

Road Infrastructure Monitoring: An Experimental Geomatic Integrated System

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Abstract. Road infrastructures systems are critical in many regions of Italy, counting thousands of bridges and viaducts that were built over several decades. A monitoring system is therefore necessary to monitor the health of these bridges and to indicate whether they need maintenance.

Different parameters affect the health of an infrastructure, but it would be very difficult to install a network of sensors of various kinds on each viaduct.

For this purpose, we want to finalize the use of geomatics technologies to monitor infrastructures for early warning issues and introducing automations in the data acquisition and processing phases.

This study describes an experimental sensor network system, based on long term monitoring in real-time while an adaptive neuro-fuzzy system is used to predict the deformations of GPS-bridge monitoring points.

The proposed system integrates different data (used to describe the various behaviour scenarios on the structural model), and then it reworks them through machine learning techniques, in order to train the network so that, once only the monitored parameters (displacements) have been entered as input data, it can return an alert parameter.

So, the purpose is to develop a real-time risk predictive system that can replicate various scenarios and capable to alert, in case of imminent hazards. The experimentation conducted in relation to the possibility of transmitting an alert parameter in real time (transmitted through the help of an experimental control unit) obtained by predicting the behavior of the structure using only displacement data during monitoring is particularly interesting.

Keywords: Road infrastructures · Monitoring · Models

1 Introduction

The road are the links between the cities, so the investigation of the road performance components are very important. There is system to investigate the Structural health monitoring (SHM) in short and long term. To study the safety level and the behavior of the bridge is better use long- term monitoring. Over the last 20 years, SHM is the most used technology to establish the safety condition of bridge and viaducts [1–3]. The continuously measured position data is used to estimate the status of deformation. The

© Springer Nature Switzerland AG 2020
O. Gervasi et al. (Eds.): ICCSA 2020, LNCS 12252, pp. 634–648, 2020.
https://doi.org/10.1007/978-3-030-58811-3_46

global positioning system (GPS) is widely used to measure deformation applications, also through sensor in smart structures.

Examining the movements and deformations of road infrastructures have a fundamental rule in bridge safety evaluation to know the bridges performance and to predict in the future their safety [4]. In the past, many procedures were used to predict the nonlinear GPS measurement, but, because they provide only an approximate description of movement behavior, an artificial neural networks (ANN) have been widely used to mitigate GPS error and predict the behavior of the road infrastructures [5–7].

In recent years, research has focused on identifying the response of an infrastructure as a result of damage or failure. In some research a wavelet transform of beam translation is used [8, 9] or acceleration [10] response to a moving vehicle to identify damage in a beam, while in other empirical mode decomposition to the acceleration response is applied [11, 12]. Most of these studies allow the operators to detect damage by analyzing the differences between two consecutives signals. Gonzalez and Hester investigate the damage anomaly in an acceleration response by dividing it into three components: static, dynamic and damage components, then they demonstrate and determine that the distance between the sensor and the damage is correlated to the amplitude of the anomaly [13]. He and Zhu [14] investigate the dynamic response of a supported beam as a combination of two components: the moving-frequency and the natural-frequency components;, then they use a discrete wavelet transform could localized the damage. The method is time saving and easy to implement as it utilizes single sensor measurements.

In [15], the authors apply a Moving Force Identification algorithm to the translation response and use the calculated force histories as indicators of bridge damage, this methodology is a kind of indirect approach. At the same way Li and Au [16] from multiple vehicles passes calculate the modal strain energy of the acceleration signals and localize the damage from the extracted frequencies of healthy and damaged bridges. Others use strain response to identify damage from the main beam neutral axis position's change in the position of the neutral axis of the main beams [17–20]. In [21] the authors develop a novel damage localization technique for a long suspension bridge based on stress influence lines (SILs) obtained using strain responses of a bridge to be traversing vehicles.

The aim of this research is to create a real-time risk predictive system that simulating many various scenarios on various infrastructure behaviors under investigation, it is able to provide an alert those in charge, in case of imminent hazards, through the use of the proposed system, that integrates data of a different nature (preventive used to define the various behaviour scenarios on the structural model). Then it reworks them through machine learning techniques, in order to train the network so that once inserted only the monitored parameters (displacements) as input data can return an alert parameter.

