Geomatics and Soft Computing Methods for Infrastructure Monitoring

[1]VINCENZO BARRILE, [2]ROSSELLA NOCERA, [1]SALVATORE CALCAGNO

[1]DICEAM – Civil, Energy Environmental and Material Engineering Department
Mediterranea University,Località Feo di Vito, 89124 Reggio Calabria, ITALY

[2] (DiBT) – Biosciences and Territory Department,
University of Molise, Via Duca degli Abruzzi, 86039 Termoli (CB) Italy, ITALY

Abstract: - Our society is heavily dependent on many interdependent and complex critical infrastructures. Deficiencies in the functionality of the transportation network (e.g., vehicular traffic interruptions or limitations) can cause enormous inconvenience to communities and people. The Italian transport infrastructure heritage and new infrastructure construction is so relevant that the issue of its preservation and safety has become a priority. Specialistic advice is therefore required to understand if the static behaviour of these infrastructure has changed significantly after extraordinary events (e.g., earthquakes, landslides). With the advent of the internet of things (IoT), infrastructures are becoming smart and procedures simpler. In the framework of smart infrastructure development, we implemented an experimental system that integrates soft computing and geomatic methodologies for solving early warning problems. This system, which has been tested on the Petrace bridge (Southern Italy), is able to generate forecasting information on the infrastructure behaviour over time, mainly exploiting geomatic parameters. We built this "early warning/predictive" system through integration of several significant (geometric/structural) infrastructure models, which have been merged into a final "type" model. The results derived from various possible scenarios have been implemented in a neural network. The only system's input is represented by displacement measurements acquired by sensors placed on the infrastructure, and the output consists in an estimation of different risk levels.
Sensor data are then transmitted to a control unit that sends them to a processing server, where the calculation system is hosted. All received data and model results are displayed on the Wordpress platform with colour codes calibrated on the calculated risk thresholds.

Key-Words: - infrastructure monitoring, neural network, early warning, uav inspection.

Received: January 23, 2021. Revised: April 22, 2021. Accepted: April 29, 2021. Published: May 5, 2021.

1 Introduction

Our society is heavily dependent on numerous complex and interdependent critical infrastructures. Due to technological development, transport networks have become sophisticated, complex, and essential for people, companies, and municipalities. In fact, any limitation of the functionality of transport networks (interruptions or attenuation of traffic) can have serious consequences for people. The transport system is therefore necessary for the health and functionality of modern society, which depends on it not only for the daily mobility of people and for the transport of goods, but also as a lifeline for emergency management. The transport system heritage, in form of existing networks and infrastructures, is so significant that the problem of its safety and conservation is a priority for our country.

The projected life cycle cost of transport infrastructures is an important factor that should be taken into consideration for optimal infrastructure design and management. The uncertainty of the expected life cycle cost depends on potentially damaging events and on the physical conservation of the infrastructures. The best economization strategy consists in minimizing the expected life cycle cost while maintaining a given infrastructural safety level. These issues can be addressed with a multiscale approach, from the analysis of individual infrastructural elements (bridges, viaducts, tunnels and geotechnical systems) to the risk assessment and management of the entire network infrastructure [1, 2]. This multiscale approach is often ignored during infrastructural design, so transport infrastructures in Italy are generally in poor conditions, mainly due to the almost total lack of a central risk control and monitoring mechanism.

The tendency to "economize" in the initial design phase can be ascribed to the lack of consideration for the costs arisisng from damages (caused by evaluation errors) are much higher than the potential "savings" that would be obtained by adopting in advance a methodology capable of evaluating the state of infrastructure and its future evolution. This issue is presently of great interest and impact in the context of smart cities. Smart cities are already a reality, where we try to optimize the utilization of resources and guarantee the safe and reliable development and growth of various sectors. As known, the definition of smart city introduces, alongside the concept of "intelligent", also that of "sustainable": an intelligent and sustainable city is an urban core that uses information and communication technologies (ICT) and other technological tools to improve the quality of life, the efficiency of services and urban activities, and competitiveness, respecting the needs of present and future generations from an economic, social and environmental point of view. Therefore, smart cities are not only a concentrate of technologies, but also a complex ecosystem based on the active participation of citizens, municipal authorities, local companies, industries, as well as different communities and interest groups.

The experimentation of an innovative system for monitoring infrastructures proposed in this work is intended to the needs of today's evolving smart cities, especially with respect to their sustainability, through a combination of geomatic and soft computing techniques. The proposed system exploits the continuous technological development of data collection and processing tools to evaluate the structural characteristics and the level of damage of infrastructures, allowing to forecast of its evolution and generate early warnings. Monitoring the infrastructure's health means increasing its safety level in its different life stages, from construction to demolition. The implementation of monitoring systems is, in fact, an instrument that allows authorities to identify criticalities and classify them. Therefore, the creation of a continuously updated database of monitoring results, allows to optimize the use of resources and improve the quality of the interventions to be planned.

To date, monitoring systems are varied and diversified but in general, despite their increasing diffusion, their function as a supervisory and inspection tool is often limited to little more than a collection of data whose interpretation is difficult to implement in practice. Traditional monitoring systems have the following characteristics:

- Data are acquired by the instrumentation and stored
- It is verified that the acquired parameters fall within the set threshold values
- Monitoring reports are limited to the past evolution of physical parameters
- Data interpretation is requires a specialist
- The consistency between expected and measured infrastructural behavior is not verified.

This means that a specialist advice is required to assess the integrity of structures after potentially damaging exceptional events. In this context, the monitoring system becomes be a burden for the authorities in face of little benefits. This work shows how the above mentioned limits of traditional monitoring systems, can be overcome with the integrated use of geomatics and soft computing techniques. Our proposed system can be safely applied to most of the civil infrastructures in country, including those that have reached the final stage of their useful life, and those subjected to loads many times greater than those calculated in the design phase. It is exactly in a delicate scenario like this that the benefits and potential of continuous and efficient structural monitoring are most appreciated over time.

