

Digital transformation of bridges inspection, monitoring and maintenance processes

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ABSTRACT: New communication and information systems and technologies – known as ICT (Information and Communication Technologies) – have immense potential to aggregate new functionalities and services to the management of infrastructure assets. This phenomenon, known as 'Digital Transformation', has influenced the evolution of various sectors of our society, such as the emergence of 'Industry 4.0'. New wireless communication technologies, such as 5G networks (large capacity communication, high reliability, great coverage and low consumption, for information processing and management – such as Cloud Computing, Edge Computing, Big Data, Machine Learning and Artificial Intelligence – are considered as the enabling technologies of this digital transformation, integrated with the concept of IoT(Internet of Things). High connectivity capacity and intensive automation enable, for example, changes in inspection paradigms and asset maintenance by transferring product focus to service platforms ('Everything' as a Service – XaaS), bringing gains for efficiency, productivity, comfort and operational safety, as well as cost reduction. Bridges constitute an important part of the infrastructure and are subjected to damage caused by their continuous use over time. In addition to the effects of loading (fatigue, impacts, overloads, etc.), they are subjected to degradation of materials and support conditions, as well as exposure to adverse environmental conditions (storms, floods, gale, earthquakes, etc.). Scheduled inspections to assess their structural conditions are essential to ensure their proper use within the established safety limits. In other occasions, continuous or repeated monitoring of structural responses of bridges (displacements, vibrations and rotations at critical points) may add important information for decision-making regarding its maintenance, repair and reinforcement. The use of these data, together with techniques of structural reliability for the treatment of the uncertainties, allows predictions about the structural behavior to be elaborated with the consideration of different loading and degradation scenarios. The new ICTs can greatly contribute to the improvement of maintenance capacity and, consequently, to the reliability of the assets and to the operational availability of the system. Thus, the development of new predictive maintenance approaches, which make use of the large amount of data available, can improve the efficiency of maintenance processes, producing more accurate and reliable anticipated diagnostics. In this way, Digital Transformation can reduce maintenance costs (avoiding unnecessary maintenance events) and improve system availability, reducing operational losses. The use of Big Data Analytics, incorporating Artificial Intelligence and Machine Learning, are innovative solutions that can be introduced. The adoption of Digital Twins, that incorporate all these tools, can lead to a reduction in the total cost, allowing predictive and proactive maintenance. The concept of a Digital Twin for a railway bridge will be illustrated in this paper.

1 INTRODUCTION

Bridges are an essential and sensitive part of the infrastructure. Bridge integrity management is one of the most important issues for infrastructure operators. Engineers in charge of making decisions about management priorities face a daunting challenge: they must weigh many complex structural and load features, and also consider structural deterioration (fatigue, corrosion, e.g.), historical and social conditions, inspection data to balance operational needs

and budget constraints. Very often, managers and engineers do not have enough or appropriate data access to make these decisions in a quantitatively and data-oriented way. Therefore, they generally resort to qualitative judgments to balance the many priorities and decide on a course of action. This is a problematic point for managers themselves and exposes a systematic risk to operators and users.

An interesting way to go beyond qualitative judgment and try to apply quantitative data-driven approaches is to make use of new technologies that can

capture and manage more data on the current state of assets.

Digital transformation, associated with innovative computational techniques, is rapidly paving the way in this direction, providing the following interesting features: (a) Collection, organization and analysis of existing information (design, tests, inspections, monitoring and other information available); (b) Traditional and noninvasive techniques for inspection with the use of new technologies. (c) More affordable SHM (Structural Health Monitoring) systems and the Internet of Things (IoT) to generate new monitoring and analysis possibilities; (d) Implementation and application of automatic methodologies based on performance indicators and metrics for detailed classification and diagnosis of the bridge integrity, including the bridge deck, piers, abutments, foundations and bearings (Ghosn et al. 2016); (e) Development of Digital Twins for bridges and the use of Extended Reality (Zhu et al. 2019); (f) Integration of the collected information.

1.1 An example of endurance: The Alcantara Bridge - Spain

The roman bridge of Alcantara in Spain, also known as Trajan's Bridge at Alcantara (Fig. 1), is a stone arch bridge built over the Tagus River between 104 and 106 AD. It was commissioned by the Roman emperor Trajan in 98 AD. The bridge has a total length of 180m with 6 arches with spans between 13 and 28m. Despite its age, the bridge is still in operation. Because of recent bridge failures, it is an embarrassing confirmation that longevity can potentially be achieved for bridge structures.



Figure 1. Alcantara Bridge – Spain – 106AD.

The idea of longevity was so strong and well-accepted during the construction period of the bridge that its designer Caius Julius Lacer decided to display a daring statement on plaques at the bridge tower:

Pontem perpetui mansurum in saecula mundi fecit divina nobilis arte Lacer ... (Permanent bridge will remain forever in the world Lacer (designer) made by the famous art ...)

Caius Julius Lacer was apparently right in his statement, but he completely underestimated deterioration, hazards and the necessity of maintenance. In fact, the Alcantara Bridge had many partial destruction-reconstruction cycles along its long life motivated by wars, invasions and, more recently by floods. The construction of a dam in the area led to a serious flood in 1967, and because of that the base of the columns had to be fully repaired and recovered. Since then, the bridge has received a lot of attention from engineers and new technologies such as TLS (Terrestrial Laser Scanning) and GPR (Ground-Penetrating Radar) have been applied (Fig. 2). Through these techniques, the expected degradation of the stone blocks and the fillings has been confirmed and may lead to local failure. Recent studies using numerical modeling and limit plastic analysis are then used to access the safety and serviceability conditions of the bridge continuously (Cortés et al. 2018).

The endurance of the Alcantara Bridge is fantastic. But Lacer's statement and pride of his beautiful, well designed and constructed bridge was just a starting point to guarantee its longevity. Inspection, repair, retrofit and maintenance activities are essential engineering procedures that are necessary to achieve a considerable life span. In a certain way, all these activities have been applied to this bridge over its long life.

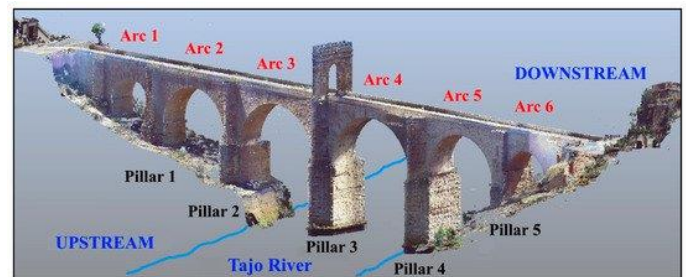


Figure 2. Application of nondestructive techniques (Terrestrial Laser Scanning (TLS) and Ground-Penetrating Radar (GPR) (Cortés et al. 2018).

1.2 Bridge Maintenance Modern Challenges

The fundamentals for the design and construction of roman bridges were established in the second half of 1st century BC by the roman architect Marcus Vitruvius Pollio, known simply as Vitruvius, in his treatise "The Ten Books on Architecture", based on the rules of harmony (Rowland & Howe 1999). The key point of the treatise is the Vitruvian Triad: *firmitas, utilitas, venustas* (strength, utility, beauty). These ideas have been recuperated by Leonardo da Vinci in the renaissance and are still the fundamental core of structural and architecture design. The ultimate and service limit state analyses, and the search for comfort and esthetics are closely related to the Vitruvian Triad, but not enough to face the new demands of a sustainable planet.

Durability and sustainability are important issues to be addressed too. The concepts of structural robustness and resilience are also necessary to achieve sustainability (Biondini & Frangopol 2016, Bocchini et al. 2014), not only for the individual structural systems but for their network as well. Structural robustness can be viewed as the ability of the system to suffer an amount of damage not disproportionated with respect to the causes of the damage itself (Saydam & Frangopol, 2011), while resilience is the ability of a system or a network of systems to absorb or avoid damage without suffering complete failure. It is an important new objective of design, maintenance and repair of bridges and infrastructure in general, as well as communities. Robustness and recovery of the transportation network depend strongly on the performance of its individual bridges. Bridges are the weakest links in any road transportation system because of their vulnerability to hazards and deterioration (Akiyama & Frangopol 2018).

Reliability-based performance indicators have been used recently to account for the uncertainty in resistance and loads. Reliability based performance indicators can provide adequate information on the safety of bridge components and individual bridges, but they lack the ability to reflect the outcome of a failure event in terms of economic losses. Therefore, risk and risk-based performance indicators need to be introduced to offer additional information on the performance of structural systems under various hazards. Risk allows combining the probability of component or system failure with the consequence of the event.

Under the current level of social conscience and knowledge about infrastructure, maintenance demands Lacer's statement sounds very naive for our present society. The challenges to make our infrastructure more reliable and resilient are considerable, but they are fascinating. In this context, the introduction of new technologies and digital transformation possibilities will make the whole process more accessible and comprehensive. Digital Transformation can reduce maintenance costs (avoiding unnecessary maintenance events), improve system availability, while reducing operational losses. The use of Big Data Analytics techniques, incorporating Artificial Intelligence and Machine Learning, are innovative solutions that can be introduced. The adoption of Digital Twins, that incorporate all these tools, can lead to a reduction in the total cost, allowing predictive and proactive maintenance. The future is there to be created.

1.3 Infrastructure demand and environmental conditions

It is well known that civil infrastructure is subjected to progressive deterioration due to aggressive environmental changes or sudden deterioration due to natural or manmade hazards.

The human population increased dramatically over the last two centuries, from 1 billion habitants in 1800 to 7,6 billion in 2018. To accommodate the demands of its crescent population the development of the infrastructure has been necessary and this process ended up producing a gigantic increase in the CO₂ emissions (Fig. 3). As a direct consequence of the rise of the CO₂ emissions, an increase of the average temperature of the planet has been observed (Climate Central 2019).

