.94	99.4	98.81
T3	0	0	0	0	0
T4	21.43	93.3	29.46	12.35	0
T5	8.63	13.84	0	6.1	0
T6	6.25	96.73	0	2.38	0
T7	5.65	9.08	0	36.01	0
T8	29.76	94.94	0	92.56	0
T9	24.7	47.17	0	55.65	0
T10	6.55	0	0	0	0
T11	6.4	95.39	97.77	91.67	83.63
T12	16.22	71.43	24.70	92.86	95.24
T13	3.13	0	0	0	0
T14	1.93	0	0	0	0
T15	0.74	0	0	1.49	0

Table 5. Candia Bridge - Model Validation

a dropout layer with a ratio of 0.1, another dense layer of 105 neurons and a single neuron in the output layer). The activation functions are all *ReLu*s, except for a *linear* one in the last layer. The metric used in training is the *mean absolute error* (MAE). Before fitting the data, all channels are separately scaled by means of z-scores, so that all their distributions show 0-mean and a standard deviation equal to 1. Analogously to what has been done in the previous section, the value of the signals in May is modified by ±5% and ±20%, one channel at a time. Finally, the residuals generated by the iterative model are averaged throughout the month, and then a bar plot is generated per every scenario. For the sake of simplicity, only some channels and damages are here discussed. Figure 12 shows the averaged residuals (MAE) obtained for the real data, namely when no damage is contemplated. Considering that the outputs are scaled by means of z-scores, a maximum error of 0.07 in validation represents a relatively low error. In figure 13, the residuals are obtained by adding a 5% on the 9^{th} tiltmeter. Notice how the scale has changed after the introduction of the damage, whereas a spike is obtained exactly in correspondence with the modified channel.

In figure 14 and 15, the results that were obtained for a simulated damage of +20% and a damage of -20% for the tiltmeter number 5, respectively. Clearly, the information on the sign of the simulated damage cannot be drawn from these barplots, but the results are consistent for damages equally distant from the nominal situation. Moreover, the spike is extremely evident also in this case. However, this is not always the case. Consider for instance figure 16, obtained by subtracting a -5% from channel 7. There are 3 clear spikes, and it is consequently not possible to draw conclusions on what is the sensor closer to the damage. Although it might

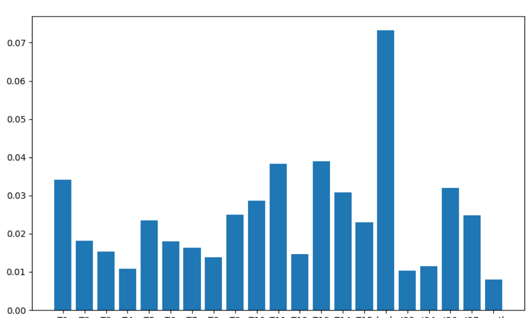

Figure 12. Average residuals (May) with no damage introduction.

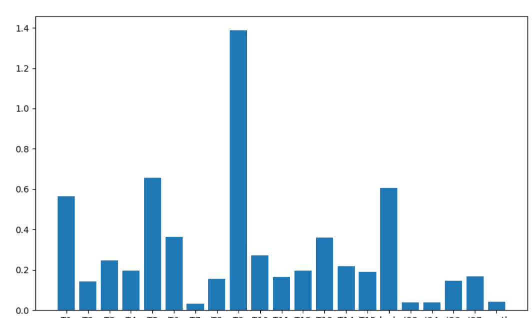

Figure 13. Average residuals (May) with a damage of +5% in tiltmeter 9.

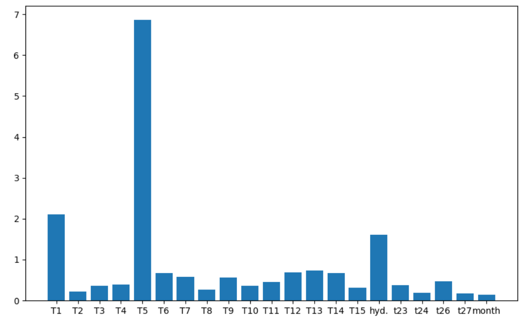

Figure 14. Average residuals (May) with with a damage of $+20\%$ in tiltmeter 5.

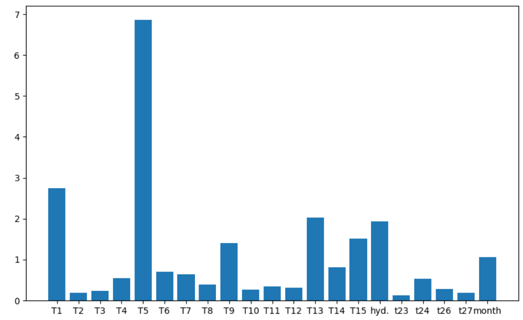

Figure 15. Average residuals (May) with with a damage of -20% in tiltmeter 5.

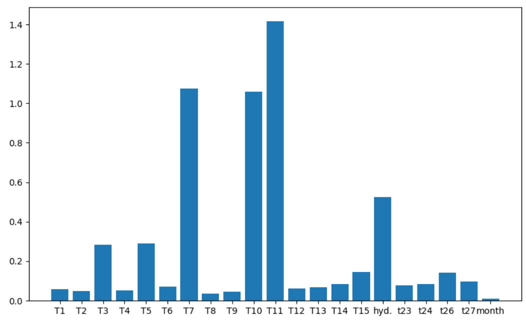

Figure 16. Average residuals (May) with with a damage of -5% in tiltmeter 9.

not be always feasible to uniquely identify the damage, the iterative model still gives a subset of sensors that should be investigated, as well as an estimate of the damage extent. Therefore, the iterative model reduces the tasks related to visual inspections for human operators.

6. CONCLUSIONS

In the paper, an analysis of possible structural health monitoring approaches based on regression methods has been carried out. The first method, based on linear or elliptical regressions with one input variable only, appears comprehensible and easily interpretative for the human eye, although it requires manual tuning, while the performance is not extraordinary. Besides, the second method based on *iterative models* turns out to be fast in deployment - the algorithm can be totally automated - even though some considerations should still be done on the residuals. This aspect is particularly relevant when damage close to one sensor produces high residuals on other channels as well.

The idea of mutual control among sensors in the field of structural health monitoring looks promising. The next steps in the research involve the application of iterative models to other bridges or other structures equipped with low-frequencies acquisition systems. Other possible applications of the iterative models could involve the exploration of their behaviour with dynamic signals, instead of static values in a single time instant (this could be done for example by using convolutional/recurrent neural networks).

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