To date, various geomatics methodologies (e.g., remote sensing, GNSS) have been applied to structural health monitoring, including radio detection and measurement (RADAR), light detection and measurement (LiDAR), photogrammetry, multispectral satellite imagery, synthetic aperture radar (SAR), ground penetration radar (GPR) and digital image analyses, such as digital image correlation (DIC) [3, 4, 5]. However, there are also many other non-purely geomatic systems used for quasi-static deformation measurements, (e.g., fiber optic technology), and for monitoring dynamic (e.g., seismic) seismic events (accelerometry). For instance, these distributed sensor systems enable the early identification of structural damage or failure of monumental architectural structures through the continuous and remote monitoring of the dynamic and structural behavior of masonry. Some relevant examples can be found in [6] and [7].

Vaghefi et al. (2012) and Harris et al. (2016) compared several of the above-mentioned methods for monitoring and evaluating the performance of bridges and viaducts. Their results indicate that the most effective approaches where those based on the parallel use of different techniques [8], while certain combinations of detection technologies were the most efficient in identifying defects at specific locations [9]. The performance of a viaduct has three types of motion components: static, semi-static and dynamic [10, 11]. The static and semi-static movements of the structure are mostly measured using robotic total stations and displacement sensor techniques [12, 13]. Dynamic displacements can be obtained from accelerometer measurements by integrating acceleration data [14, 15, 16, 17, 18, 19].

Here, we present the implementation of a system that integrates geomatic methodologies with soft computing methodologies in order to automate the collection, processing, forecasting and transmission of data for infrastructural early warning and behavior prediction purposes. First tests on the implementation of this approach has been proposed in [20] and [21]. The ultimate goal consists in creating a real-time risk prediction system that allows the simulation different scenarios for the behavior of the infrastructures under investigation, and is capable of sending alerts in the event of imminent dangers. The proposed system integrates different types of data previously used to define the various behavior scenarios of the structural model, synthesizing critical threshold parameters through machine learning techniques. The proposed system is applicable to infrastructures not affected by subsidence.

The proposed integrated system is based on:
a 3D model detected by drone (useful for having the initial state of art and the geometric information of the infrastructure to be monitored available);
a final structural model (at instant "0" on which several boundary conditions are varied to simulate as many scenarios);

- a sensor acquisition data system
- a data transmission system
- a soft computing system, where data, in form of static and dynamic displacements, feed a neural network
- a visualization platform that displays early warning signals and predicted infrastructure behavior.

2 Materials and methods

2.1 Case Study

The proposed integrated infrastructure monitoring system was tested on the viaduct over the Petrace river (Fig. 1). The Petrace bridge is an imponent work that crosses the valley between the territories of Gioia Tauro and Palmi. The bridge runs at a height of >40 m above the river on a straight line, with spans supported by three arches, each in turn consisting of three arches side by side, set directly on the foundation works and connected in key, for a total length of 274 m. The deck, consisting in a single carriageway, is made with ribbed plates of reinforced concrete, with longitudinal and transversal ribs set together and supported by vertical uprights. The deck has a variable section, unloading on the three main arches. The three arches, with a tapered section towards the top, include a wider central arch and two side arches.

Fig.1 – Petrace Bridge.

2.1.1 Survey

A DJI Inspire 1 drone (Figure 2) was used for the on-site inspection and for the acquisition of data used for the construction of the geometric 3D model.

Fig.2 – Dji Inspire 1.

This UAV weighs ~3 kg with battery and camera included. The camera has a 12.4MP sensor and 20 mm focal length with the ability to record 4K videos at 30fps and 1080p videos at 60fps. The 20 mm camera objective provides a 94° wide angle field of view without distortion. The system also comes with a 3-axis gimbal for stabilization.

Analysis of images acquired by drone reveals several deterioration signs, which are partially visible even with the naked eye (fig. 3 4). Widespread degradation is testified by humidity stains and/or efflorescence, concrete deterioration, uncovered and oxidized ordinary steel reinforcements of the arches, uprights and cantilevered parts of the decks, detachment of the edges and uncovering of the hooping brackets, and crawl spaces and areas with fine concrete matrix washout.

Fig.3 - Visible deterioration.

These deterioration signs are generically attributable to the aggression of atmospheric agents and inadequate rainwater drainage, due to the absence of downspouts both in continuation of the collection vents and in correspondence with the ten joints that interrupt the spans.

A 3D model of the viaduct has been constructed from the drone images using classic photogrammetric techniques (SFM). After extracting the geometric characteristics from the 3D model, a static structural model has been implemented to identify possible critical issues emerging from static calculations.

3 The sensor system detection

The sensorial system is one of the most important elements of structural monitoring. The physical quantities considered for structural monitoring are of two types:

- environmental parameters (wind, temperature, seismic activity),
- structural responses (displacement, deformation, acceleration and inclination).

A survey was carried out using WiseSensing (Datasheet v 2.0) sensors, which include:

- Displacement and inclination sensors (fig. 4): used respectively to evaluate displacements and rotations of the structure. Displacement sensors are mainly used to monitor the sagging and widening of the edges of the lesions and the displacements of the joints, while inclinometers measure the relative rotation of whole sections.
- Temperature and humidity sensors: installed respectively to monitor temperature and humidity gradients. They are also useful for verifying possible correlations with environmental parameters.
- Accelerometers: used to assess vibrations in terms of accelerometric histories.
- Anemometers: used to monitor wind direction and speed.

Fig.4 - Linear displacement sensor.

The sensors were installed on pillars and beams (Figure 5). In our case, they provide three types of parameters: 1. Load sources: environmental (wind, seismic action) or artificial (traffic), 2. structural responses: displacement, deformation, acceleration and inclination, 3. Environmental effects: temperature, precipitation, humidity.