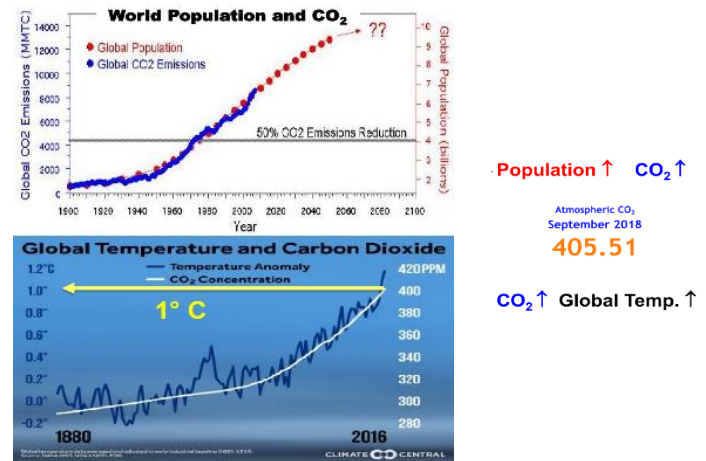


Figure 3. Climate change and average temperature rise (Climate Central 2018).

Officially the atmospheric CO₂ concentration reached an alarming 405.51 ppm in September of 2018, and there is some nonconfirmed indication of a value of 415,26 ppm in 2019 (Agence France Press 2019). Average global temperature data show an increase due to the increase of carbon dioxide concentration in the atmosphere of around 1°C in 2016 since 1880. Although it seems not to be a considerable increase, there was a shift also in the extreme events known as global warming effect (Fig. 4). This shift brought more frequent extreme level events of temperature and humidity. The environment is becoming more aggressive in general and the deterioration processes, already underway, may be potentially accelerated, specially carbonation and corrosion. Moreover, climate change may have an important impact on natural hazards like for example floods, storms, hurricanes, fires, etc. not only in terms of intensity but also in terms of frequency.

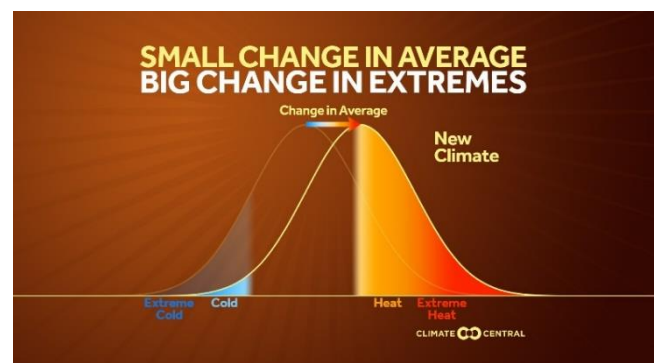


Figure 4: Change in average lead to change in extreme events (Climate Central 2018).

Corrosion is the most important deterioration problem of the infrastructure (ASCE Infrastructure Report 2017), and it is directly affected by temperature, CO₂ concentration and changes of humidity. To mitigate the corrosion associated problems in general, it is estimated that an amount of around US\$ 2 to 3 trillion is spent annually in the world. In the US this cost is estimated to be US\$ 1.1 trillion (around US\$ 9 dollar a day per capita). According to the ASCE Infrastructure Report of 2017, the overall grade of the infrastructure in the US is D+, with some improvements with respect to 2013. An increase from 2.5% to 3.5% of U.S. Gross Domestic Product (GDP) by 2025 of investments is necessary to meet future needs and restore the competitiveness of the country. These numbers demonstrate the importance and the impact of the correct management of the current and future infrastructure.

Fatigue is another important deterioration problem. With the rise of the population, a strong demand in terms of load cycles for transportation of people and goods is applied to our infrastructure. The change in the loading regime (natural or manmade) is an important issue to be taken into account as well.

2 THE PROBLEM OF DETERIORATION AND STRUCTURAL FAILURE IN BRIDGES

Recent bridge failures around the world are an evident demonstration of the need of a better understanding and new approaches to manage our infrastructure. The sudden collapses of the I-35W Mississippi River Bridge in Minneapolis and the Morandi Bridge in Genova, in 2007 and 2018 respectively, brought a lot of attention to the problem of bridge maintenance and future design provisions. The losses in terms of human lives in these two recent bridge failures have been irreparable, but the direct and indirect economic and social problems caused by the two collapses are enormous as well.

The conditions of bridges are not very different around the globe (Fujino 2018, Oliveira et al. 2019). The lack of a good Quality Control Plan for bridges affects the everyday life of many people in different countries. In Brazil, for example, there has been a sequence of bridge failures in the recent years with different causes, but the most evident one is poor maintenance (Fig. 5). These failures were not so catastrophic as the ones observed in the US and Italy, but they indicate a need of emergency and urgent actions to avoid or anticipate these situations. The sudden collapses also highlight the absence of plans to mitigate the consequences of bridge failures, especially for large and populated cities.

The bridge manager needs to plan and execute timely intervention (maintenance) in order to cope with the following challenges: (a) potentially unsafe bridges that are designed using old design codes; (b)

bridges with reduced resistance due to deterioration or mechanical damage; (c) bridges exposed to natural hazards that are not adequately considered or not even considered in design; (d) increasing traffic volume and axle loads; (e) increased exposure of bridges to natural hazards due to climate change. (Hajdin 2018)



(a) Guararapes Bridge in Belo Horizonte-MG, Brazil. September, 2014.



(b) Eixão Bridge in Brasília, Brazil – February, 2017.



(c) Marginal Tietê Bridge, São Paulo, Brazil. November, 2018.



(d) Marginal Tietê / Via Dutra Bridge, São Paulo, Brazil. Interdicted in February, 2019.

Figure 5: Recent and repeated bridge failures in Brazil.

Structural safety and serviceability are primary concerns in bridge design, as known and practiced since the Roman times. In the current inspection procedure, the most important aspects of bridge service life are addressed indirectly by a qualitative measure,

defined by the condition state, or condition index, which is based upon observable damages recorded during inspections. The condition state, defined by the condition index, is only a qualitative value loosely correlated to safety, serviceability, and more recently durability. In the Brazilian Code, the condition indexes are scaled from 1 to 5, where 1 is the worst value and 5 is the best (ABNT-NBR 9452 2016).

3 FUNDAMENTAL CONCEPTS

The digital transformation of the process of bridge maintenance requires a clear understanding of some underlying concepts. Some of them are presented briefly in the following subtopics.

3.1 Bridge inspection

The term bridge inspection comprises a set of technical and specialized procedures that include the collection of data necessary for the formulation of a diagnosis and prognosis of the bridge behavior, in order to maintain or re-establish the requirements of structural safety, functionality, durability, etc. Bridge inspection is directly connected with bridge maintenance.

Depending on the scope and frequency, bridge inspection may be classified as: (i) initial or registration inspection (for new or retrofitted bridges), (ii) routine (basic inspection, carried out usually once or twice a year), (iii) special (or detailed inspection carried out at least every five years), and (iv) extraordinary (carried out by highly qualified experts according to technical needs after extraordinary or accidental situations (e.g. after floods, earthquake, blasts, hurricanes) to indicate rehabilitation or modernization needs) (Radomski 2001, ABNT-NBR 9452 2016).

The determination of the optimum inspection planning and timing is crucial for minimizing the life cycle cost while maintaining the performance levels of the structure.

3.2 Bridge maintenance

Maintenance or conservation of bridges comprises actions or strategies that prevent, delay or reduce the deterioration of bridges or their elements. It intends to restore the functionality of existing bridges, maintaining bridges in good condition and in order to achieve or increase their service life.

Proper maintenance requires good management procedures in which a network of bridges is cared for from its conception to the end of its service life. The goal is to preserve the bridge functionality at least for the specified design life, along which the entire structure, or part of it, is intended to be used with the

planned maintenance without the need of major repairs.

Ordinary maintenance work comprises intervention resulting from the existence of anomalies of lesser importance, such as cleaning or protection of elements of a bridge. On the other hand, repair work involves changes in the resistant capacity or structural operation, the replacement of resistant elements or bearing appliances. They are characterized by greater complexity, the need for design and sometimes the use of heavy equipment.

In general, three types of maintenance schemes are used: preventive maintenance (expected to delay the deteriorating process with no significant gain of performance), corrective or essential maintenance (more expensive, but more effective in restoration of performance), and predictive maintenance (designed to help determine the condition of in-service equipment in order to estimate when maintenance should be performed). This approach promises cost savings over routine or time-based preventive maintenance because tasks are performed only when needed. This approach is heavily based on large amounts of data and suitable for the introduction of new technologies like machine-learning, for example.

3.3 Bridge management systems

Bridge Management Systems (BMS) can be defined as a process or a set of engineering and management functions that, if considered simultaneously, comprehend the actions necessary to manage the resources to keep a group of bridges in operation.

BMS terminology is often associated with the packages of *software* used for bridge networks management. However, the *software* used for bridge management is simply BMS tools. In practice, the software subsidizes the bridge manager with the information necessary for decision making based on engineering criteria and knowledge of administrative engineering.

In several countries, the creation of large national databases began, with standardized and uniform records according to standards and procedures, based on Condition or Performance Indexes. For management and support analyses in decision making, current BMSs use a *Life-Cycle Costs Analysis (LCCA)* tool.

LCCA's main approach is to consider not only the initial costs of bridges, such as projects, construction and execution, but also long-term costs such as operation, maintenance, repairs and rehabilitation. The data resulting from inspections are usually the major entries into the analysis modules. These analysis modules are divided into three: a cost module, a degradation module, and an optimization module.

3.4 Bridge monitoring – Structural Health Monitoring (SHM)

Structural Health Monitoring (SHM) consists of verifying the service structural behavior, based on relevant quantities measured by sensors of different technologies. These provide meaningful information regarding the structural conditions, identifying situations that require preventive actions, for instance, the decision of either blocking the access to the bridge/building or restricting its use (Wenzel, H. 2009).

