Challenges in Concrete Structures Health Monitoring

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ABSTRACT

Structural health monitoring needs to produce actionable information regarding structural integrity that supports operational and maintenance decision making that is individualized for a given structure and its performance objectives. An effective Prognostics and Health Management (PHM) framework for aging structures (subjected to physical, chemical, environmental, and mechanical degradation) needs to integrate four elements – damage modeling, monitoring, data analytics, and uncertainty quantification. This paper briefly discusses available techniques and ongoing challenges in each of these four elements of PHM, in the context of concrete structures. A Bayesian network approach is discussed for integrating heterogeneous information from multi-physics computational models of degradation processes, full-field measurement techniques, big data analytics, and various data and model uncertainty sources. Such a comprehensive framework can quantitatively support decisions regarding appropriate risk management actions.

1. INTRODUCTION

The purpose of structural health monitoring is to provide information to the decision-maker in a manner that is suitable for risk management with respect to structural integrity and performance. Risk management decisions include sustainment decisions regarding inspection, maintenance and repair, as well as operational decisions regarding the mission demand limits for the system and its operating conditions. In all engineering systems, such decisions are made in the presence of uncertainty that arises from multiple sources. The various types of uncertainty include natural variability (in loads, material properties, structural geometry, and boundary conditions), data uncertainty (e.g., sparse data, imprecise data, missing data, qualitative data, and measurement and processing errors), and model uncertainty (due to approximations and simplifying assumptions made in diagnosis and prognosis models and their computer implementation). An important challenge is to aggregate the uncertainty arising from multiple sources in a manner that provides quantitative information to the decision-maker about the future risks for structural integrity and performance, as well as the risk reduction offered by various risk management activities, thus facilitating quantitative risk-informed cost vs. benefit decisions.

The information available in structural health monitoring is quite heterogeneous, since the information comes from a variety of sources in a variety of formats. The heterogeneous sources include mathematical models, experimental data, operational data, literature data, product reliability databases, and expert opinion. In addition to the specific system being monitored, information may also be available for similar or nominally identical systems in a fleet, as well as legacy systems. Even within the system being monitored, information may be available in different formats (e.g., numerical, text, image). It is also worth noting that information about different quantities may be available at different levels of fidelity and resolution. An important challenge in data analytics for PHM is information integration, i.e., fusion of heterogeneous information available from multiple sources and activities.

Health monitoring systems have used either data-driven techniques or model-based techniques for diagnosis and prognosis. An effective framework for health diagnosis and prognosis of aging structures (subjected to physical, chemical, environmental, and mechanical degradation) needs to make use of all the available information through damage modeling, monitoring, data analytics, and uncertainty quantification techniques. This paper suggests a dynamic Bayesian network (DBN) approach for information integration, data analytics and uncertainty quantification in diagnosis and prognosis. The Bayesian network approach enables both the forward problem (uncertainty integration) and the inverse problem (risk management, resource allocation). Methods have recently been developed to

integrate various sources of uncertainty (natural variability, data uncertainty and model uncertainty) in order to quantify the overall uncertainty in health monitoring outcome. Such methods need to be quantitatively linked to decisions regarding appropriate risk management actions through the use of structural reliability theory (Naus, 2009).

A particular problem of current interest to the authors is the application of the above concepts to the monitoring, diagnosis, prognosis, and health management of concrete structures. Concrete structures are affected by a variety of chemical, physical and mechanical degradation mechanisms such as chloride penetration, sulfate attack, carbonation, freeze-thaw cycles, shrinkage, and mechanical loading. Each of the four elements mentioned earlier – damage modeling, monitoring, data analytics and uncertainty quantification – is a difficult challenge for a heterogeneous material such as concrete. This paper outlines research needs and possible directions through a few illustrative damage modeling and health monitoring techniques for concrete structures.