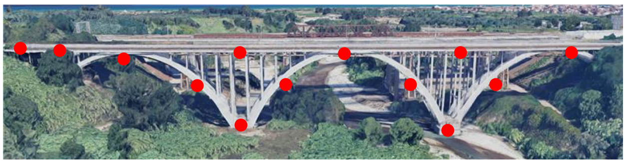

Fig.5 - Sensor positioning.

Selected sensor records are shown in Figs. 6,7,8. Acceleratiosn (figure 6) were calculated in steps of Δt = 5 ms. Recordings of the response associated with traffic for a total duration of the order of 60 minutes were obtained for each measurement configuration.

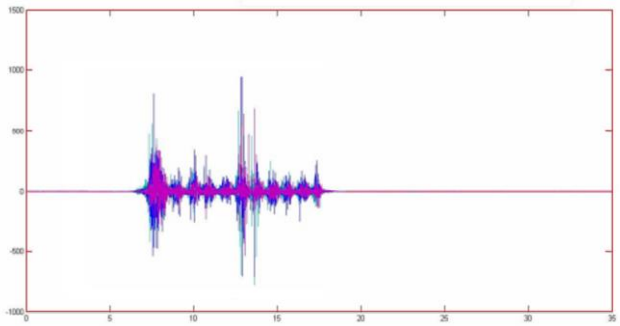

Fig.6 – Accelerometer record.

Humidity and temperature records are shown in fig.7, while Figure 8 shows an inclinometer record.

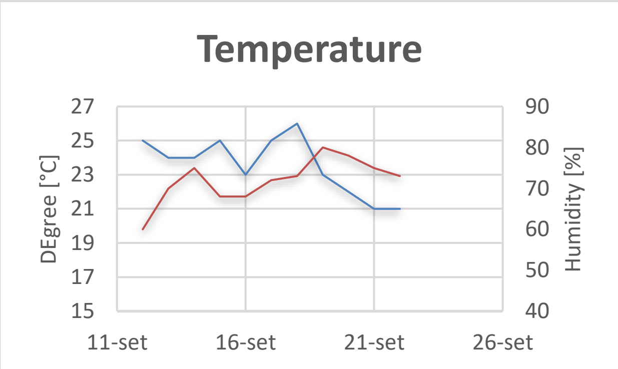

Fig.7 - Temperature measure.

Fig.8 - Inclinometer measure.

As mentioned above, direct displacement measurements are particularly important for the monitoring phase. Displacement data were collected by a base station receiver (master station) placed near the viaduct. Communication antennas, on the other hand, are positioned inside the sensors and at other suitable points.

Kinematic GPS data have been acquired in real time (RTK). We use a LEICA-GMX902 receiver (24-channel L1/L2 code and phase, 20Hz data rate, Smart Track technology for high precession, 1mm ± 0.5ppm horizontal accuracy, 2mm ± 1ppm vertical accuracy). The GPS receivers are connected via Internet to the server. The coordinate components of each observation have been converted to a local bridge coordinate system (BCS) for analysis and evaluation procedures. In this coordinate system, the *x*-axis is aligned with the traffic direction and the *z*-axis points to the vertical. GPS measurements were filtered by denoising the time series of the GPS receiver outputs after conversion to the local coordinate system [11, 27, 28]. Quasi-static movements of the pillars were calculated after application of a low-pass moving average (MA) filter with 0.025 Hz corner frequency for dynamic noise removal. (Fig.9).

Fig. 9 shows examples of displacements measured over time on a pillar (a) and on a point positioned on the central span (b).

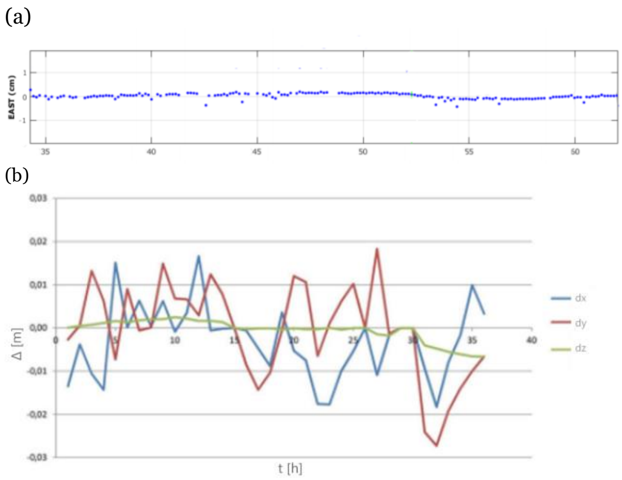

Fig.9– GPS monitoring results: (a) pillar, (b) central span.

The data acquired in tabular form at pre-set time intervals can be consulted from a remote location by anyone with access credentials. The processed time records of all sensors can be displayed graphically for immediate identification of possible anomalies.

4 Structural model

In order to obtain an initial model, it is necessary to train the neural network and then proceed with the forecasting phase of the infrastructure behavior over time, according to the following steps:

- Acquisition of geometric and construction details from relief and 3D modeling obtained with the drone;
- Estimation of mechanical properties of construction materials and soils through the project documentation.

- Estimation of infrastructure loadings through the on-site sensor system;
- Creation of the final structural model using FEM.

In general, the static and dynamic behavior of bridges and viaducts can be investigated through a simplified Finite Element Model (FEM) based on 1D elements (such as beams, trusses and rigid meshes) with properties equivalent to those of real elements. This simplification results in a significant reduction in the computational load and memory required for analysis. Furthermore, our choice of a simplified model is motivated by the observation that essential data on subsidence, is not presently available, since the bridge is considered stable. This prevents a direct comparison of the results obtained from the model with the time series collected by the sensors. Therefore, our aim is limited to methodological tests, rather than a precise assessment of static issues.

The simplified FEM provides only some information on the overall behavior of the structure, useful in the preliminary design phase. More realistic models based on a finer discretization improve the accuracy of the final results but are computationally demanding, being therefore less suited to real-time processing.

