Condition assessment of reinforced concrete structures: state of the art knowledge and case studies in the TG3.3 fib Bulletin

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ABSTRACT: Reinforced concrete structures are exposed to deterioration due to aggressive environments, excessive loads, extreme events worsened by climate change effects and, in some cases, lack or insufficiency of maintenance interventions. Effective maintenance management approaches are needed to guarantee or increase their service life, while adhering to budget constraints. The optimal scheduling of maintenance actions, under a predictive regime, requires targeted and condition-informed actions to ensure a maximal return on investment, while guaranteeing a safe and performant infrastructure. A focal activity of the international federation for structural concrete (fib), developed as part of Commission 3, lies in providing guidance for the assessment of existing concrete structures. In this context, the Task Group 3.3 has recently developed a Bulletin containing practical state-of-the-art guidelines for condition assessment and support of decision-making procedures for the through-life management of existing concrete structures. The Bulletin is organized into 6 chapters that cover the topics of data acquisition, condition and performance assessment and decision-making procedures. The document is complemented with a portfolio of case studies that report practical applications to real world structures. This contribution overviews chapters 3 and 6 of the Bulletin; the former outlines methods and best practices for condition assessment, whereas the latter exemplifies application of these tools on selected case studies on actual full-scale structures.

1 THE TG3.3 BULLETIN

A very large number of reinforced concrete structures built in the 1950s and 1960s are nearing or have exceeded the end of their design lifespan. In certain cases, owing to deterioration and maintenance backlogs such structures are operating under conditions that substantially deviate from original design assumptions. In addition, the projected effects of the ongoing climate change will place further pressure on future structural performance in terms of accelerated deterioration in the face of natural hazards that are so-far unaccounted for in the original design. Inadequate performance of infrastructures, such as bridges, is known to bear adverse effects on economic growth and, as exemplified by the recent collapse of the Morandi bridge in Genoa, also comprise notable risks to the safety of people and can lead to a loss of trust in management and governance. Thus, understanding the current and future performance of reinforced concrete structures and infrastructures is essential for future social, economic, and environmental developments. However, structural integrity management remains a challenging task and current best practices prove limited, primarily with respect to the acquisition and utilization of data and information on structural performance. At large scale the acquisition of structural performance data is still based on outdated and underperforming methodologies such as visual inspections that_affect the availability of infrastructures, the safety of operators, and the efficiency of maintenance interventions generating reduced functionality and relevant economic social costs.

Despite the large research efforts devoted in the last decades, Structural Health Monitoring (SHM) methods, which continuously collect and automatically process structural health data, are not yet implemented at large. The lack of technical standards on SHM has played a key role in the past and still constitutes one of the main barriers for the extensive adoption of these technologies in the condition assessment of structures and infrastructures.

The first SHM guidelines were issued in Canada in 2001 (ISIS, 2001) and were followed by other documents published all over the world (Rucker et al., 2006), (GB 50982-2014. Technical Code for Monitoring of Building and Bridge Structures, 2014), (Osterreichische Forschungsgesellschaft StraBe; Schiene;Verkehr, 2012), (UNI, 2016). The most recent technical documents on SHM have been issued in Italy in 2020 (Ministero delle Infrastrutture e dei Trasporti, 2020), (Limongelli et al., 2020) and are specific for bridges. In 2020, the fib Task Group 3.3 on ‘Existing Concrete Structures: Life Management, Testing and Structural Health Monitoring’ took the initiative to prepare state-of-the-art guidelines (Bulletin) on this topic to support the development of the relevant parts of the Model Code 2020.

The Bulletin is organized into 6 chapters that cover the value chain of data management, which is overviewed in chapter 1; data acquisition is dealt with in chapter 2, data processing to extract information for condition diagnosis and performance prediction in chapters 3 and 4 respectively, while the use of information to support decision-making is finally covered in chapter 5. The document is complemented with a listing of case studies that report practical applications to real world structures, which are collected in the sixth chapter of the Bulletin. This paper overviews chapters 3 and 6: the former outlines methods and best practices for condition assessment (diagnostic process), whereas the latter exemplifies application of these tools on selected case studies on actual full-scale structures. .