Sensors collect various types of data, periodically or continuously. Once acquired, they are analyzed and stored for future analyses. The objective is to have a better understanding of the structural behavior, detecting damages in advance and, therefore, leading to a better planned and less expensive management.

The integration of structural health monitoring (SHM), inspection, and updating provide a powerful method to reduce uncertainty, calibrate, and improve structural assessment and performance prediction models. Life-cycle management is very efficient in providing a practical predictive evaluation of cost, safety, and condition, but is not very effective in providing actual structural performance. On the other hand, SHM techniques effectively capture structural behavior and the demands on a structure but are not as effective in translating this information to bridge managers' actions. Consequently, it is very important for the integration of SHM and updating techniques in the life-cycle management framework.

There are several reasons for the use of SHM:

- Collect data to validate design hypotheses: a better understanding of the structural behavior.
- Search for valuable information to extend the structure remaining service life: early detection of damage.
- Improve structural safety through information based on operating conditions. Therefore, it is possible to detect, in advance, evidence of the acceleration of deteriorating processes.
- Know, in real-time, the structural behavior corresponding to all stages of constructive or repair (retrofit) processes.
- Improve planning on maintenance and structural integrity.
- Promote cost-efficiency.
- Structures for which innovative solutions, materials and construction processes are utilized.

SHM is closely associated with and benefits a lot from structural inspection, non-destructive and semi-destructive testing, and numerical modeling. The use of calibrated models constitute a powerful tool for anticipating or testing imaginary scenarios of loading or hazards. These systems are used commonly

nowadays to study the behavior of critical structures, for their economic and social importance, structures with significant uncertainties regarding geotechnical conditions, seismic risk, environmental aggression, weathering condition or vulnerability during construction, existing structures with identified deficiencies or which conditions raise doubts. SHM requires the application of sensors and supportive technologies, the generation of appropriated signals for the structural behavior diagnosis, signal transmission and processing, identification and interpretation of occurrences, and implementation of an integrated operational system to evaluate the structural health. All these activities can benefit a lot from the new technologies for digital transformation.

SHM can be applied in a portable or fixed condition (usually online). A portable scheme is usually applied in short-term controlled tests, like static or dynamic load tests or in evaluations based on non-destructive or semi-destructive techniques.

The use of a short term SHM scheme has been applied to study the retrofit of old steel bridges company along the Vitoria-Minas Railway (Fig. 6). Close observations of the responses from monitoring and modeling show that the global behavior of the structure can be captured very well by the calibrated numerical model, but there are clear differences in the strains in the connections and bearings (Fig. 7). These strain/stress fluctuations are very important in the fatigue analysis of the bridge for the estimation of its residual life (Ticona Melo et al. 2019).



Figure 6. Suaçuí River Bridge - Warren truss with 41m span.

Online long-term fixed monitoring systems are applied usually in important or historical bridges where a close look in the life-cycle process is needed. A system like this has been developed to study the rehabilitation of the Dom Pedro II Bridge (Colombo et al. 2016). This bridge was built in England in 1870 and was assembled over the Paraguaçu River in 1885 (Fig. 8). Four isostatic puddled iron trusses of 96 m in length compose the total structure of the bridge. The deck was originally covered in wood in order to allow the passing of not only rail cars but regular road traffic.

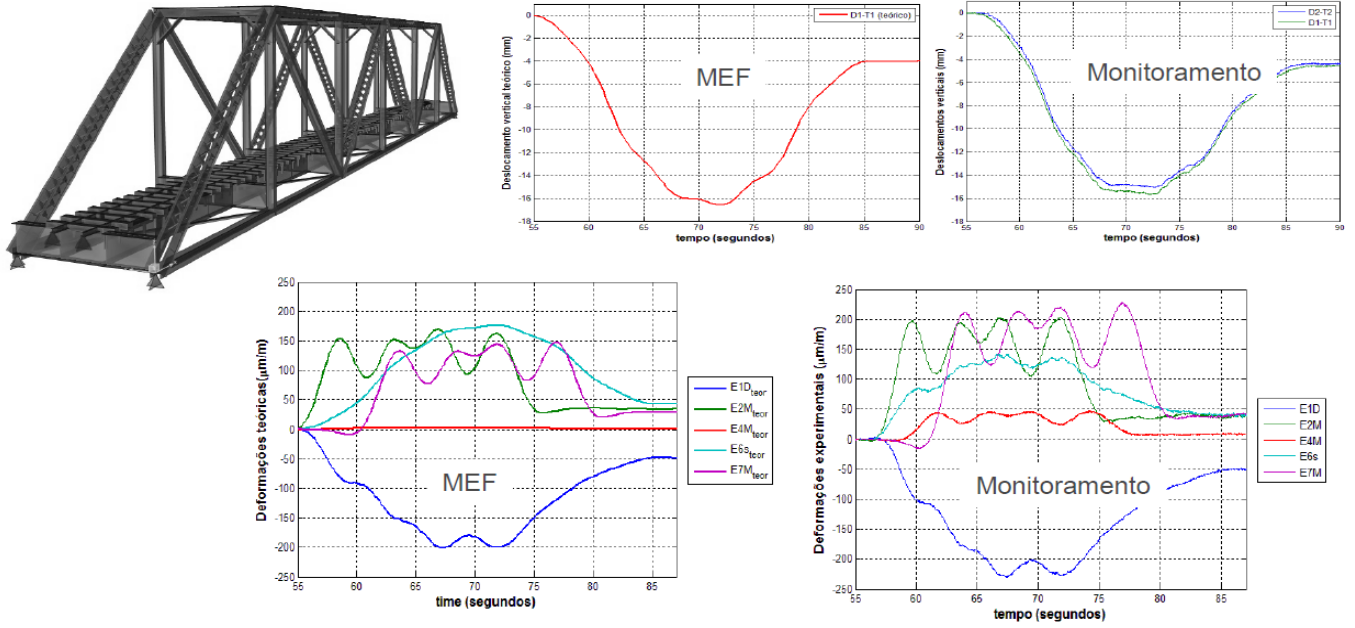


Figure 7. Comparison of results from monitoring and numerical analysis.



Figure 8. Dom Pedro II Bridge, a four span puddled iron truss bridge – Monitoring System using Cloud Computing.

Dom Pedro II Bridge connects the cities of São Felix and Cachoeira in the State of Bahia. The traffic is open to road vehicles, pedestrians and trains. In 2002 this bridge was declared a National Historic Landmark. The bridge has passed through some renovations and some major rehabilitation due to severe corrosion deterioration. The replacement of some parts of the structure has been extremely sensitive, causing some overloading in the remaining parts. Because of that, the whole operation had to be followed by monitoring (Fig. 9). The complete restoration and the replacement of the bearings are now being monitored by this long-term system. A lot of data is generated as expected. Cloud Computing technologies have shown to be very helpful in data manipulation and visualization, and alarms set up as well.

3.5 Reliability

Structural reliability is defined as the probability that a component or a system will adequately perform its specified purpose considering a defined period and particular conditions. Either component or system reliability can be computed. A failure of a single

component or a combination of individual components may initiate the failure of the system. Let R and S be the resistance and the load effect, respectively, with the probability density functions (PDFs) f_R and f_S , characterizing these respective random variables. The probability that S will not exceed R , $P(R > S)$, represents the reliability. The time-variant probability of failure $P_F(t)$ can be expressed in terms of joint PDF of the random variables $R(t)$ and $S(t)$, $f_{R,S}(t)$, as:

$$P_F(t) = \int_0^\infty \left(\int_0^S f_{R,S}(t) dr \right) ds \quad (1)$$

And the reliability index can be expressed as:

$$\beta(t) = \Phi^{-1}(1 - p_F(t)) \quad (2)$$

where $\Phi^{-1}(\cdot)$ is the inverse of the standard normal cumulative distribution function (CDF). In addition to the evaluation of the probability of structural failure at a given point in time, characterizing an ultimate limit state, the consideration of various functionality aspects such as serviceability limit states is also possible.

3.6 Life-cycle cost

In the evaluation of bridge performance, a crucial performance indicator is life-cycle cost. The proper allocation of resources can be achieved by minimizing total cost while keeping structural safety at a controlled level. The expected total cost C_{ET} during the lifetime of a bridge structure is commonly expressed as:

$$C_{ET} = C_T + C_{PM} + C_{INS} + C_{REP} + C_F \quad (3)$$

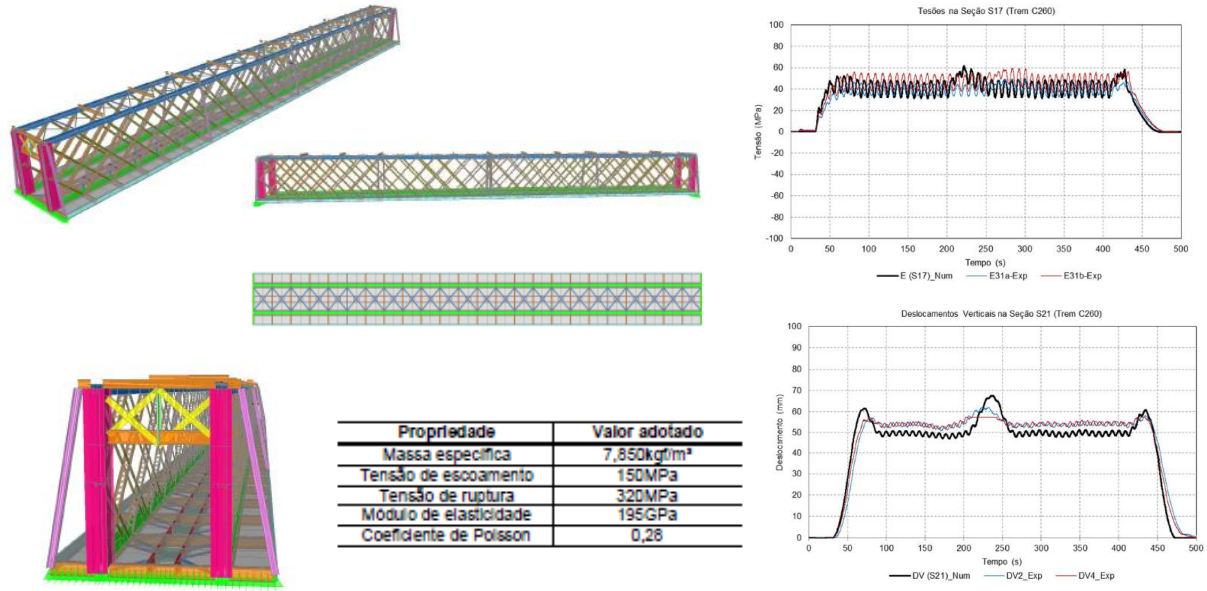


Figure 9. Dom Pedro II Bridge – Calibrated numerical model response compared to monitoring data.

where C_T is the initial cost, C_{PM} is the routine maintenance cost, C_{INS} is the expected cost of inspections, C_{REP} is the expected cost of repair, and C_F is expected failure cost. Optimum planning for life-cycle management of infrastructure assets, including bridges, is achieved when cost and performance are balanced.