2 Materials and Methods

In this work we applied the methodology on a girder bridge with a deck in a mixed steel-concrete structure was examined in order to verify its main structural. The selected bridge elements (in order to verify through the use of this predictive system that the bridge does not enter into alert and its collapse occurs). The bridge under inspection is located in the area between Palmi and Gioia Tauro (South Italy); it has an overall length of 520 m (Fig. 1).



Fig. 1. Case study: road bridge in Reggio Calabria (between Palmi and Gioia Tauro) South Italy

A UAV survey was carried out in order to identify the geometric features of the structure. For the aerial photogrammetric survey, a UAV (or APR) was used, that is a remote piloted aircraft, model DJI Phantom 4 Pro (Fig. 2) equipped with the OcuSync high resolution transmission system, with 1″ 20 megapixel sensor capable of producing 4K video at 60 fps, and to take 14 fps photos.



Fig. 2. UAV Phantom 4 Pro

A flight height of 20 m has been set in order to obtain a GSD on the ground equal to 0.68 cm/pixel. The acquisition time was 17 min, taking 181 images overall for each survey [22, 23]. A total of 10 measurements were made.

The processing of 3D model construction, useful to extract geometry includes four standard main steps:

- Alignment of pictures, the software looks for common points on pictures to blend in.
- Generation of a dense point cloud that can be modified and classified before proceeding with the export or generation of the three-dimensional mesh model.
- Reconstruction of the surface of a 3D polygonal mesh that represents the object based on the dense cloud of points obtained from the previous phase.
- Mesh reconstruction and orthophotos restitution.

In particular, the beams have an asymmetrical double T cross section with a height of 3.0 m and a wheelbase of 4.10 m. Each beam is made up of 43 segments joined together by welded joints. For all the segments, it was decided to keep the thicknesses of the cores and platelets constant to facilitate the realization of the metal structural work. The dimensions of the beams are shown in Table 1, on each of which stiffeners have been positioned.

A long-term SHM system has been installed on the bridge to monitor its performance. The system used provides the possibility to install gps and/or accelerometric modules [24, 25]. The sensors are necessary to measure the vertical and horizontal vibrations and displacements (Gps: Static Hz 3 mm ± 0,5 ppm V 5 mm ± 0,5 ppm; Accelerometer: Sampling frequency: 1024 Hz; Minimum level measured: 0.0005 mm/s, Dynamic range: 120 dB; Frequency range: 0.8–100 Hz (315 Hz); Maximum measurable value: 8 g; Spectral noise: 1 μg/Hz-2 at 1 Hz; Cross Axis Sensitivity: <5%; Noise in the band (0–100 Hz): 15 μg; Sensitivity: 1000 mV/g; Frequency response: 0.8–600 Hz; Resonance frequency: 16 kHz; Sampling frequency: 1024 Hz; Linearity: ±1% Max; Dynamic range (of the sensor, in band): 120 dB; Dynamic range AD Converter (24 bit): 130 dB). In the specific case, only the data obtained from GPS units installed to monitor the bridge deck movements in three directions were used, and compared with those obtained from accelerometers (which are expected to be used later for subsequent dynamic analyzes). The 12 receivers are installed on the road in correspondence of the pier and in the middle of the span and on some known external points near the infrastructure [26–28].

The installation points of the sensors, (some points of the viaduct and some fixed points external to the bridge) were also measured in static mode through the use of an external GPS network consisting of 6 points capable of guaranteeing a high precision. This operation was necessary in order to mitigate the uncertainty of the sensor measurement and optimize the overall accuracy of the system by referring it to a single reference system by correlating the measurements obtained from the sensors to the measurements obtained from the instrumentation [29, 30] (Fig. 3).



Fig. 3. Sensor position

In order to investigate the stability of the slope, a (previously described) sensor system was installed on pillars and beams, and at the same time GPS measurements were made. These parameters were used to recreate the condition in the various scenarios required for neural network training.