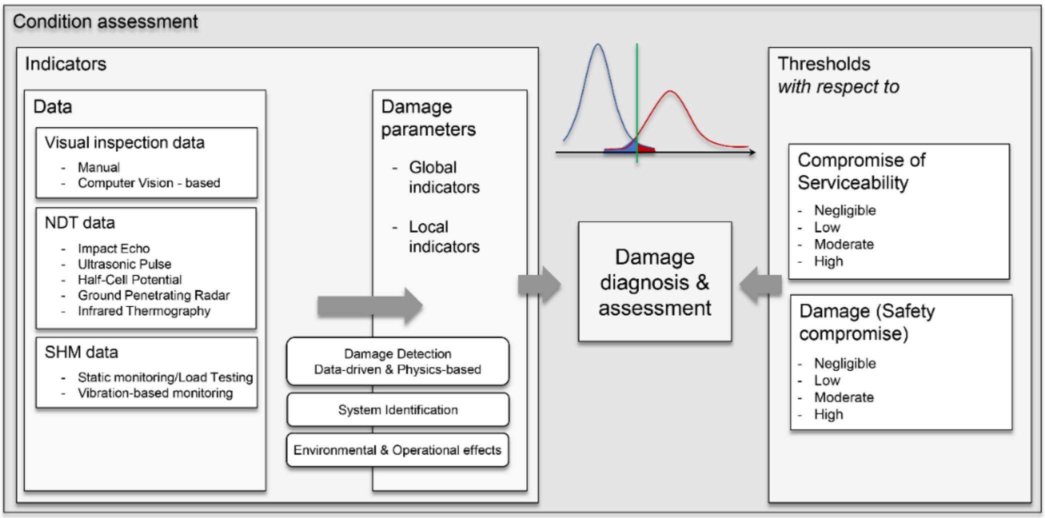

Figure 1. Conceptual framework for condition assessment (Bulletin fib Task Group 3.3, 2022)

2 CONDITION ASSESSMENT

The conceptual framework of condition assessment, which is adopted in the Bulletin, is summarized in Figure 1. It relies on derivation of a set of indicators within the context of functionality (serviceability) and safety. Data acquired through Visual Inspections (VI), Non Destructive Testing (NDT) and SHM are used to compute indicators that describe the state and the loading on the structure. While SHM relies on continuous tracking of the structural response, NDTs and VIs are usually performed periodically or occasionally. The indicators are classified according to the method used to gather the information (VI, NDT, or SHM) and the level of the assessment. The latter can be either global or local.

A major part of chapter 3 is dedicated to methods and tools that are applied in the SHM context, which relies on continuous tracking of structural response, typically in the dynamic (vibration-based) sense. Different approaches of damage detection, data driven and physics based, are described, and the influence of environmental and operational conditions which can often harden a robust estimation of damage indicators, is discussed together with the issues involved in the definition of thresholds for reliable assessment of structural condition in terms of relevant limit states.

3 DATA ACQUISITION FOR CONDITION ASSESSEMENT

SHM and NDT involve the observation of the structural state and the assessment of deterioration, aging and degradation through non-invasive techniques that can have an either continuous (SHM) or a periodic (NDT) implementation character in time.

The information collected by monitoring and testing the structure provides a data-informed basis for engineering decision making and an important tool for performance assessment that can support the management of structures and infrastructures throughout their life-cycle. Data-driven condition assessment generally adheres to a stepwise process requiring:

- extraction of *damage parameters*, also referred to as *damage sensitive features*, from data gathered from NDT and SHM
- computation of *damage indicators* from these damage features; these should additionally feature robustness against effects of operational and environmental variability.
- assessment of condition through comparison of the derived damage indicators with *thresholds*, which define different condition limit states.