3.7 Risk

Risk is quantified by combining the probability of occurrence and the consequences of events generated by hazards. The instantaneous total risk (R) of a structural system can be formulated as:

$$R = \iint \dots \kappa(x_1, x_2, \dots, x_m) f_X(x_1, x_2, \dots, x_m) \cdot dx_1 \cdot dx_2 \dots dx_m \quad (4)$$

where $\kappa(x)$ denotes the consequences associated with events resulting from hazards and $f_X(x)$ is the joint PDF of the random variables. The integral in Eq. (4) is difficult to assess and often cannot be solved. Under certain assumptions, a simpler expression for total risk can be obtained. A simplistic approach for calculating instantaneous total risk R is (Ellingwood 2005):

$$R(t) = \sum_{i=1}^n C_m \cdot P_{F|H_i}(t) \cdot P(H_i) \quad (5)$$

where C_m represents the consequences of failure, $P(H_i)$ describes the probability of occurrence of a hazard, $P_{F|H_i}(t)$ is the conditional failure probability given the occurrence of a hazard, and n is the total number of hazards considered within the analysis.

3.8 Robustness

Structural robustness is understood as the ability of a structure to withstand natural or manmade hazard events like fire, explosions, impact or the consequences of human error, without being damaged to an extent disproportionate to the original cause - as

defined in EN 1991-1-7 of the Accidental Actions Eurocode (EN 1991-1-7 Eurocode 1 2006). Usually, three alternative measures are applied, sometimes simultaneously, to achieve structural robustness and reduce the risk of disproportionate collapse: (a) reducing the possibility of occurrence of accidental loading, (b) preventing the propagation of a possible initial failure and increasing redundancy, (c) designing the structure to withstand accidental loading (load resistance method). Of course, to address these issues more elaborated structural analysis and load records are necessary.

3.9 Resilience

Resilience is the ability to absorb or avoid damage without suffering from complete failure. It is an objective of design, maintenance and restoration of bridges and infrastructure in general, as well as communities. Resilience considers the impact of infrastructure damage, failure, and society recovery when subjected to hazards with a low probability of occurrence and potentially high consequences. Resilience is closely related to sustainability (Bocchini et al. 2014). Sustainability relates to current and future resource management and addresses the impacts of planning and development on the economy, society, and the environment. Resilience and adaptivity are necessary features of long-term sustainable infrastructure.

The general approach to quantify the resilience of an individual structure, a group of structures, or a network of interrelated structures is to compute the parameter RE (resilience) as the integration over time of the functionality:

$$RE = \frac{1}{t_r} \int_{t_0}^{t_0+t_r} Q(t) dt \quad (6)$$

in which $Q(t)$ is the functionality, t_o is the occurrence time of the extreme event, and t_r is the investigated time horizon. (Frangopol et al. 2016).

3.10 Bayesian update and Bayesian networks

In the reliability analysis of bridges, the random variables of the degradation model can be obtained from historical data of similar bridges, located in similar aggressive environment regions. However, this type of approximation can result in very different predictions from those found in the real structure. One way to minimize these differences is to obtain monitoring data from the structure itself, either through visual inspections, structural tests or through Structural Health Monitoring (SHM) techniques (which may allow real-time monitoring of the Structure).

Bayes theorem can be used to update the variables of the degradation model from the bridge monitoring data. During recent decades, the Bayesian approach has found great acceptance in the scientific community and has been applied in several areas (Colombo, 2016).

Assuming that a degradation rate for a bridge type, located in a given aggressive environment, is known and can be approximated depending on θ variable. If no inspection has been carried out on the bridge, the reliability of the bridge should be estimated by the θ variable. However, if an inspection is carried out, and the degradation rate obtained through inspection can be approximated by the variable x , according to the Bayes Theorem, the probability density function is $\pi(\theta|x)$ or probability a posteriori, since the x event was observed, can be written as:

$$\pi(\theta|x) = \frac{p(x|\theta)\pi(\theta)}{\int p(x|\theta)\pi(\theta)d\theta} \quad (7)$$

where $p(x|\theta)$ is the conditional probability density function of x given θ , $\pi(\theta)$ is the function of distribution of probability a priori, θ is the vector of the variable a priori and x is the vector of the subsequent observations.

Therefore, from the data obtained in the inspection performed, the reliability of the bridge can be estimated. The probability density of the degradation rate $\pi(\theta|x)$, given that x was observed in the inspection, enables greater assertiveness in terms of the actual conservation status of the bridge. If a new inspection is carried out, the deterioration rate can be updated again from the probability density function obtained from the first inspection, and so on if further inspections are to be made. The successive repetition of this procedure will result in a better estimate since more and more monitoring data are being incorporated into the model.

Bayesian network, also known as belief network, decision network, Bayesian model or probabilistic directed acyclic graphical model, is a probabilistic graphical model that represents a set of variables and

their conditional dependencies via a directed acyclic graph. Bayesian networks are ideal for taking an event that occurred and predicting the likelihood that anyone of several possible known causes was the contributing factor. For example, a Bayesian network could represent the probabilistic relationships between diseases and symptoms. Given symptoms, the network can be used to compute the probabilities of the presence of various diseases.

Efficient algorithms can perform inference and learn in Bayesian networks. Bayesian networks that model sequences of variables are called dynamic Bayesian networks. Generalizations of Bayesian networks that can represent and solve decision problems under uncertainty are called influence diagrams.

4 BRIDGE PERFORMANCE EVALUATION

Under the current level of knowledge, it is much more reasonable to address safety, serviceability and durability directly in the inspection process, using the information on bridge performance (performance indicators) defined during the design and construction. There are several performance indicators that can be related to the possible occurrence of local and global failures, including system ductility, failure times, redundancy, robustness, and resilience (Biondini & Frangopol 2016). These performance indicators need to be included into the practical design codes of bridges (Biondini & Frangopol 2018; Ghosn et al. 2016). The performance indicators change over time due to structural deterioration and time-variant resistance. The development of a generalized framework for assessing bridge life-cycle performance and cost is necessary. This framework must emphasize analysis, prediction, optimization, and decision making under uncertainty. A life-cycle approach to bridge engineering provides a rational basis for making decisions regarding design, construction, inspection, monitoring, maintenance, repair, rehabilitation, replacement, and management of bridges under uncertainty by using multi-objective optimization in order to balance performance and cost, having risk under control. (Frangopol et al. 2016)

Different maintenance scenarios have a direct effect on the performance profile (Figure 10). The probabilistic aspect of the performance prediction (the reliability index of the performance indicator e.g.) is illustrated by the probability density functions (PDFs) of the initial performance index, deterioration initiation, rate of deterioration, and service life with (i) without maintenance (or *do nothing* scenario), (ii) with preventive maintenance (PM) only, and (iii) with both preventive and essential (or corrective) maintenance (EM). Preventive maintenance includes actions of replacing small parts, repairing concrete surfaces,

injecting cracks, checking lubricants, and cleaning and painting exposed parts of a deteriorating bridge. In this sense, the preventive maintenance is expected to delay the deteriorating process with no significant gain of performance. However, this gain of performance may be important to increase the service life of the bridge. As can be observed in Figure 10, essential (or corrective) maintenance intends to restore performance when a predefined threshold is reached. These corrective interventions usually are much more expensive, but they have a strong potential to improve the performance level to higher values. Typically, EM actions include repair, strengthening and replacement of bridge components. They can be time consuming and may the availability of the bridge. Figure 10(b) shows the cumulative maintenance cost as a function of time for preventive and essential maintenance interventions and the cumulative effect on the total cost of the bridge management.

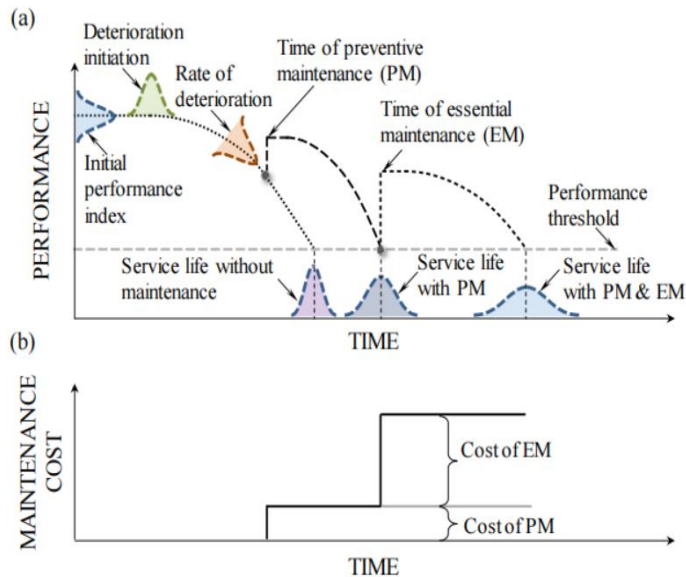


Figure 10: Probabilistic structural performance profiles considering the effects of deterioration with preventive and essential interventions (Frangopol et al. 2016).