The movements were also monitoring through the use of two GPS (rover and base).

Therefore, the coordinate's data were converted to a local bridge coordinate system for the analysis and evaluation procedures. In this coordinate system, x-axis is aligned with the traffic direction and z-axis gives the vertical direction of the viaduct.

Using the sensors previously described we obtained the accuracy deflection is on the order of 1.5 mm (horizontal) and 2 mm (vertical). The accuracy dynamic deflection is on the order of 10 mm (horizontal) and 15 mm (vertical). However, the accuracy for dynamic deflection measurement can be improved by post-processing methods [31].

3 Results and Discussion

3.1 Database for Load Actions on the Structural Model

In order to create a predictive model, it is necessary to know the response of the structural model subjected to various loading actions on the infrastructure. In this regard, in addition to the effects of the wind, the water flow rate on the batteries and the average daily traffic, we also used the deterioration parameters of the materials in order to create a structural model that varies over time.

In particular, while for the effects of wind flow and average daily traffic, the classic standard formulas for calculation have been used [32], to calculate the deterioration of the materials, we proceeded using the "mechanistic model" which allows determining the micro response of the structure, caused by the acting loads, environmental conditions that uses soft computing, and neural network techniques to obtain the variation of the parameter to be inserted in the model [33]. Such a micro-response includes the

nucleation of the damage, the growth of this defect and the impact that it can have on the safety and maintenance of the structure. These models are used for the project level analysis and for the safety analysis of the structures, where the damage is described by measurable indicators such as: resistance, voltages, displacements, etc. [34]. The damage mechanisms of a bridge can be described in three types:

- Excessive damage due to total or partial collapse (ductile or fragile), yielding, instability problems (local or global), cracks and large deformations;
- Problems of wear by materials, related to problems of fatigue and corrosion;
- Combination of the two mechanisms described above.

The following are the parameters (whose values are partially imposed by legislation and other variables over time) constituting the dataset implemented for the construction of the structural model [35]. An example is shown on Table 1.

Table 1. Load examples

Wind	F_x = 18.312 kN/m	F_y = 14.856 kN/m	M_z = 202.478 kNm/m
Traffic	Q = 300 kN/m	q = 9 kN/m^2	TGM = 8659
Flow	Qin = 180 m^3/s	Qe = 0	R = R(kN) = 2483,17
Deterioration	Low = 1,1	Medium = 1	Alto 0,8

3.2 Integrated Predictive System

To detect the geometry of the viaduct in question and implement a structural model, a survey was carried out with a drone and a subsequent three-dimensional modeling as described in paragraph 2.

Once the model was obtained, the geometry was extrapolated. In Fig. 2 the longitudinal profile of the bridge is shown, its characteristics are shown in Table 2 (Fig. 4).

Table 2. Bridge metrics characteristics

Pier	High [m]	Span	[m]
P1	3.60	1	60
P2	4.70	2	80
P3	5.75	3	80
P4	7.80	4	80
P5	8.80	5	80
P6	3.60	6	60

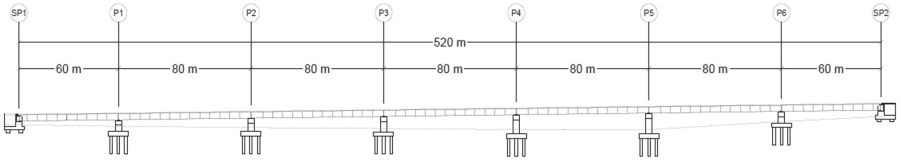


Fig. 4. Longitudinal deck profile

Therefore the infrastructure model was built (Fig. 5) applying the established loads and the failures detected (or established in the network test phase).



Fig. 5. Bridge model

A simplified Finite Element Model (FEM) using one-dimensional elements (as beams, truss, and rigid links) with properties equivalent to those of the real elements, was then used to obtain the infrastructure response to the stresses of the loads previously highlighted [36].

From the structural model, given the particular position of the building, it has been verified that the third span is the span subject to greater stresses (Fig. 6).