Depending on the model used, a distinction must be made between the design phase and the operation phase. Static and dynamic load actions are known during the design stage, and this theoretical knowledge is combined to obtain the prediction of the structural response under various conditions of interest (state of interest limit of service and last state limit). On the other hand, the structural response of existing manufacts to given stresses [22] must be measured in situ or estimated with laboratory tests. In this case, contrary to the design phase, an unknown structural model must be determined from known stress responses. Accordingly, the design and operation phase require forward and the inverse problem solutions, respectively.

The main objective of monitoring is, in fact, to create a final model that can be used, for example, to analyze the behavior of the applied loads. For this purpose, a-priori information from monitoring must be combined with structural information obtained experimentally during inspections and from material tests [23, 24, 25]. The geometric model is built on dimensional data (e.g., project drawings, UAV surveys, Laser Scanner surveys). The structural model is obtained from an eligible software, and is unavoidably affected by errors arising from (1) discretization, (2) boundary conditions, and (3) material parameter uncertainties.

One of the solutions proposed to overcome structural modeling errors (in particular those related to discretization) consists in implementing a so-called “final model” through the integration of geomatic surveys and structural monitoring. This final model enables to analyze the behavior of the structure under variable loads. The goodness of the final model can be evaluated by comparing detected stresses with those obtained during in-situ tests.

Along with this solution, the final model of the Petrace viaduct has been obtained by integrating the finite element structural model (Fig. 10a) with the geomatic information extracted from the UAV-based 3D model (Fig. 10b). The response characteristics of this concrete manufact are then derived from a structural dynamic analysis.

(a)

(b)

Fig.10 - Structural models: (a) FEM (b) final model.

Our model is characterized by the following assumptions:

1. the arches, the vertical rafters, the deck trellis and the transversal connection elements the members were simulated using finite elements of 2-node beam where the deck slab is described by means of 4-node flat elements, equipped with both membranal and flexural stiffness;
2. the specific weight of all linear elements (deck trellis, arches, rafters and transoms) was assumed to be 24.0 kN/m^3 whereas for the deck plate a fictitious volume weight of 27.0 kN/m^3 to take into account both the structural self-weight and the weight of the road pavement at the same time;
3. a Poisson ratio of 0.20;
4. the constraint at the base of the arches has been assimilated to a perfect joint;
5. the deck at the ends is rigidly bound to the vertical and transverse translation where the effect of the longitudinal deformability of the asphalt packet that fills the gap between the abutments and the deck was simulated by means of elastic elements.

Next, we proceeded with a calculation of the response at the damage limit (Fig. 11), in order to verify whether the modelled structure reacts correctly to the applied loads or collapses.

Considering the age of the viaduct and the analyzes carried out during the design check, we came to the conclusion that the infrastructure likely maintains an adequate capacity to absorb seismic actions up to the damage limit through the ductility of the resistant elements. Our simulations also predict that pillars are the elements with greater flexibility towards shear stresses and to a lesser extent towards bending stresses in the node sections, denoting an insufficient resistance to the limit state of collapse. The arch, on the other hand, possesses sufficient shear and bending capacity at the limit state of collapse.

(a)

(b)

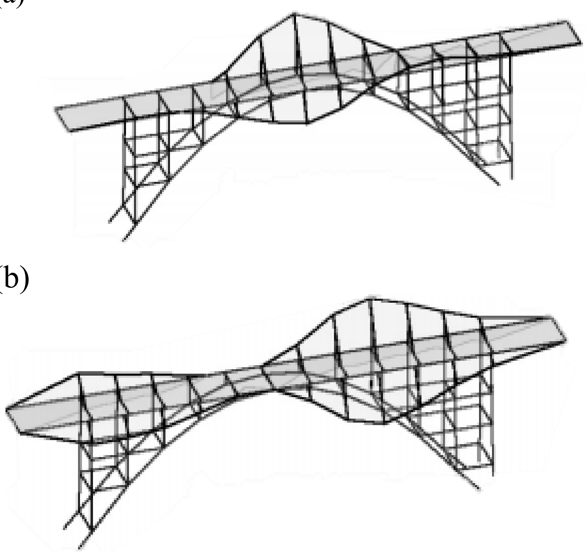

Fig.11 - Structural behavior at the damage limit: (a) $f = 11.451$, (b) $f = 13.738$.

These simulations provided useful indications for optimal sensors placement, for the definition of early warning thresholds, and for infrastructure behavior predictions in ~800 different loading scenarios.

4.1 Calculation of early warning thresholds

Once the final model was built, ~1000 different scenarios were calculated by varying infrastructure loads, in order to obtain failure values and corresponding risk classes. Four risk classes have been identified according to these calculations:

- Class A: Negligible risk. Infrastructures that do not show significant alterations or defects, (all elements are displayed in green on the platform).
- Class B: Low risk. Infrastructures featuring some slightly defective elements (highlighted in yellow on the platform).
- Class C: Moderate risk. The infrastructures belonging to this class contain elements with significant defects (highlighted in orange on the platform).
- Class D: High risk. The infrastructures belonging to this class contain elements with very significant defects (highlighted in red color on the platform).

Once the risk classes have been defined and setting threshold values properly set, the proposed model can be used for early warning purposes. The system has been programmed in such a way that threshold values are compared with corresponding sensor records sent by the control unit to the central processing system consisting of a PC installed in the Geomatics Laboratory. An alarm is produced in case of threshold violations.