4 IDENTIFICATION OF INDICATORS

As part of the Bulletin (section 3.2.1), we initiate by outlining indicators that are directly linked to a damage process (e.g., corrosion or fatigue) and the associated damage parameters. For instance, for the case of corrosion-related damage, relevant damage parameters can be *moisture, corrosion rate, chloride presence,* or *electrical resistivity,* while the corresponding indicators are *porosity, degree of water saturation,* or *chloride concentration at rebar surface*. We subsequently list indicators aimed at quantification of acting environmental conditions and loads (section 3.2.2), such as earthquake intensity (or ground acceleration amplitude) for the case of seismic loading. We further briefly refer to the classical approach of visual inspection and associated indicators, particularly those assisted by recent advances in optical & remote sensing (3.3). However, the main instrument to structural assessment stems from indicators relating to structural status and response, which are overviewed in sections 3.4 & 3.5 of the Bulletin.

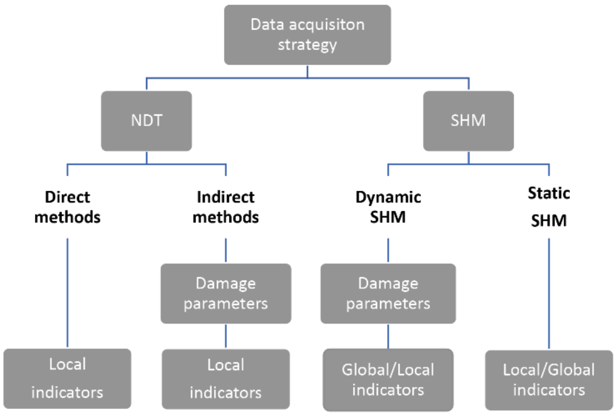

Figure 2. Monitoring-driven Indicators extracted via NDT versus those inferred via SHM.

We distinguish between NDT (section 3.4) versus SHM schemes (section 3.5), as summarized in Figure 2. A main distinction between these two schemes lies in the scale of the conveyed information. NDT can offer more targeted assessment in terms of localized damage phenomena, while SHM information is most typically referring to global quantities, especially when relating to vibration-based SHM. As part of the Bulletin, we further distinguish between two main evaluation schemes for assessing structural condition (Aktan et al., 2019)

- Empirical schemes – these schemes do not include analysis procedures. They pertain to use of visual observations, information from measurements in their raw form (e.g., deflection/strain measurements), and analysis of the engineering drawing ad specification documents.
- Scientific schemes – these schemes rely on use of refined analysis procedures (e.g., structural identification, statistical processing, time series analysis, machine learning, fusion of experimental data and models via the process of updating).

Measurements that are indirectly linked to structural condition (“state”), such as ultrasonic or vibration-based measurements cannot be straightforwardly linked to empirical schemes and will thus require what we termed the “scientific” approach.

4.1 *NDT-based condition Indicators*

The majority of NDT methods aims at identifying flaws, such as cracks or fouling within the monitored structural medium. NDT methods have already been extensively overviewed as part of (Fib Bulletin N° 22. Monitoring and Safety Evaluation of Existing Concrete Structures., 2003). Typical methods include Radiography (x-rays or gamma rays), ultrasound, magnetic particles, eddy current, thermography, Impact Echo, and Ground Penetrating/Pulsar radar systems. The afore-listed methods aim at detection cavities, corrosion and distortions in the composition of a material (Omar & Nehdi, 2018). Indications about the material strength can be obtained through methods such as rebound hammer or pulse velocity tests. It is worth noting that several NDT technologies can be adopted for use under an SHM regime, i.e., in a continuous and automated fashion. For instance, acoustic emission sensors (Tonelli et al., 2020) and Guided-Wave assessment based on PZT transducers (Ostachowicz et al., 2012) that are able to serve as both actuators and sensors, or reinforcement corrosion sensors can be permanently deployed on structures, thus serving for SHM.