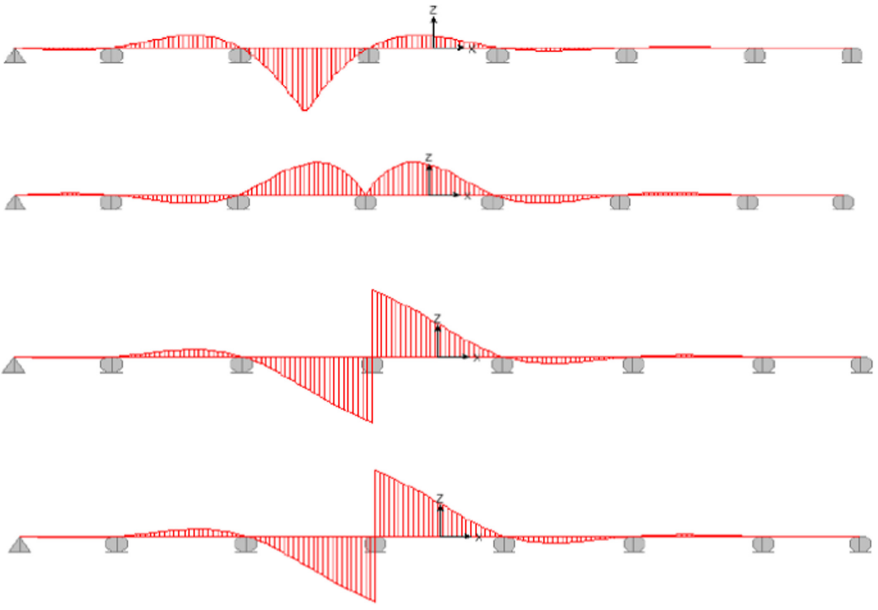


Fig. 6. Lines of influence for the maximum moment in span (a) and on the pillars (b); maximum cut in span (c) and pillars (d);

Structural monitoring of existing works is an engineering practice that, from a theoretical point of view, rediscovers the roles played by the information used at the design stage. When designing a construction, the actions (static or dynamic) are known and the structural model is possessed, this knowledge is combined to get the prediction of the structural response in the various conditions of interest (service limit of the state of interest and last state limit). In this case, then, we are aware of the response and the actions, while what we want to determine is the model. In the first case we manage a direct problem, while in the second case we deal with the reverse problem.

In the specific case, only the static model described above has been examined, it is good to observe that to better analyze elements it will be necessary to use complex models that takes into account both static and dynamic actions, which is expected to be done in a subsequent phase, not yet carried out as a test model.

In order to identify an alert signal from the FEM analysis, it is necessary to identify threshold values of the various risk classes with which to associate the response of the structural model.

Four risk classes have therefore been identified according to the various software processes, see Fig. 7:

Class A: Negligible. Infrastructures that do not show significant signs or defects, (on the calculation sheet all elements are displayed in green color).

Class B: Low. Infrastructures that manifest some elements with slight defects. (some elements with yellow coloring appear on the calculation sheet).

Class C: Moderate. The infrastructures belonging to this class show elements with significant defects (some elements with orange coloring are displayed on the calculation sheet).

Class D: High. The infrastructures belonging to this class show elements with significant defects (on the calculation sheet some elements are displayed in red color).

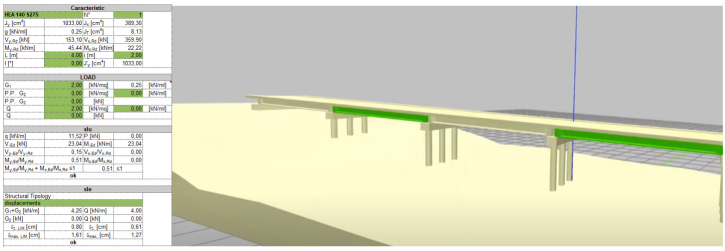


Fig. 7. Example verification and classification (Color figure online)

As can also be highlighted in the Fig. 7, the level of risk depends on several variables (loads, deformations, displacement, material).