Fig. 12 shows the assignment of individual risk classes for each measured element (pillars). In particular. In this case, green cells in the left table indicate a very low risk level, since all sensor data have never exceeded the preset threshold. The plot to the right shows the risk value (green line), the infrastructure displacement (blue line) and rotation (red line), and the resulting risk curve (purple line).

	s	ϕ	status
1-2	0,002	0	ok
2-3	0,002	-0,001	ok
3-4	0	0	ok
4-5	0,01	0	ok
5-6	0,03	0	ok
6-7	0,02	-0,002	ok
7-8	0,002	-0,002	ok
8-9	-0,01	-0,002	ok
9-10	-0,01	-0,002	ok

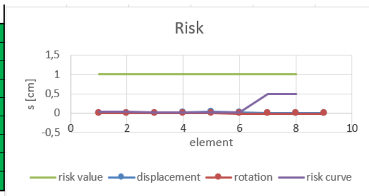

Fig.12 – Early warning result.

5 Infrastructure behaviour, predictive phase, and soft computing analysis

From the structural model and available data, a neural network was implemented to obtain forecast values of infrastructure behavior as the measured displacements vary. FEM model parameters and measured loads have been used to create boundary conditions for hypothetical scenarios used to train the neural network on which the predictive system is based [13].

The database (Table 1) used for the training validation and testing phases has been constructed on the bases of the following elements:

- geometric characteristics (e.g., piles, spans, bases, roadways, traffic islands, gutters, slabs, sidewalks, crossbars, parapets),
- construction materials (e.g., pre-stressed reinforced concrete arches),

- permanent loads (structure weight, ground thrust, hydraulic thrust), and inserting as input evaluated variable data (settable and variable from time to time in the model)
- the load parameters acting on the model
- subsidence, rotation and bending data
- risk levels (ranges between values thresholds)

Table 1. Dataset used for training, validating, and testing

	Scenario 1	…	Scenario *N*
Wind	4.14 kN/m^2	…	2,18
ADT	56.8 kN/m^2	…	42
Flow rate actions on piers	1.5 kN/m^2	…	0,8
Oscillations	0.007 m	…	0.007
Failures on bases	0.02 m	…	0.002
Failures on beams	0.05m	…	0.002
Failures on spans	0.12 m	…	0.05
Failures on abutments	0.06 m	…	0.001
Threshold level	2	…	1

Once all model and displacement data are available, infrastructure behavior forecasts are generated using soft computing techniques. In our case, a suitable neural network has been implemented using the Google Colab platform to execute codes in Python language. We built a 3-layer neural network with two input layers (displacements, loads), two hidden layers and one output layer. The number of nodes in the input layer is determined by the dimensionality of our data. Similarly, the number of nodes in the output layer is determined by the number of classes. The dimensionality (the number of nodes) of the hidden layer is a compromise between model flexibility, which increases with the number of nodes, and the limit imposed by the required computational power. A larger number of metrics also means that the output becomes more sensitive to input uncertainties.

A back-propagation algorithm was used to implement the neural network. It was chosen because of its simplicity and its ability to extract useful information from the examples. The back-propagation algorithm stores information implicitly in form of weights. The algorithm compares the output value of the system with the desired value (target) and modifies the synaptic weights of the neural network, making the set of output values progressively converge towards the desired ones. It was found to be much more performing than the feed-forward algorithms, whose output is determined only by the current input.

The back-propagation algorithm is developed in two phases: an initial phase and a feedback phase. During the forward phase, the output of a layer is used as input for the next layer. A dataset composed both by the actions acting on the infrastructure and by the responses of the structure itself is used for this purpose. In this scheme, input values x represent the action (wind load, seismic activity, traffic) and structural responses (displacements), and the output y consists of two correlated values (y_1 for the risk level and y_2 for the displacement y_2). Each neuron is activated by the weighted sum of all incoming signals A:

$$A = x_1\, w_1 + x_2\, w_2 + \dots + x_n\, w_n + b$$

where b is a constant and $w_1 \dots w_n$ are the weights, while the output is given by

$$y = \frac{1}{1+e^{-A}}$$

Starting from random values of w and b a first test is performed using input data with known output. The test error Δy is calculated as the difference between the known and calculated outputs.

Traffic load conditions have been calculated from the average daily traffic, but we are working to obtain better estimates based on a numerical counter, as for instance the vehicular recognition system based on the Yolo neural network. For neural network training purposes, the risk levels were experimentally established by combining the loads of the different risk parameters on structural software.

The same procedure cannot be applied to intermediate levels of the network as the output level, because of the lack of known expected reference values. Therefore, the internal neuron weights, have been calculated by back-propagation in the second processing phase. This involves a backward path through the network, during which the error signal Δy (i.e., the difference between the desired and obtained output) is calculated and suitably propagated from the output layer to the input state. This operation yields new weights to be used for updating the neural network. Error propagation through all network and simultaneous adjustment of all connections between weights and bases brings the calculated output closer to the desired value. The back-propagation algorithm can be divided into two phases: (1) initialization of weights and bases, (2) presentation of the desired input/output pairs.

The syntax for creating the network structure built on the Colab platform in Python language is very compact. The number of nodes that make up the hidden layers of the network can be easily varied to test various configurations and find the most performing one based on the characteristics of the survey, while the number of neurons in the output layer must necessarily be equal to the number of outputs we want to get. It should be emphasized that only data generated by the model were used during the training phase, while the operating phase is based only on sensor data.

An example of comparison between the expected displacelemt and corresponding value predicted by the neural network is shown in Fig. 13.

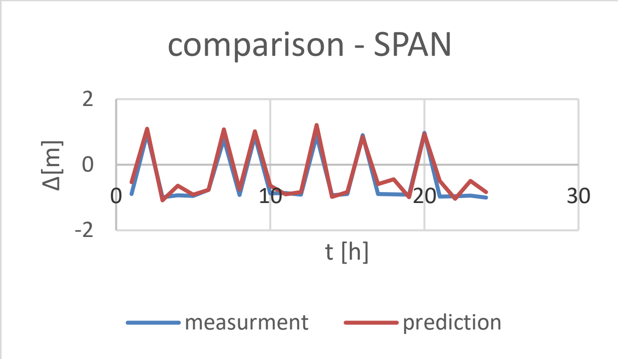

Fig.13 - Comparison between expected and obtained result.