Another important point to mention is that approaches for the life cycle management of bridges involving reliability performance indicators usually consider uncertainties associated with loads and resistance but are not able to account for the consequences incurred from bridge failure. Risk-based indicators provide the means to combine the probability of structural failure with the consequences associated with this event (Ellingwood 2005)

Considerable progress has been made in the topic of bridge maintenance in recent years (Furuta et al. 2015; Bittencourt et al. 2016; Powers et al. 2018). But still, some challenges remain in order to try to take some advantage of new digital technologies, in order to make the process more automatic and robust. Establishing the best inspection, maintenance and retrofit schedules requires a robust optimization process which integrates the proper damage occurrence and propagation models with the previous knowledge

about the safety and financial constraints. In this regard, information obtained by manual or automated inspections, non-destructive inspection and SHM indicates clearly the current condition state of the bridge under investigation, and also provides useful data that can be used to update the performance prediction models. Within the last decades, multiple approaches have been proposed for updating the performance prediction models based on inspection outcomes and/or SHM data. The usual approaches apply the Bayesian updating of model parameters. In the updating process, information from inspection or SHM is used to represent the likelihood function which can be combined with the prior information on model parameters to find their posterior distributions (Frangopol & Soliman 2015). The use of dynamic Bayesian networks has been recently applied in fatigue reliability analysis to try to establish optimal inspection/repair plans with the lowest expected life-cycle cost (Yang & Frangopol 2018; Heng et al. 2019).

There are in general three categories of life-cycle management techniques applicable to civil infrastructure: (i) Condition-based Markov decision processes, (ii) Reliability and Risk-based management and (iii) Renewal Theory-based life-cycle cost models (Yang & Frangopol 2019). The first has been widely used in the recent years, constituting an important tool available in the main Bridge Management Systems (BMS). The second has been extensively studied in the recent years. Civil infrastructure is exposed to both progressive (gradual) deterioration (corrosion, fatigue, etc.) due to aggressive environmental conditions and sudden (shock) deterioration processes due to natural or manmade hazards (earthquakes, hurricanes, floods, fires, explosions). The capability of the renewal-reward models to deal with progressive and sudden and systematic replacement, based on performance thresholds, makes it a very promising approach for the future.

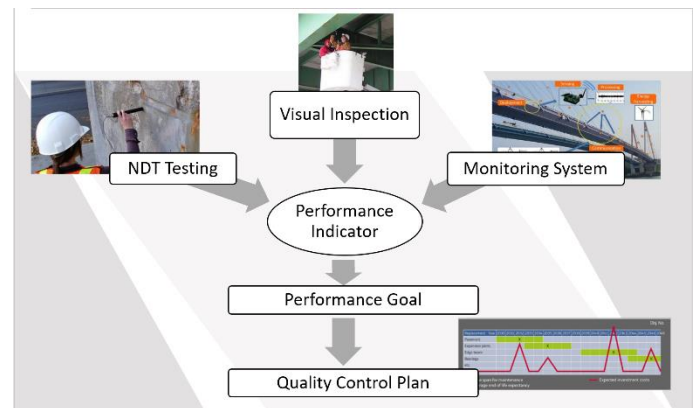


Figure 11: Quality control of bridges (COST TU1406 2019).

Future Bridge Management Systems will be able to bridge performance indicators allowing systematic assessment of safety, serviceability and durability based on visual inspection results, non-destructive

testing and Structural Health Monitoring (SHM) (Fig. 11).

By including Bridge Digital Models (Hüthwohl et al. 2018; Wikipedia 6D BIM, 2019), the next generations of BMS will become a key decision-support tool not only for maintenance planning but also for managing heavy load permits and risk assessment due to hazards. Another promising possibility is the development of digital twins of bridges for maintenance purposes. While Bridge Information Modeling (BIM) is a process involving the generation and management of digital representations of physical and functional characteristics of a bridge/building, applied in the design and construction phases and maintained throughout its life cycle, a Digital Twin is a dynamic virtual representation of an object or physical system throughout its lifecycle, using real-time data to enable understanding, learning, and reasoning. A Digital Twin refers to a digital replica of physical assets, processes and systems that can be used for various purposes, like bridge maintenance e.g. (Dang et al. 2018).

Digital Twins solve the practical problems, generating a virtuous cycle with BIM and other technologies, which are present, but in an integrated way (Shim et al. 2017). Digital Twins use models, scans, sensors, machine learning, data analytics, artificial intelligence, etc. It always focuses on offering an easy navigation and visualization environment, which will allow for a better understanding of the built environment. BIM offers structured and consistent data management in a collaborative environment for Digital Twins technology, which will use this basis to advance the operation and maintenance phase to the end of the bridge lifecycle (demolition and retrofit). It is expected that the application of the Digital Twin technology may offer benefits such as: downtime reduction, predictive analysis, preventive maintenance, sustainability optimization and transparency. The use of BIM or Digital Twins need to be closely associated with the recent developments of bridge inspection and maintenance planning (Fig. 12).

A clear organization of ideas and entities involved in the process is highly necessary. An ontology for bridge quality control, indicating the relationship between the different entities has been recently proposed by COST TU 1406 (COST TU1406. 2016, 2017, 2019) (Fig. 13). Quality Control, as intended, has two meanings: (i) verify, check or inspect and (ii) command, direct or rule. A quality control plan defines the extent and the interval of inspections or investigations and data necessary to estimate key performance indicators (KPI) and forecast their future evolution.

Safety and serviceability are the natural choices of Key Performance Indicators (KPI) for existing

bridges. They may also be combined with other indicators like durability, stability, costs and functionality, etc. In COST TU1406, the proposal for KPI (qualitative, between the scale of 1-5) is defined as:

- i. *Safety, Reliability and Security (S, R, S) - a combined KPI;*
- ii. *Availability and Maintainability (A, M) - a combined KPI;*
- iii. *Economy \$\$ (i.e. Costs);*
- iv. *Environment (E)*
- v. *Health and Politics (H, P) - a combined KPI.*

The current framework considers the following KPI (Key Performance Indicators) with associated definitions:

- i. *Reliability - the probability that bridge will be fit for purpose during its service life. It is the complement to the probability of structural failure (i.e. safety), operational failure (i.e. serviceability) or any other failure mode.*
- ii. *Availability - the proportion of time a system is in a functioning condition. It is not reliability-related disruption of bridge users but originates from planned maintenance interventions (e.g. additional travel time due to an imposed traffic regime on bridge).*
- iii. *Safety - related to minimizing or eliminating the harm to people during the service life of a bridge. The loss of life and limb due to structural failure is not included (see Reliability).*
- iv. *Economy - related to minimizing long-term costs and maintenance activities over the service life of a bridge. Herein the user costs incurred due to detours and delays are not included.*
- v. *Environment - associated with minimizing the harm to environment during the service life of a bridge.*

The bridge performance is represented by a 'Spider Net' diagram (Fig. 14). The larger the area in the diagram enclosed by the KPI values, the better is the bridge performance and KPIs values in the green area are desirable. This format is supposed to be applicable for a single or a group of bridges.

The key-performance indicators are correlated to established performance indicators associated to failure modes in the so-called vulnerable zones. In COST TU1406, all KPI are scaled from 1-5, where 1 is the best value and 5 is the worst. Notice that the qualitative value of the KPI for the *Safety, Reliability and Security* dimension may be associated with the usual Condition Index (for the Brazilian Code is just a question of inverting the scale). The difference lies in the fact that the KPI is obtained from a computed PI (Performance Indicator), in addition to the information from the other dimensions of the Spider-Net diagram.

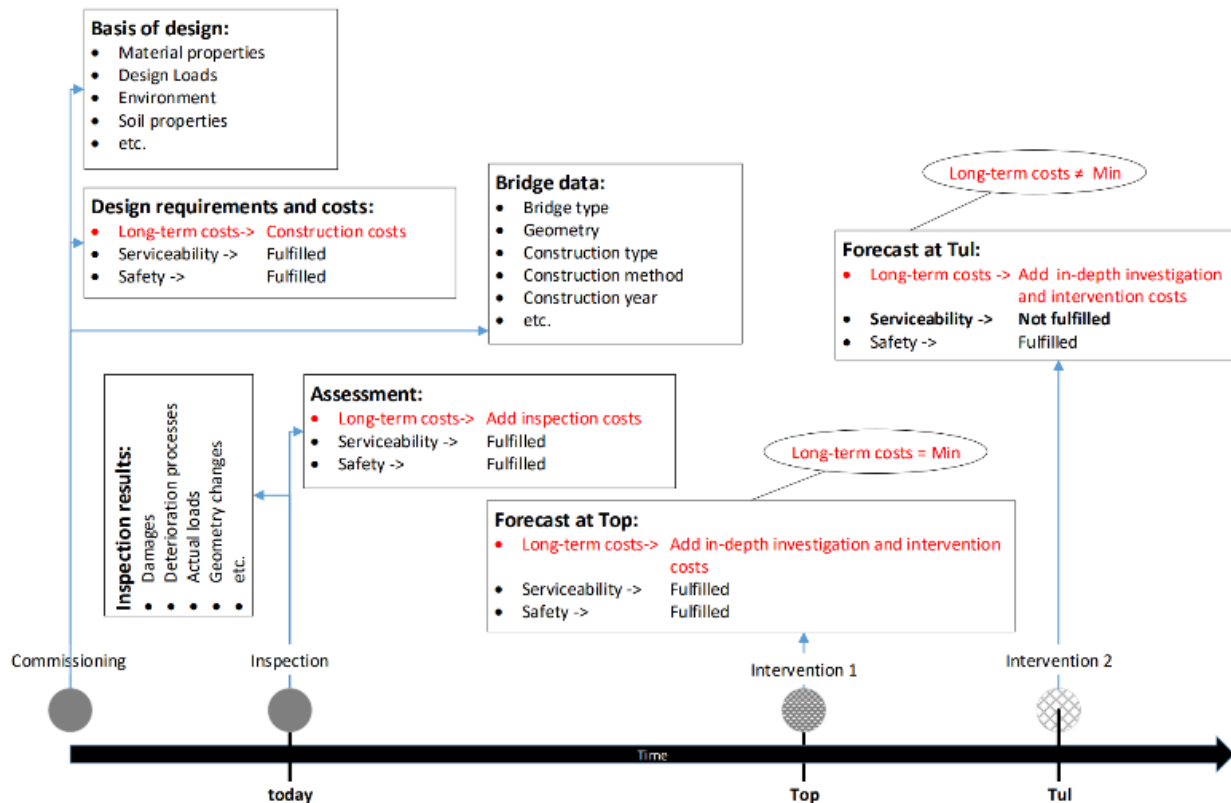


Figure 12: Long-term maintenance planning (COST TU 1406 2019).