The value of the proposed note lies in the possibility of evaluating, through the soft computing techniques used, the risk class and therefore predicting the behavior of the structure using only the movements and not all the parameters that in determining the level of risk, parameters which instead were used in an initial phase exclusively to train the neural network.

In this regard, it is necessary to previously train the neural network based on the back-propagation algorithm, given its easy of use and ability to implicitly store information in the form of connection weights.

The neural network was trained as follows:

- Various loading actions (wind, earthquake …) and different displacements (associated with settlements chosen for training the network) have been implemented on the structural software in different scenarios in order to highlight the different responses of the structure.
- Out of 800 implemented scenarios, 100 were used as tests to verify the correct training of the neural network by entering as input only the displacement data previously chosen set and used (Fig. 8); thus comparing the correspondence of the risk levels obtained between software and neural network in various scenarios.

At this point, once the network has been trained, the displacement (s) and rotation (r) values obtained by the sensors are applied as input (Fig. 8), using the procedure described above in order to mitigate the uncertainty of the sensor measurement. Moreover, the overall accuracy of the system is thus optimized by referring it to a single reference system, by correlating the measurements obtained by the sensors with the measurements obtained by the mode.

Profilo	s[cm]	r [°]
1-2	0,060	0,01
2-3	0,081	0,00
3-4	0,104	0,00
4-5	0,129	0,00
5-6	0,158	0,00
6-7	0,188	0,00
7-8	0,224	0,00
8-9	0,262	0,00
9-10	0,167	0,00
10-11	0,199	0,00
11-12	0,247	0,03
12-13	0,304	0,00
13-14	0,360	0,00
14-15	0,423	0,00
15-16	0,204	0,00
16-17	0,267	0,00
17-18	0,337	0,00
18-19	0,426	0,00
20-21	0,512	0,00
21-22	0,613	0,00
22-23	0,092	0,00
23-24	0,117	0,00
24-25	0,175	0,00
25-26	0,086	0,00
26-27	0,106	0,00
27-28	0,134	0,00
28-29	0,160	0,00
29-30	0,188	0,00
30-31	0,220	0,00

Fig. 8. Example displacement data input

It should be noted that unfortunately (for our research activities) or fortunately (for the viaduct stability) no displacements were measured that could test the goodness of the system.

The predictive system (presented in this note) therefore allows to know the structural behavior of the viaduct following the measurement of the displacements only, the method is therefore capable of sending an alert signal with a respective risk class of ownership each time certain movements occur, in order to provide an early warning in the event of important movements or rotations.

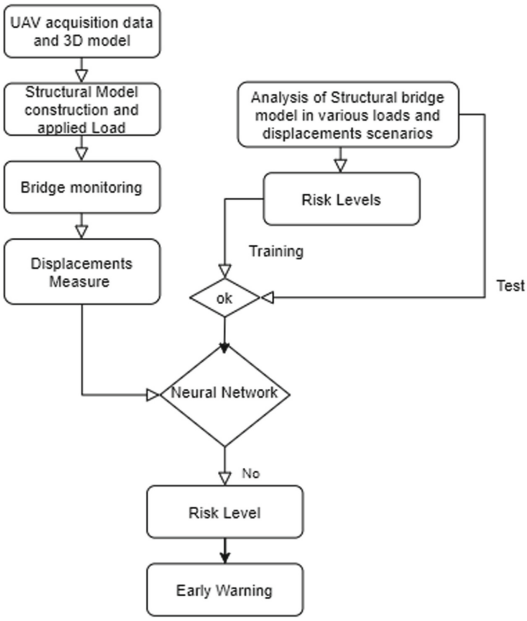


Fig. 9. Flow chart of monitoring system

Figure 9 shows how the proposed system works.

Specifically, the central part of the system concerns soft computing techniques and the implementation of the neural network. Therefore, we have implemented soft computing techniques that can provide an outbound forecast value related to load forecasting, which is necessary to know the behavior of the infrastructure in advance.