This example shows a good adaptability of the predictive model, as seen by the small errors of predicted displacements variations with respect to measurements.

5.1 Proposed system: processing, transmission e visualization

The proposed system analyses various scenarios of infrastructure behaviour constructed on the basis of artificial (e.g., average daily traffic) and natural (wind, water flow around the piles, ground capacity) loads using the general architecture illustrate in Fig.14), which consists of:

– a data acquisition system (UAV, GNSS, accelerometric sensors)
– a data transmission system
– a soft computing system that uses a suitable neural network both in the training phase (using the different infrastructure behaviour scenarios) and in the forecasting phase, which requires only static and dynamic displacement data to estimate the risk levels
– a central system for data processing and visualization.

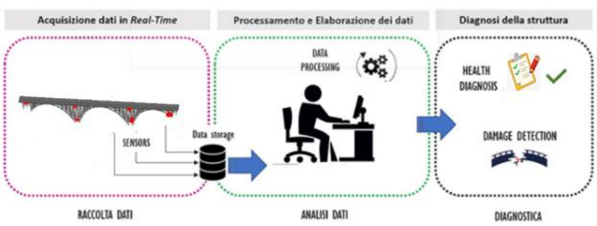

Fig.14 - Process of acquisition, diagnosis, processing and data transmission.

The monitoring system for the trasmission and visualization data (early warning and prediction phase) consists of three main steps: data acquisition, data processing, and structure diagnosis (figure 15).

Fig.15 - Data transmission, from sensors to software.

The data acquisition step makes use of sensors appropriately installed on the infrastructure. The acquired parameters (e.g., accelerations and displacements) are compared with threshold values previously determined through structural analysis, in order to assess the risk level in early warning. Moreover, the same data are processed through a predictive neural network system and compared with the same threshold values to determine a possible future risk level. In both cases the warning signals are transmitted to a central server via connection to local networks.

The central server currently consists of a PC installed at the DICEAM Geomatics Laboratory of the Mediterranean University of Reggio Calabria, and is based on the following components:

- A structural analysis software (RFEM) used for producing the final model
- SQLite3 (C-language library)

- Google Colab (platform to execute code in Python language) used to implement the neural network
- Pythontutor (web platform for viewing the code of strings and libraries)
- Wordpad (software for reading .csv files)
- Wordpress (web platform that allows monitoring platform)

The connected sensors transmit the acquired data to the control unit through a ZigBee Wireless Protocol Stack. ZigBee protocols are designed for use in embedded applications that require a low transfer rate and low power consumption. The goal of ZigBee is to define a non-targeted, low-cost, self-managing Wireless mesh network. The resulting network will have such low power consumption that it will be able to operate for one or two years using the embedded battery in individual nodes. The sensors are equipped with an on-board processor, which transmits only requested and pre-processed data, instead of sending raw data to the nodes responsible for data collection.

Data are subsequently sent to the central server through the 4G LTE CAT-M1/NB-IoT internet network and stored on a Raspberry system through the SQLite C-language library, which is a DN engine (Version extended) lightweight, fast and compatible with Python. Sensor data are made available on a daily basis through updates scheduled by a daily backup of the SQLite DB. A web server was also created to store data using the Python web.py library. Sever Web; the same is started on system boot. Daily measurement data are then exported to .csv files created within a single folder. Once all model and displacement data are available in .csv format, soft computing techniques provide a forecast output value.

At this point data processing continues with the following steps:

- *Early warning*. Sensor outputs are compared with the data obtained from risk classes previously defined through the structural software)
- *Predictive phase*. Forecast data (i.e., the displacement y_2) returned from the neural network is compared with risk class thresholds (y_1 predicted by the neural network) in order to assign a risk class.

The data processing phase is followed by the display phase. The same visualization platform, implemented in the WordPress® environment, is used for both for the Early Warning phase and for the structural behavior prediction phase. This platform integrates SSL security protocols, which provide a minimum level of online security, essential when transmitting sensitive information.

For early warning purposes, the platform displays all sensor outputs in tabular form, followed by a color-coded box indicating the hazard status of the structural element on which the sensor is installed (Fig. 12). The predictive system display includes, in addition to measured displacement values and plots, also the values predicted by the neural network, along with the corresponding risk classes. Infrastructure components (e.g., beams, pillars, spans, bases) are represented using colors corresponding to their predicted risk class: green (very low), yellow (low), orange (high), and red (very high) (Figure 13)

An example of the system response visualization for early warning and predictive phase results is shown in Fig. 16. A comparison between measured and predicted displacements is shown on the right. A plot of real-time sensor outputs and a table sensor readings and associated risk classes for each structural element monitored are shown on the left as part of the predictive phase, along with a plot of the risk curve and the threshold values obtained from the finite element structural analysis illustrated in Section 3.

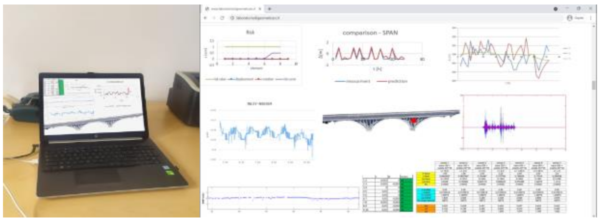

Fig.16 - Monitor screen.

4 Conclusions

We have examined different aspects of the infrastructure monitoring problem. The structural model used in this trial represents a simplified version of a complete monitoring system. Improvements include a more complex structural model, based on variable loads, and validation on a test infrastructure where more important displacements can be monitored. To date, the trained neural network has been calibrated for 24-hours displacement predictions (scenario n+1), in a four-week cycle (really close to the early warning signal).

Further checks are needed to verify the forecast reliability, since both the training and the test phase took place on a virtual model, without comparisons with the real behavior of the infrastructure, which, in this case, is not affected by critical displacements required for a complete test.