4.2 *SHM-based condition Indicators*

SHM describes a continuous process of data acquisition and automated processing, most typically requiring scientific, as opposed to empirical, means of evaluation. Although monitoring campaigns can also be executed over shorter deployment intervals, the concept of SHM typically refers to long-term sensor deployments.

Uncertainties relating to the sensing modules and uncertainty quantification methods form an indispensable part of the SHM-based structural identification and condition assessment process. A complete condition assessment process relies on sound data treatment, reliable structural identification procedures, as well as coupling with expert engineering judgement, oftentimes supported by updated numerical models of the structure (Simoen et al., 2015)

Indicators from Static Monitoring

Methods intended to provide information with respect to the static behavior of a structure include both short- and long-term monitoring methods. For instance, the evaluation of relative or plastic deformations may be achieved both by means of a topographic network with measurements repeated in fixed time intervals, but also via a more refined continuous monitoring system comprising sensors able to monitor movement, displacement or rotations of the structure (Sousa, 2020). Similarly, for the task of crack detection, a defect can be quantified and evaluated via direct measurements, e.g., by means of periodic or one-off non-destructive tests (e.g., ultrasonic velocity tests, hammer sounding) or by means of a (continuous) SHM system comprising displacement transducers that monitor cracking evolution over time. The advantage of utilizing a continuous SHM system lies in the possibility to detect damage processes prior to their visual manifestation and to provide near-real time alerts when the deterioration mechanisms evolve. As a further means to obtaining direct performance indicators from static monitoring one could also consider the diagnostic and proof (static) load tests. In complement to load tests, long-term monitoring allows for assessing further parameters with important influence on the structural behaviour of concrete structures, such as the evolution of creep and shrinkage of concrete. Although a number of relatively recent and comprehensive models have been suggested, there is a lack of consensus on their utilization due to substantial scatter in their predictions. This uncertainty may be reduced via static monitoring information (e.g., via use of strain-gauges installed in spans and support sections, displacement transducers in bearing devices, and tracking of deflections).

Indicators from Vibration-based Monitoring

The most established SHM methods, the so-called Vibration Based Monitoring (VBM) methods, rely on dynamic monitoring data, such as acceleration or velocity recordings. VBM schemes operate on both forced, free, and ambient vibration data, however - in the context of SHM - ambient vibrations are generally employed (Limongelli et al., 2016). VBM methods are based on the premise that damage induces a shift in the stiffness, mass or energy dissipation capacity of the structure. The vibrational response is analyzed by mean of system identification methods to identify a mathematical model able to describe the structural behavior. The parameters of this model can be physical properties, such as for example stiffness and mass properties that are directly linked to modal parameters, or statistical properties such as for example the coefficients of a regression function. Among these parameters, those sensitive to the variation of the dynamic characteristics of the structure, can be assumed as *damage parameters* or *features* and the *indicators of damage* can be defined in terms of a demonstrated shift from a reference condition. It must be noted that environmental changes, related for example to temperature, humidity, wind speed, etc. as well as operational changes due to the variability of the traffic loading on bridges or, more generally, the changes in applied loads and/or masses may affect these damage features. Their effect must thus be removed or accounted for in the damage detection procedure in order to avoid false or missing damage identifications. The treatment of environmental and operational effects can be carried out during the system identification procedure or can be included in the algorithms of damage identification. A schematic illustration of the VBM chain for condition assessment, from the initial stage of measurement collection to the stage of damage diagnosis, is reported in Figure 3.