The back-propagation algorithm was used for its simplicity and its ability to extract useful information from examples. In fact, its ability to implicitly stores information in the form of connection weights and its applicability to digitally or analog models [37].

The back-propagation algorithm can understand two phases: an initial phase and a feedback phase. In the first step we have to enter the displacements x value (clearly other rotations loads and deformations can also be used) which are obtained from the structural model given the stability of the bridge under investigation and therefore the impossibility of acquiring its real data.

We inserted and propagated the displacement values x through the multilayer network; to calculate the correct output value y (displacements and risk class).

The second phase of propagation backwards, on the other hand, involved a backward path through the network, during which the error signal was calculated and, between the desired output d and the y obtained and then propagated appropriately from the output layer to the input state, in order to update the values of the weights and bases. In fact, this error signal was reported through all the layers of the network adjusting or modifying at the same time all the values of the connection between weights and bases, thus bringing current output closer to the desired output. In

particular, the learning using the back-propagation algorithm takes place in the following steps (Fig. 10):

(1) initialization of weights and bases,
(2) presentation of the desired input/exit pairs. At this stage, we presented a vector with N input components and specified the desired output vector.

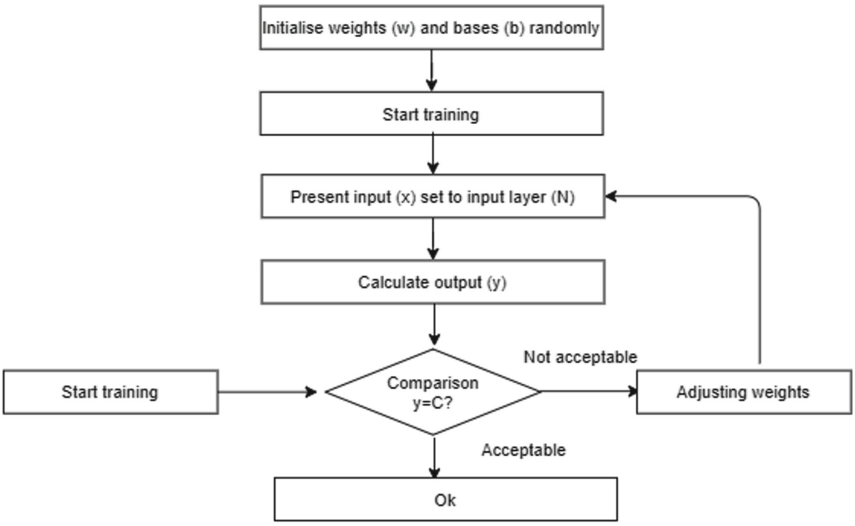


Fig. 10. Flowchart back propagation neural network

This procedure was then repeated with the presentation of new input/output pairs for a number of iterations that depend on the stop condition that is typically defined based on the difference between total errors obtained in two successive iterations until we get the weight and base values and then assigning them to the neural network.

In the testing phase, the sensor-captured data were compared (specifically, we report data acquired and calculated on the beam of the span with data obtained from the model to verify the goodness of the model itself) [38].

The network thus constructed therefore allows to obtain the desired outputs at any time (risk classes) according to the inputs (displacements) displayed on a table which is sent to a control center by means of a special control unit.

In the specific, we used a control unit to manage the output data (Fig. 11). In particular, the processed signal is sent, through communication channels, to a hardware system. It records the data and compare signal with the previous ones. If there are any change it informs the operator of possible crisis of the structure or simply change of risk class.