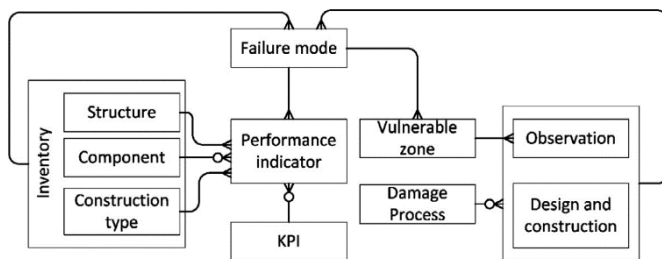


Figure 13: Quality control ontology (COST TU 1406 2019).

The quality control framework is designed to have two stages - static and dynamic. The first one comprises preparatory work, inspection tasks and preliminary assessment of the KPIs. The second mode implies assessment of remaining service life, KPI development over time and finding an optimal maintenance scenario for decision-making purposes. To predict future performance Monte Carlo simulation, degradation and maintenance models may be used in conjunction with multi-objective optimization techniques to search for the optimal maintenance schedules in terms of the minimization of degradation and maintenance costs (Denysiuk et al. 2016).

General frameworks for life cycle analysis and optimization considering uncertainty, generate a powerful tool for assessing bridge conditions in a systematic way and should be incorporated in new systems for bridge management, taking advantage of the new digital technologies available.

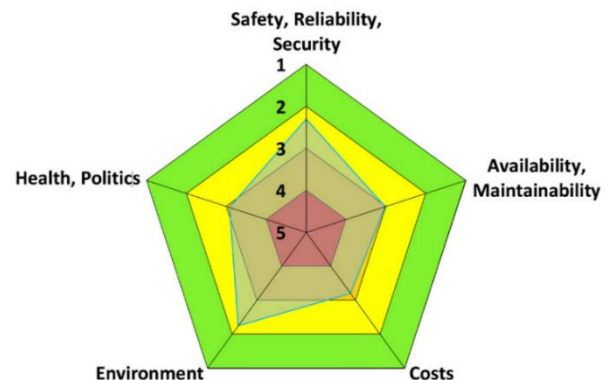


Figure 14: Spider Net diagram for bridge assessment (COST TU 1406 2019).

5 DIGITAL TRANSFORMATION

Digital Transformation is a process in which companies make use of technology to improve performance, increase range and ensure better results. It is a structural change in organizations where technology has an essential role. At the present time, along with the wave of Industry 4.0, the rapid development and advances in digital technologies are rapidly transforming the traditional manufacturing industry. Digital representation provides the elements and dynamics of how an Internet of Things device operates and lives throughout its lifecycle.

Artificial intelligence, advanced prediction tools, cloud and edge computing, big data analytics, new generations of robots and sensors can be all integrated to create a new environment where the assets,

represented by their digital twins, can interact, denominated the Internet of Things (Fig. 15). It is expected that all this process can bring simplicity to complex situations, like the maintenance of bridges, following Leonardo Da Vinci's statement: "Simplicity is the ultimate sophistication".



Figure 15. New technologies applicable to bridge inspection, monitoring and maintenance.

5.1 Internet of Things

The Internet of Things (IoT) refers to an ongoing trend of connecting all kinds of physical objects to the internet, especially ones that one might not expect. This can mean everything from common house objects like refrigerators and lightbulbs, to business assets like shipping labels and medical devices, to unprecedented wearables, smart devices, infrastructure assets and even smart cities. A typical IoT system, like a smart bridge, works by continuously sending, receiving, and analyzing data in a feedback loop. Depending on the kind of IoT system, analysis can be conducted either by humans or artificial intelligence and machine learning (AI/ML), in near real-time or over a longer period. In order to predict the optimal time to inspect or maintain a bridge, the IoT system may connect to the Google Maps API (Application Programming Interface) data about real-time traffic patterns in a region, as well as utilize long-term data for deterioration processes collected by different types of smart sensors or robots. IoT data collected from every smart sensor can be analyzed by bridge owners in larger-scale optimization efforts. The Internet of Things (IoT) is a dynamic global information network consisting of Internet-connected objects, such as sensors, actuators, as well as other instruments and appliances that comprise the future Internet.

5.2 Digital Twins

A digital twin is a digital replica of a living or unliving physical entity. By uniting the physical world and the virtual world, the data is transmitted transparently, allowing the virtual entity to exist simultaneously with the physical entity.

More precisely, "A Digital Twin is an integrated multi-physics, multi-scale, probabilistic simulation of a product or system that uses the best available physical models, sensor updates, etc., to mirror the life of its corresponding twin", as defined by Glaessgen & Stargel (2012). A Digital Twin consists of three components: a physical part, a virtual part, and the connections between the physical and virtual part, and has three basic characteristics:

- Real-time reflection: both physical and virtual parts exist in Digital Twin, the virtual part can keep ultrahigh synchronization and fidelity to reflect its physical counterpart.
- Interaction and convergence: it happens in both physical part, virtual part and between physical and virtual part. Also, the interaction and convergence between real-time data and historical data can make the Digital Twin data more comprehensible and useful.
- Self-evolution: a Digital Twin can collect and update data in real-time, the virtual part can be continuously self-improved by comparing the virtual part with the physical part.

The connection between the real and the virtual worlds is established in real-time through data obtained through sensors. A Digital Twin provides interesting features in production and design, remote diagnostics and service. A Digital Twin relies on the continuously accumulated data and real-time presentation of the collected data to simultaneously update and modify its physical counterpart. On the other hand, the manipulation and interpretation of the huge amount of collected data and information in an intuitive manner remains a big challenge.

Extended reality (XR) is very helpful in this aspect because it allows the user to visualize and interact with Digital Twin data by integrating graphics, audios and real-world objects. (Zhu et al. 2019). XR has been recently implemented in various areas of the industry from product design, to data management, assembly instructions, and maintenance.



Figure 16. Digital Twin capabilities.

The Digital Twin of a bridge is a virtual and real-time representation of its structural system and

components. Therefore, it is capable to represent distinct aspects of performance, environment, geometry evolution, anomalies detection, maintenance and condition states based on the continuously collected data, updates and changes from its physical counterpart. All this data evolves with time (Fig. 16), enabling the Digital Twin to continuously evaluate its structural integrity risk (Faridafshin et al. 2019). (Fig. 17).

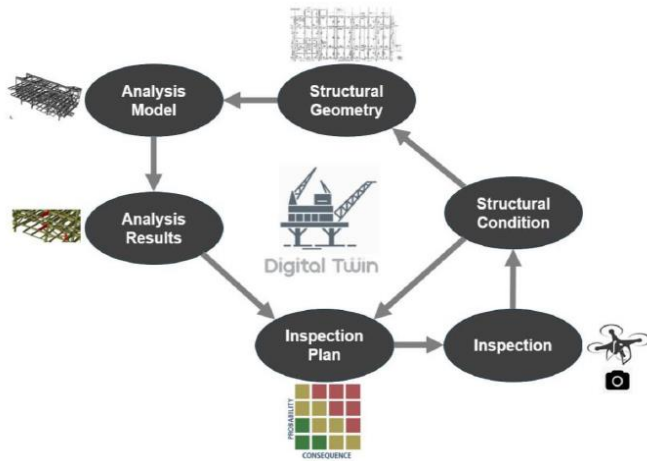


Figure 17. Risk-based structural integrity management (Faridafshin et al. 2019).

Reliable assessment of the bridge requires well-organized life-cycle information from design to operation. 3D digital twin bridge models are natural candidates for the next generation of bridge maintenance systems. 3D geometry models can be generated by the combination of 3D scanning and wire-based parametric modeling. Damage anomalies are linked to the elements of the bridge. Environmental conditions including temperature, humidity, loading history, non-destructive and monitoring data provide essential information for future performance prediction of a structural member. The bridge digital twin is then updated by each inspection or maintenance record and by non-destructive or monitoring data. The digital twin model allows big data analysis and artificial intelligence applications for more reliable prognosis of future performance of the bridge.

Automated systems for bridge maintenance have always been a difficult problem for bridge managers. 3D digital BIM technologies are widely used now for design and construction. They can be associated naturally to the digital twin, where more efficient ways to handle data is developed to avoid all the complexity of the parametric models and their interaction. Adapting machine vision concepts, it is possible to detect the structural anomalies in real-time. Inspection data can be generated by humans, by mobile devices, by drones, or other wearable/XR devices. Post-processing of the data to determine the extension of the anomalies provides the support for the decision-making process from a remote workstation. (Dang et al. 2018, Hühthwohl & Brilakis 2018, Hühthwohl et al.

2018). All these features can be naturally incorporated in the Digital Twin of an existing bridge.