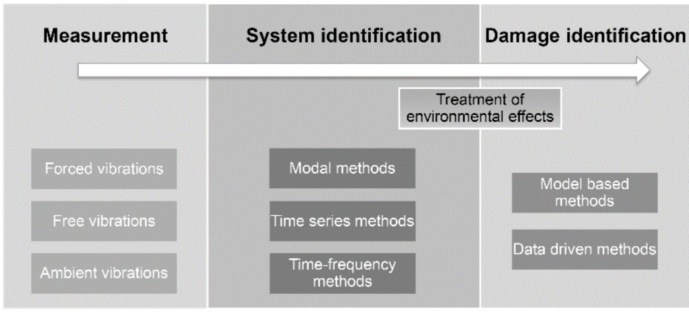

Figure 3. VBM methods for condition assessment.

It is important to note that, due to their nature, vibration-based indicators typically provide information that is relevant to variations of stiffness, mass and energy dissipation capacity, but not direct information on the variation of structural strength.

Methods for structural identification

The term *system identification,* also known as *structural identification* (St-ID), when used in the context of civil structures, forms the essence of what was in our introduction defined as the “scientific” approach to assessment. The term St-ID is used in different ways depending on the respective context. Engineering applications use numerical models such as, for example, finite element models that are directly related to physical parameters of a structural system. In these, cases the term *system identification* often refers to the estimation of physical model parameters, such that the numerical model best reflects the structural behavior observed experimentally. This procedure is more appropriately termed model updating or model calibration. However, the term *system identification* more broadly pertains to the identification of a mathematical system model describing an input-output relation of a considered system without a direct relation to physical properties such as geometry or material parameters.

5 TREATMENT OF OPERATIONAL AND ENVIRONMENTAL EFFECTS

Particular attention ought to be paid to the influence of varying Environmental and Operational Conditions (EOCs)(Sohn, 2007) on the collected data. Environmental variability is usually related to temperature, humidity, wind speed, etc., whereas the operational changes involve the traffic loading on bridges or, more generally, the changes in applied loads and/or masses. EOCs often influence damage indicators by masking true damage effects (Laory et al., 2019). It is worth noting that the removal of EOC effects has been heavily addressed in the literature for the case of natural frequencies, which are highly susceptible to EOC variability. Remedial methods are clustered in two main categories: i) output-only methods (unsupervised) aiming to eliminate the EOC influence on the basis of output-only information (Kullaa, 2011), (Cross et al., 2011) and ii) input-output methods (supervised), which establish a functional dependence between the measured vibration data and/or the extracted features and the measured EOCs (Spiridonakos et al., 2016). Output-only methods include the Principal Component Analysis (PCA) (Magalhães et al., 2012) or its nonlinear variants (kernel PCA, Factor Analysis). PCA is a multivariate statistical tool, relying on a linear transformation of the dataset onto a new set of independent variables, designated as principal components (PC), that can describe the variance in the original data. The tools essentially identify inherent trends in the measured/identified features, allowing to separate EOC influences. The model-based (supervised) class is usually expressed in terms of a regression problem, where EOC information is obtained by appropriate environmental or operational. Once the effect of all external factors on the measured/identified parameters has been successfully minimized or removed, any further variation in the monitored features can be attributed to structural change. In its simplest form, the supervised class relies on regression relationships between the investigated features and the EOCs. Depending on consideration of EOC measurements on only the current, or additionally previous, time instant(s), these methods are characterized as *static* or *dynamic*, respectively. When dealing with static regression models, the Multiple Linear Regression (MLR) is the statistical technique generally adopted to express the relationship between a single dependent variable (such as natural frequency, rotation, strain, deformation, etc.) and one or more independent variables or predictors (such as temperature, humidity, etc.). The objective of MLR is to use the independent variables, whose values are directly measured, to predict the selected dependent parameter (Hair, Joseph F., 2009). When a regression relationship is established between the dependent variable (e.g., the modal frequency) and the predictors (e.g., the temperature and the humidity), the value of the dependent variable is obtained through a linear or non-linear multiple regression equation. It is worth mentioning that, among the supervised methods described in the system identification literature for removing the EOC effects, Auto-Regressive models with eXogenous input, see e.g. (Ljung, 1998) are probably the most general methods, since they can address both static and dynamic regression, as special cases.