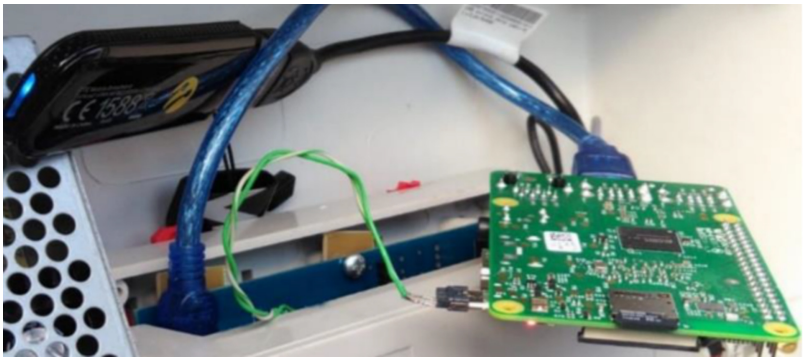
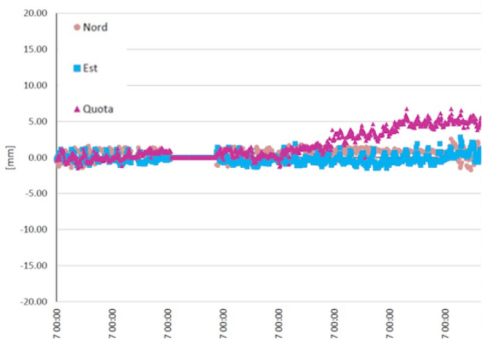


Fig. 11. Prototype of integrated monitoring system

The system was designed in EasyEDA® environment. The board was properly designed and integrated with components needed for data processing. Data were transmitted with 4G LTE to the monitoring platform. The simple platform is implemented in the WordPress® environment.

Specifically, the our integrated predictive system produce the displacement values measured by the sensors and the risk classes calculated by the neural network, and shown in a corresponding color, as shown in Fig. 12; from this response we can observe on the left side the sensor value monitoring during the time, and on the right side a table with the value used as input, and associated risk classes in the column C (that in our case is highlighted in green, if the displacement measured should made change the class of risk, automatically also the coulor of the correspondent value change in red, yellow orange o).

The result attests good adaptability of the model to the real state with an average error of about 10%.



Profilo	s[cm]	r [°]	C
1-2	0,060	0,01	A
2-3	0,081	0,00	A
3-4	0,104	0,00	A
4-5	0,129	0,00	A
5-6	0,158	0,00	A
6-7	0,188	0,00	A
7-8	0,224	0,00	A
8-9	0,262	0,00	A
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18-19	0,426	0,00	A
20-21	0,512	0,00	A
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22-23	0,092	0,00	A
23-24	0,117	0,00	A
24-25	0,175	0,06	A
25-26	0,086	0,00	A
26-27	0,106	0,00	A
27-28	0,134	0,00	A
28-29	0,160	0,00	A
29-30	0,188	0,00	A
30-31	0,220	0,00	A

Fig. 12. Data output from sensor and neural network (Color figure online)

4 Conclusion

Note how specifically the tests carried out with a neural network on a structural model returned a correspondence of 90%, indicating a good adaptability and functioning of the system. The System is currently being tested on the real case which, however, does not present good stability and consequently does not allow a more in-depth analysis to test the goodness of the expected results.

Today, understanding the structural behavior of an infrastructure takes on a more fundamental role. Analysis of infrastructure behavior models is still under development, but by solving the reverse problem it can be used both to monitor existing structures and as a control system in newly built buildings and bridges. So that you can:

1. Evaluation of the bridge's original capacity based on the stresses induced by the loads with which it is assumed to have been designed (model realization).
2. Possible reduction of the original capacity taking into account the state of degradation of the bridge and estimation of the speed of progress of degradation (model of deterioration).
3. Determining the ratio of the original reduced capacity to the demand calculated based on real traffic data (current model).

The experimentation conducted has allowed us to highlight the potential of a speedy method for alerting. In addition, on the other, appreciate the good results achieved specifically.

In confirmation of this, it should be noted how specifically the tests carried out with neural network on a structural model returned a correspondence of 90%, indicating a good adaptability and functioning of the system.

It is clearly aware that an improvement could be achieved by including dynamic analysis.

To date, the monitoring carried out has not shown any shifts for which it was possible to test the goodness of the neural network only in relation to the structural model.

In the future, we will work in such a way as to be able to apply the same system (appropriately also modifying the structural model) on a viaduct where it is assumed that there are more deformations that are important.

In this sense, we are working to identify another case study, with possible significant failures in progress in order to carry out further checks.

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