5.3 Extended reality (XR)

Extended reality (XR) is one of the critical technologies in Industry 4.0. It has been widely used in the manufacturing environment. XR technology usually has the following three characteristics: combination of the real and virtual worlds, interaction in real-time, and registration in the three dimensional space. It also has at least six classes of potential applications, including medical visualization, entertainment, manufacturing and maintenance, process planning, and military aircraft navigation and targeting.

XR is usually divided into three classes: Virtual Reality (VR), Augmented Reality (AR) and Mixed Reality (MR). While, Virtual Reality (VR) is a 100% digital content and can be enjoyed in a fully immersive environment (Videogames, Simulators, etc.), Augmented Reality (AR) superimposes digital content on the real world. In addition, Mixed Reality (MR) is a digital overlay that allows interactive virtual elements to integrate and interact with the real-world environment.

XR, mainly in the AR and MR forms, allows the user to see the physical world, with virtual objects overlaid onto the physical world, rather than completely replacing it. It also enables the users to interact with the physical world, where the information by the virtual objects help them to conveyed perform tasks in the physical world. It may include multiple sensory modalities, such as visual, auditory, haptic, somatosensory, and olfactory. The development of new XR features and new devices for visualization (from Cell Phones to high-tech display devices, like the Microsoft Hololens) is rapidly bringing new possibilities to extend the capabilities of the bridge inspector and bridge manager (Fig. 18).

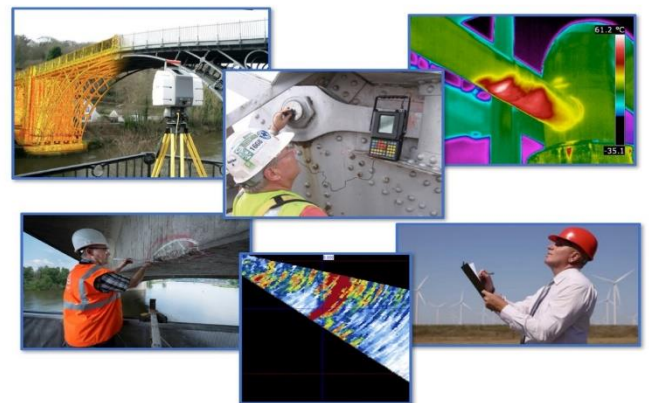


Figure 18. XR applications to structural integrity inspection and maintenance.

The ability to visualize hidden parts of the structure and associate the images with anomalies and the degree of degradation allows more precise

diagnostics of the structural integrity of the bridge. In addition, a sequence of more precise diagnostics will lead to more reliable prognostics of the bridge performance, opening promising possibilities for predictive maintenance.

6 UNDERLYING NEW TECHNOLOGIES

Digital Transformation has become a reality with the introduction of some underlying technologies. The whole idea of Digital Transformation is to orchestrate these technologies to make the design, the construction and the maintenance processes of bridges more comprehensible and more natural to apply.

Among these emerging technologies, Artificial Intelligence, Cloud and Edge Computing, Big Data, Computer Vision and the new generation of robots and sensors are worth mentioning and presenting a brief definition.

6.1 Artificial intelligence (AI)

In computer science, artificial intelligence (AI), sometimes called machine intelligence, is the intelligence demonstrated by machines, in contrast to the natural intelligence displayed by humans. Artificial intelligence is often used to describe machines (or computers) that mimic "cognitive" functions that humans associate with the human mind, such as "learning" and "problem-solving". The traditional problems (or goals) of AI research include reasoning, knowledge representation, planning, learning, natural language processing, perception and the ability to move and manipulate objects. General intelligence is among the field's long-term goals. Approaches include statistical methods, computational intelligence, and traditional symbolic AI. Many tools are used in AI, including versions of search and mathematical optimization, artificial neural networks, and methods based on statistics, probability and economics. The AI field draws upon computer science, information engineering, mathematics, psychology, linguistics, philosophy, and many other fields. AI is proving to be an efficient alternative approach to classical modeling techniques. AI refers to the branch of computer science that develops machines and software with human-like intelligence. Compared to traditional methods, AI has advantages to deal with problems associated with uncertainties. In addition, when testing is not possible, AI-based solutions offer alternatives to determine design parameters, resulting in significant savings in terms of human time and experiments. AI makes the process of decision making faster, decreases error rates, and increases computational efficiency. Different AI techniques such as machine learning (ML), pattern recognition (PR), and deep learning (DL) have been recently applied in structural engineering problems (Yan et al. 2019,

Salehi & Burgueño 2018) and are establishing themselves as a new class of intelligent methods for use in structural inspection and maintenance.

6.1.1 Machine learning (ML)

Machine learning is an important area of artificial intelligence that deals with the development of algorithms to identify complex patterns from experimental data, without assuming a pre-established equation as a model, and can provide more accurate results, thus enabling decision making intelligently, in real-time, without human intervention. (Taffese & Sistonen 2017)

Machine learning algorithms adopt various methods from multiple fields, for example, pattern recognition, data mining, statistics, and signal processing. This allows machine learning to take advantage of the synergy of all these fields, which in turn leads to robust solutions that use different knowledge domains (Fig. 19).

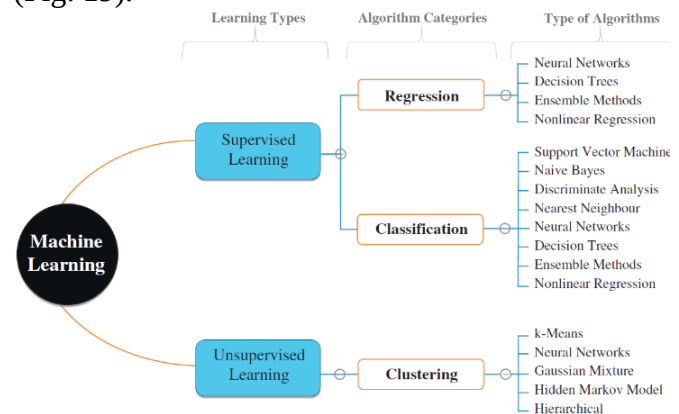


Figure 19. Machine learning algorithms. (Taffese & Sistonen 2017)

Machine learning can be classified as supervised, unsupervised, and semi-supervised learning. In general, machine learning algorithms to detect structural damage are classified as supervised learning, as data on the conditions of structures and variables that can influence such a condition, usually associated with degradation mechanisms, are needed. Machine learning algorithms can be used in modeling degradation processes (corrosion, carbonatation, fatigue, etc.) and are a powerful prediction tool for the prognostic process of structural behavior required for predictive maintenance of bridges and other structures.

6.2 Cloud and edge computing

Cloud Computing is the on-demand availability of computer system resources, especially data storage and computing power, without direct active management by the user. The term is used to describe data centers available to many users over the Internet. Large clouds, predominant today, often have functions distributed over multiple locations from central

servers. If the connection to the user is relatively close, it may be designated an edge server.

In contrast, Edge Computing is computing that takes place at or near the physical location of either the user or the source of the data. By placing computing services closer to these locations, users benefit from faster, more reliable services while companies benefit from the flexibility of hybrid cloud computing. Edge computing is one way that a company can use and distribute a common pool of resources across a large number of locations.

6.3 Big Data

Big data is a field that studies ways to analyze, systematically extract information from, or otherwise deal with data sets that are too large or complex to be dealt with by traditional data-processing application *software*. Data with many cases offer greater statistical power, while data with higher complexity (more attributes) may lead to a higher false discovery rate. Big data challenges include capturing data, data storage, data analysis, search, sharing, transfer, visualization, querying, updating, information privacy and data source. Big data was originally associated with three key concepts: volume, variety, and velocity. When handle big data is handled, one may not sample, but simply observe and track what happens. As a consequence, big data usually includes data with sizes that exceed the capacity of traditional *software* to process it within an acceptable time and value. Big data analytics comprises the complex process of examining large and varied data sets to uncover information such as hidden patterns and unknown correlations that can help organizations make managing decisions.

With the accumulation of information coming from inspections over the years, non-destructive testing and monitoring of bridges campaigns, the application of big data analytics is crucial to detect and anticipate trends in deterioration and their correlation to structural performance. (Kim & Queiroz 2017, Kobayashi & Kaito 2017)

6.4 Computer vision

Computer Vision Techniques, together with the acquisition of images via portable cameras and Unmanned Aerial Vehicles (UAVs) offer promising solutions for the evaluation of bridges. The goal of such systems is the automatic and accurate conversion of images and videos into data that help in the decision making of engineers and managers. These systems are an alternative to traditional monitoring and inspection methods that can be laborious, time-consuming, high cost. They can be used in places that are difficult or dangerous to access allowing a close contact with the structure. (Spencer et al. 2019, Catbas et al. 2018)

When the inspection is concerned, one of the main objectives of Computer Vision is the identification and classification of pathological manifestations. Two ways to accomplish such a task are often applied: feature extraction or machine learning recognition.

Computer Vision can also be applied for displacement measurement using cameras and UAVs (Unmanned Aerial Vehicle). It has gained space within the context of monitoring structures due to the possibility of contactless measurements, long distance, and multiple points measurements, associated with high precision, good cost-benefit and time reduction.

Generally, the monitoring process complies with the following requirements (Dong et al., 2018): (i) capture of the structure image and determination of the scale. Usually, the process is performed from a marker (element with known shapes and dimensions); (ii) identification of regions of interest in data collection, through image processing; (iii) determination of image characteristics that can be compared frame by frame; (iv) introduction of corrections to the image, if necessary; (v) calculation of frame-to-frame offsets and conversion of measurements to millimeters by using a target as a reference.

6.5 Robots and sensors

The inspection, monitoring and maintenance of bridges take a lot of advantage from the new generation of robots and sensors.

An Unmanned Aerial Vehicles (UAVs), or a drone, is essentially a flying robot that can be remotely controlled or fly autonomously through software-controlled flight plans in their embedded systems. They work in conjunction with onboard sensors and GPS for positioning. The use of this type of equipment is widely spread, but the possibilities of new generations of onboard thermal and high-speed cameras open new promising applications.