6 DAMAGE DETECTION

The St-ID methods described in the previous section infer the main system properties of the system or a model that can be used to reproduce its response to a given excitation. Section 3.5.2.2 of the Bulletin introduces the concept of Damage Sensitive Features (DSF) and the methods that can be used for their estimation from measurements. The DSF must be able to capture robust information about deviations of the system from a reference, or 'healthy', condition. In Figure 4 are reported some of the DSFs that can be extracted using the System identification methods previously described. DSFs. could be monitored variables or to more indirect properties, such modal parameters. Damage indicators (DIs) defined in terms of variations of the DFSs - for example the change of the frequencies or mode shapes - are the metrics that quantitatively describe damage.

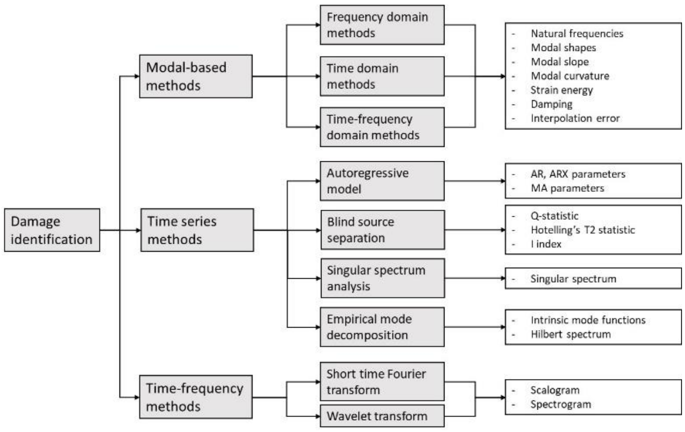

Figure 4. Conceptual framework for condition assessment

Vibration based methods for damage detection allows assessing changes in the dynamic behaviour of the structure e.g., due to variations of stiffness, mass or energy dissipation capacity. They are classified in data-driven and model-based methods. The latter, described in Section 3.5.2.2.2, update models of the structural behaviour to identify changes in the DSFs, the former only rely on data for the extraction of the DSFs. Data-driven methods, described in Section 3.5.2.2.1, are less computationally intensive and thereby attractive for real time processing but they only allow damage identification. Model-based methods on the other hand entail the computation cost of the updating process but enable a more refined characterization of damage according to the Rytter (Rytter, 1993) classification up to classification and quantification. Damage identification through data driven methods operating in the frequency domain is carried out using as DSFs modal or operational parameters -or function of those. Methods that operate in the time-domain use more often parameters without a direct physical meaning such as, for instance, the coefficients of auto-regressive models or the covariance properties of the measured time series. The higher level of damage detection, that is localization, requires the use of DSF with a spatial definition - such as for instance modal or operational shapes - able to detect irregularities in the deflected profile of the structure. The methods take their name from the DSF on which they rely: energy (Kim & Stubbs, 1995), flexibility (Zhang & Aktan, 1998), Interpolation error (Limongelli, 2010), wavelet transform (Wang et al., 2013), transmissibility (Chesné & Deraemaeker, 2013). These features can be extracted from the response to vibrations preferably measured in terms of acceleration since localized damage is more likely to affect the higher modes that are better captured by such measurements. Uncertainties related for instance to noise contamination and to approximations introduced during signal processing affect the estimates of the DSF. Recently strain based modal shapes, eliminate some sources of uncertainty - for instance they do not require double differentiation for the computation of curvature – and have recently been used for damage localization (Anastasopoulos et al., 2018). Improvement in this field is also supported by the increasing precision and decreasing costs of MEMS based sensing solutions and by the availability of large dataset of measurements processed using Artificial Intelligence techniques. Damage quantification using data driven methods can only be performed in relative sense, that is from the variation of the damage features with respect to the reference state (Zhou et al., 2015), (Ou et al., 2017), (Yeager et al., 2019). However, this variation does not provide an estimation of the deterioration in terms of the structural parameters such as stiffness, mass or damping. Differently model-based methods update the model parameters using the DSF, and thereby allow to obtain a quantification of damage through the variation of the structural parameters extracted from the model. The model updating task can be performed through numerical or probabilistic models (Friswell & Mottershead, 1995). Both stochastic, e.g. Bayesian (Argyris et al., 2020), as well as deterministic approaches, e.g. Constrained Eigenstructure Assignment method (Ziaei-Rad & Imregun, 1996) can be used to this end. In recent years Machine Learning (ML) methods which rely on the use of Artificial Neural Networks (ANNs) have gained ground in data driven applications (Bull et al., 2020). These methods are based on the training of a model using labelled datasets and thereby require the availability of labelled datasets for the classification of damage. For damage detection can fuse various types of monitoring information and identify patterns in data. Datasets relevant to several different damage scenarios (damage locations, types and severities) seldom available for civil structures thereby they are artificially generated using numerical models. The alternative, using monitored data, is to apply unsupervised ML methods, that discern between dataset that exhibit different patterns, but they cannot label the different datasets and thereby structural sates. As previously mentioned, the use of model-based methods entails the task of model updating that can be computationally intensive when large sets of data must be continuously used to obtain real time estimate of the structural response. However, updated models can provide more information and, if prognostic modes are available, allow to perform the prognostic, beyond the diagnostic, task that is the forecast of the future structural behaviour and an estimate of the remaining service life.