An improved system based on more detailed structural models enables low-cost monitoring of infrastructures at a significantly reduced cost. Our research therefore aims at providing a proactive contribution to the solution of problems related to infrastructure monitoring and management using alternative methods. We believe that the ability to infer the behavior of the entire infrastructure from monitoring of selected parameters (e.g., displacements, can be of great interests for institutions dealing with limited maintenance resources, as well as providing an excellent instrument for guaranteeing the safety of end users.

References:

[1] Gentile, C., Cabboi, A.: Vibration-based structural health monitoring of stay cables by microwave remote sensing. Smart Struct. Syst. 16, 263–280 (2015)

[2] Harris, D.K., Brooks, C.N., Ahlborn, T.M.: Synthesis of field performance of remote sensing strategies for condition assessment of inservice bridges in Michigan. J. Perform. Constr. Facil. 30, 04016027 (2016)

[3] Vaghefi, K., et al.: Evaluation of commercially available remote sensors for highway bridge condition assessment. J. Bridge Eng. 17, 886–895 (2012) 646 V. Barrile et al.

[4] Chen, S.-E., Liu, W., Dai, K., Bian, H., Hauser, E.: Remote sensing for bridge monitoring. In: Condition, Reliability, and Resilience Assessment of Tunnels and Bridges, vol. 214, pp. 118–125. Geotechnical Special Publication, Reston (2011)

[5] Rytter, A.: Vibration BASED inspection of civil engineering structures. Department of Building Technology and Structural Engineering, Aalborg University, Denmark (1993)

[6] Alexander Makarenkot, Multiple-Valued and Branching Neural Networks, Engineering World, pp. 20-28, Volume 2, 2020.

[7] Gulnara N. Nabiyeva, Stephen M. Wheeler, Geographic Information Systems as a Tool to Support the Sustainable Development Goals, Engineering World, pp. 219-226, Volume 2, 2020.

[8] Elnabwy, M.T., Kaloop, M.R., Elbeltagi, E.: Talkha steel highway bridge monitoring and movement identification using RTK-GPS technique. Measurement 46, 4282–4292 (2013)

[9] Psimoulis, P.A., Stiros, S.C.: A supervised learning computer-based algorithm to derive the amplitude of oscillations of structures using noisy GPS and robotic theodolites (RTS) records. Comput. Struct. 92–93, 337–348 (2012)

[10] Zhu, X.Q., Law, S.S.: Wavelet-based crack identification of bridge beam from operational deflection time history. Int. J. Solids Struct. 43, 2299–2317 (2006)

[11] Zhang, W.W., Wang, Z.H., Ma, H.W.: Studies on wavelet packet-based crack detection for a beam under the moving load. Key Eng. Mater. 413–414, 285–290 (2009)

[12] Hester, D., González, A.: A wavelet-based damage detection algorithm based on bridge acceleration response to a vehicle. Mech. Syst. Signal Process. 28, 145–166 (2012)

[13] Bradley, M., González, A., Hester D.: Analysis of the structural response to a moving load using empirical mode decomposition, p. 117. Taylor & Francis, London (2010)

[14] Huang, N.E., Huang, K., Chiang, W.-L.: HHT based bridge structural health-monitoring method. In: Hilbert-Huang Transform and Its Applications, pp. 263–287. World Scientific (2014)

[15] González, A., Hester, D.: An investigation into the acceleration response of a damaged beam-type structure to a moving force. J. Sound Vib. 332, 3201–3217 (2013)

[16] He, W., Zhu, S.: Moving load-induced response of damaged beam and its application in damage localization. J. Vib. Control 22, 3601–3617 (2016)

[17] OBrien, E., Carey, C., Keenahan, J.: Bridge damage detection using ambient traffic and moving force identification. Struct. Control Health Monit. 22, 1396–1407 (2015)

[18] Li, Z.H., Au, F.T.K.: Damage detection of a continuous bridge from response of a moving vehicle. Shock Vib. 2014, 1–7 (2014)

[19] Park, J., Moon, D.-S., Spencer, B.F.: Neutral-axis identification using strain and acceleration measurements. In: The 2017 World Congress on Advances in Structural Engineering and Mechanics (ASEM 2017), Seoul, Korea (2017)

[20] Barrile, V., Fotia, A., Leonardi, G., Pucinotti, R., Geomatics and Soft Computing Techniques for Infrastructural Monitoring, *Sustainability* 2020, Vol.12, 1606. doi:10.3390/su12041606

[21] Barrile, V., Fotia, A., Bernardo, E., Bilotta, G., Modafferi, A., Road Infrastructure Monitoring: An Experimental Geomatic Integrated System, In: Gervasi O. et al. (eds) *Computational Science and Its Applications – ICCSA 2020. ICCSA 2020. Lecture Notes in Computer Science*, vol 12252. Springer, Cham 2020, pp. 634-648. Doi:10.1007/978-3-030-58811-3_46