On the other hand, an underwater remotely operated vehicle (ROV) is a mobile robot designed for aquatic work environments. The remote control is usually carried out through copper or fiber optic cables. Usually, a human operator watches in a display what the robot "sees" from a shore-based station, boat or submarine bubble. This type of technology is very important in the early detection of scouring and underwater deterioration of foundation elements.

As anticipated by Hola & Schabowics (2013), the area of non-destructive testing for buildings and bridges has evolved a lot in the recent years with the development of equipment and methods based on acoustic, ultra-sound, electro-magnetic, radar and thermal technologies, New augmented vibration and laser-based technologies can now be used to capture the dynamic signature of different types of structures (Rothberg et al. 2017).

Moreover, the evolution of GNSS (Global Navigation Satellite System: GPS, GLONASS, Galileo, BeiDou e.g.) based sensors for Structural Health Monitoring enables 3D positioning anywhere on the globe with no measurement drift. A GNSS station is able nowadays to use satellite signals and its internal clock to estimate position with accuracy up to a few millimeters. In addition, the application of affordable and spread smartphone technologies (Alavi & Buttlar 2019, Pravia & Braido 2015) is opening new possibilities for inspection, anomalies detection and monitoring of the structural behavior of bridges.



Figure 20. Information and image handling using Cloud-computing.

7 IMPLEMENTATION OF A BRIDGE DIGITAL TWIN

A computational system needs to be developed to implement a digital twin. Here, an evolution of the system **SIM** (Structural Integrity Management) developed for oil and offshore naval structural applications is used to illustrate the potentialities of a digital twin (Witte & Ribeiro 2012a). The new system is named **C4D** and it is currently under development Phdsoft (<http://phdsoft.com/technology/c4d/>). The implementation of any digital twin requires the construction of a 3D model with the most efficient representation of geometry, material properties, internal connections and boundary conditions, as well as ground localization information (Witte & Ribeiro 2012b).

In the case of a bridge, the digital twin may incorporate and manage drawings, spread-sheets, documents and technical reports, regarding the design and the construction of the bridge, as well as regulatory provisions utilized, in an easy and comprehensive way (Fig. 20). All the data is stored and managed using Cloud Computing.

The system is also capable of storing “*as built*” as well as “*as is*” information, due to the changes of the structure along its lifetime. Automatic tools for checking regulatory compliances and implementing best repairing practices are also available in the system.

Another important feature of the system is provided by the module for automatic anomaly recognition and classification (Fig. 21).

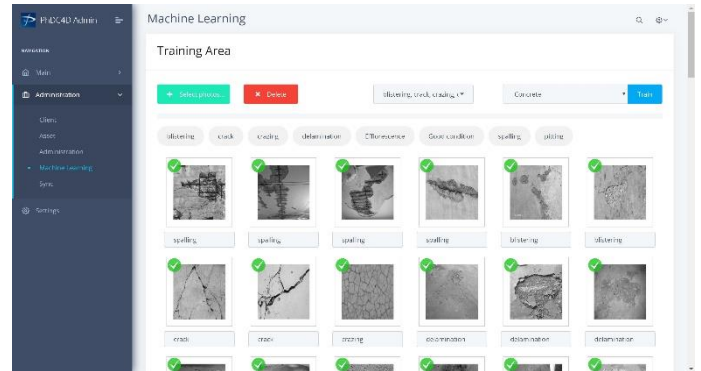


Figure 21. Automatic anomalies detection.

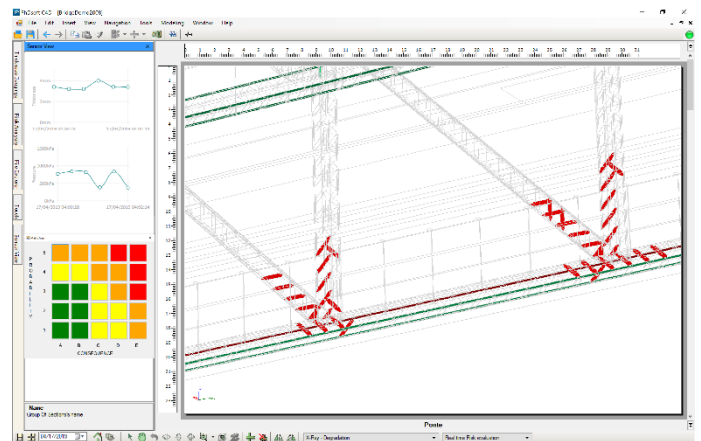


Figure 22. Digital Twin capabilities.

Images taken in human or automated inspections may be stored and classified using Deep Learning (DL) algorithms. Some previous training and technical expertise are necessary to implement the machine learning scheme. Self-evolution of the system is achieved because the: Digital Twin can collect and update data in real-time, and continuously self-improve its learning process. The digital twin can handle real-time data acquisition provided by its network of sensors. Through the information provided by the sensors and the use of prediction tools, a real-time risk evaluation can be provided at the global or at the element level. All the information is provided graphically to the users (Fig. 22) in real-time, providing important subsidies for the decision making and prioritization processes involved in the bridge maintenance.

Risk-based Predictive Maintenance (PdM) helps to determine the optimal time and date when repairing activities should be performed, offering cost savings over routine or preventive maintenance. PdM is frequently used for constant condition monitoring and

equipment evaluation. The main goal of its association with the digital twin is, by statistical process control, to determine when future maintenance will be more appropriate according to the structural condition

or performance. A general view of the integration of the technologies and information associated with the bridge digital twin is provided in Figure 23.

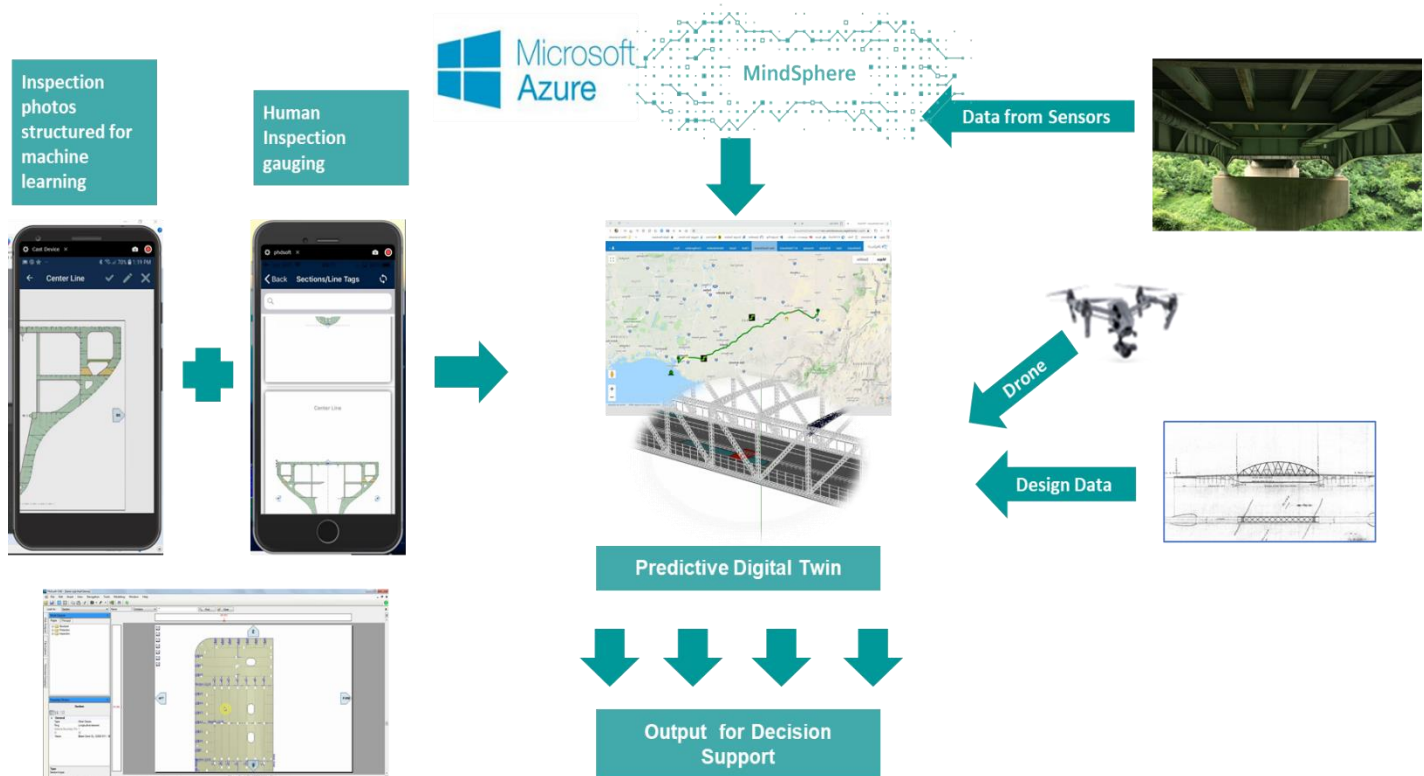


Figure 23. Digital Twin capabilities.

The integration of data coming from design and construction documentation, inspection, non-destructive testing and monitoring data constitutes a powerful tool for decision support and may be very helpful in the management of maintenance of a single or a network of bridges.

8 CONCLUSIONS

Continued inspection of bridges is essential for efficient management of these assets. Structural integrity monitoring (SHM) and modern Non-destructive Testing techniques are increasingly economically viable. Maintenance, repair and reinforcement of bridges are essential to ensure its service life.

The combination of modern inspection techniques, non-destructive testing and structural health monitoring allows much more accurate diagnoses and prognoses of the structural behavior of various types of structures, including bridges.

Digital transformation is an inevitable process and will affect the competitiveness of various sectors of industry. Bridge inspection, monitoring, maintenance and management processes can benefit greatly from introducing new technologies and digital transformation in support to all the accumulated knowledge of the field in recent years.

9 ACKNOWLEDGEMENTS

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