7 THRESHOLDS FOR ASSESSMENT

The condition indicators identified as described in the previous sections must be compared with target values (thresholds) that correspond to service or ultimate limit states. As described in Section 3.7 of the Bulletin, these values can correspond to target reliability levels or, in a risk-based perspective, to a trade-off between the direct costs related to the reliability of the structure on one side and the indirect costs related to its loss of functionality on the other (Diamantidis et al., 2019) This is a key aspect of the decision-making process underlying asset management and maintenance scheduling. Due to the several uncertainties that affect the values of the damage indicators, the definition of the threshold values requires a trade-off between the probability of false and missing indications of damage. Most often the distribution of the damage indicators in the damage state is unknown, thereby the threshold values are determined based on the distribution in the reference structural state that is fixing a maximum acceptable value of the probability of false alarms in the reference state

8 CASE STUDIES

Chapter 6 of the Bulletin contains a selection of case studies that illustrate the application on large-scale structures, of methods and tools described in the previous chapters of the document. The case studies cover a wide range of typologies of concrete structures, mainly bridges under diverse damage scenarios induced by corrosion, fatigue, or extreme events such as floods, seismic excitation, but also applications on cultural heritage buildings and bridges, dams, harbours, wind turbines, and stadiums. Each cases study is described in one page; the scope is to provide the main information related to the monitoring system and to provide references where the interested reader can find more information and, if available, an open access repository of data relevant to the case study.

9 CONCLUSIONS

This paper summarizes the content of Chapters 3 and 6 of the fib Bulletin on 'Existing Concrete Structures: Life Management, Testing and Structural Health Monitoring' that is in preparation on behalf of fib Task Group 3.3. Chapter 3 deals with methods for condition assessment of reinforced concrete structures. This task entails the extraction, from testing and monitoring data, of condition indicators that carry information about the structural condition, and their comparison with thresholds corresponding to target performance level. Both local and global indicators are described in the chapter, with particular emphasis on vibration-based indicators that can be retrieved from the response to vibrations using structural identification and damage detection methods. The definition of the values of the condition indicators, is also briefly addressed in the chapter. Several case studies in which the methods for condition assessment are applied are described in Chapter 6 of the Bulletin. They cover a wide range of structures and the entire value chain of data management from acquisition, to processing for diagnosis and prognosis and support to decision making.

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