[22] Sigurdardottir, D.H., Glisic, B.: Neutral axis as damage sensitive feature. Smart Mater. Struct. 22, 075030 (2013)
[23] Sigurdardottir, D.H., Glisic, B.: Detecting minute damage in beam-like structures using the neutral axis location. Smart Mater. Struct. 23, 125042 (2014)
[24] Sigurdardottir, D.H., Glisic, B.: The neutral axis location for structural health monitoring: an overview. J. Civ. Struct. Health Monit. 5(5), 703–713 (2015). https://doi.org/10.1007/s13349-015-0136-5
[25] Ye, X., Jin, T., Yun, C.: A review on deep learning-based structural health monitoring of civil infrastructures. Smart Struct. Syst. 24(5), 567–585 (2019)
[26] Barrile, V., Candela, G., Fotia, A.: Point cloud segmentation using image processing techniques for structural analysis. ISPRS Int. Arch. Photogramm. Remote Sens. Spat. Inf. Sci. XLII-2/W11, 187–193 (2019)
[27] Barrile, V., Candela, G., Fotia, A., Bernardo, E.: UAV survey of bridges and viaduct: workflow and application. In: Misra, S., et al. (eds.) ICCSA 2019. LNCS, vol. 11622, pp. 269–284. Springer, Cham (2019). https://doi.org/10.1007/978-3-030-24305-0_21
[28] Voutetaki, M.E., Papadopoulos, N.A., Angeli, G.M., Providakis, C.P.: Investigation of a new experimental method for damage assessment of RC beams failing in shear using piezoelectric transducers. Eng. Struct. 114, 226–240 (2016)
[29] Karayannis, C.G., Voutetaki, M.E., Chalioris, C.E., Providakis, C.P., Angeli, G.M.: Detection of flexural damage stages for RC beams using Piezoelectric sensors (PZT). Smart Struct. Syst. 15, 997–1018 (2015)
[30] Kaloop, M.R., Li, H.: Multi input-single output models identification of tower bridge movements using GPS monitoring system. Measurement 47, 531–539 (2014)
[31] Chen, Y., Xue, X.: Advances in the structural health monitoring of bridges using piezoelectric transducers. Sensors 18, 4312 (2018)
[32] Liao, W.I., Hsiao, F.P., Chiu, C.K., Ho, C.E.: Structural health monitoring and interface damage detection for infill reinforced concrete walls in seismic retrofit of reinforced concrete frames using piezoceramic-based transducers under the cyclic loading. Appl. Sci. 9, 312 (2019)
[33] Moschas, F., Stiros, S.: Measurement of the dynamic displacements and of the modal frequencies of a short-span pedestrian bridge using GPS and an accelerometer. Eng. Struct. 33, 10–17 (2011)
[34] Moschasa, F., Stiros, S.: Noise characteristics of short-duration, high frequency GPSrecords. In: Advanced Mathematical and Computational Tools in Metrology and Testing. Series on Advances in Mathematics for Applied Sciences, vol. 84, pp. 284–291 (2012)
[35] Matarazzo, T.J., Pakzad, S.N.: Scalable structural modal identification using dynamic sensor network data with STRIDEX. Comput. Aided Civ. Infrastruct. Eng. 33(1), 4–20 (2018)
[36] Qu, K., Tang, H.S., Agrawal, A., Cai, Y., Jiang, C.B.: Numerical investigation of hydrodynamic load on bridge deck under joint action of solitary wave and current. Appl. Ocean Res. 75, 100–116 (2018). https://doi.org/10.1016/j.apor.2018.02.020
[37] Wu, D., Yuan, C., Kumfera, W., Liu, H.: A life-cycle optimization model using semi-Markov process for highway bridge maintenance. Appl. Math. Model. 43, 45–60 (2017)
[38] Fukuda, Y., Feng, M.Q., Narita, Y., Kaneko, S., Tanaka, T.: Vision-based displacement sensor for monitoring dynamic response using robust object search algorithm. IEEE Sens. J. 13, 4725–4732 (2013)
[39] Lydon, D., Lydon, M., Taylor, S., Del Rincon, J.M., Hester, D., Brownjohn, J.: Development and field testing of a vision-based displacement system using a low cost wireless action camera. Mech. Syst. Signal Process. 121, 343–358 (2019). ISSN 0888-3270
[40] Li, S., Zuo, X., Li, Z., Wang, H.: Applying deep learning to continuous bridge deflection detected by fiber optic gyroscope for damage detection. Sensors 20(3), 911 (2020)
[41] Matarazzo, T.J., Pakzad, S.N.: Structural identification for mobile sensing with missing observations. J. Eng. Mech. 142(5), 04016021 (2016)
[42] Barbaro, G., Fiamma, V., Barrile, V., Foti, G., Ielo, G. Analysis of the shoreline changes of Reggio Calabria (Italy) International Journal of Civil Engineering and Technology, 2017, 8(10), pp. 1777-1791
[43] Barrile, V., Meduri, G., Bilotta, G. Laser scanner surveying techniques aiming to the study and the spreading of recent architectural structures. Proceedings of the 9th WSEAS International Conference on Signal, Speech and Image Processing, SSIP '09, Proc. 9th WSEAS Int. Conf. Multimedia, Internet and Video Technologies, MIV '09, 2009, pp. 92-95

[44] Postorino, M.N., Barrile, V., Cotroneo, F. Surface movement ground control by means of a GPS-GIS system Journal of Air Transport Management, 2006, 12(6), pp. 375-381

[45] Barrile, V., Bilotta, G., D'Amore, E., Meduri, G.M., Trovato, S. Structural modeling of a historic castle using close range photogrammetry International Journal of Mathematics and Computers in Simulation, 2016, 10, pp. 370-380

[46] Barrile, V., Candela, G., Fotia, A., Bernardo, E. UAV Survey of Bridges and Viaduct: Workflow and Application. Lecture Notes in Computer Science (including subseries Lecture Notes in Artificial Intelligence and Lecture Notes in Bioinformatics), 2019, 11622 LNCS, pp. 269-284

[47] Barrile, V., Bilotta, G., Fotia, A. Analysis of hydraulic risk territories: Comparison between LIDAR and other different techniques for 3D modeling WSEAS Transactions on Environment and Development, 2018, 14, pp. 45-52

Contribution of individual authors to the creation of a scientific article (ghostwriting policy)

Rossella Nocera contributed to the manuscript redaction.

Author Contributions: Please, indicate the role and the contribution of each author:
Example
John Smith, Donald Smith carried out the simulation and the optimization.
George Smith has implemented the Algorithm 1.1 and 1.2 in C++.
Maria Ivanova has organized and executed the experiments of Section 4.
George Nikolov was responsible for the Statistics.

Follow: www.wseas.org/multimedia/contributor-role-instruction.pdf

Sources of funding for research presented in a scientific article or scientific article itself

Report potential sources of funding if there is any

Creative Commons Attribution License 4.0 (Attribution 4.0 International , CC BY 4.0)