2. DAMAGE MODELING

The deterioration processes in concrete structures can be classified briefly into three main groups, i.e. physical processes, chemical processes and mechanical processes (Mehta and Monteiro 2001). Sources of physical deterioration may include temperature variation and the associated thermal expansion/contraction, relative humidity variation and the associated drying shrinkage/wetting expansion, freezing and thawing cycles (i.e. frost attack), wear and abrasion etc. Sources of chemical deterioration include corrosion of reinforcement embedded in concrete, chloride penetration, carbonation, leaching of concrete constituents, acid attack, sulfate attack, and alkali-aggregate reaction etc. And sources of mechanical deterioration include externally applied overload or impact, cyclic fatigue loads, differential settlement of foundation, and seismic activity. All these sources of deterioration can alter the porosity and permeability of concrete, cause or aggravate various material flaws (such as scaling and spalling, swelling and debonding, cracking and disintegration), impair the integrity and tightness of concrete structure, and lower the loading capacity of structural member.

The physical and chemical deterioration processes of reinforced concrete structures are closely interconnected and synergistic; distinguishing any single deterioration process from the joint impact is difficult. The complexity of the aforementioned classification of deterioration processes has led the technical community to model deterioration mechanisms of concrete individually. Individual deterioration processes have been studied extensively, and significant strides have been made in developing computational models. A major current challenge is how to develop an integrated computational methodology to quantitatively assess the durability of reinforced concrete structures subjected to a variety of coupled deterioration processes that are acting simultaneously. A related issue is that damage under different deterioration processes accumulates at different rates; thus multi-physics degradation analysis also needs to account for different time scales in different processes.

In the case of concrete degradation under coupled physical/chemical processes, governing differential equations that characterize the mass/energy balance and thermodynamic/chemical equilibrium of coupled heat conduction, ionic diffusion, moisture transport and chemical reaction have been developed. A variety of multi-scale methods and continuum finite element/difference methods have been utilized to solve the interactive and nonlinear governing equations. Methods have also been pursued to connect chemical reaction products to the mechanical response of concrete (e.g., stress, displacement, crack density). The accelerating effects of cracking on the transport processes of various aggressive agents have also been considered.

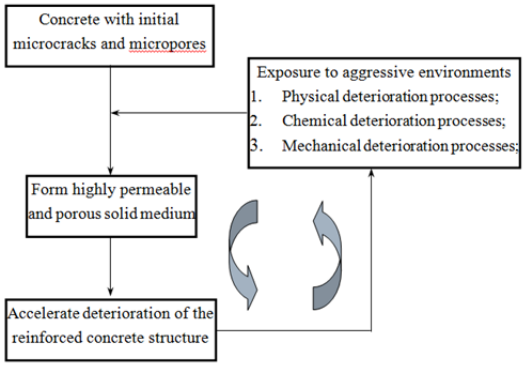

Figure 1. Multi-physics degradation of concrete

Prior to experiencing any deterioration, ordinary concrete usually possesses high porosity and low permeability. The overall connectivity of the micropore network, instead of the porosity of concrete, controls the transport properties of concrete. In other words, only interconnected micropores and microcracks in concrete contribute to the permeability of concrete and its vulnerability to deterioration. Under degrading environments, initially discontinuous micropores and microcracks grow, coalesce and finally form an interconnected network of multi-scale pores and cracks. As a result, the permeability of concrete increases, thus further accelerating the deterioration processes of the concrete structure, as shown in Fig. 1 (Chen, 2008).

Thoft-Christensen (2003) classified various deterioration models of concrete structures into three levels. Level 1 models are empirical models, which are established on the basis of direct observations on existing structural elements and do not consider the deterioration mechanism. Level 1

models have been adopted extensively in current design codes as a means of producing a rough estimate of the durability level of existing concrete structures. Level 2 models are medium level models from a sophistication viewpoint; these are based on semi-empirical or average "material parameters" (e.g., concrete permeability) and average "loading parameters" (e.g., average chloride content applied on the surface of concrete). Deterioration mechanisms are assumed to follow some formulated physical principles like Fick's law. Level 2 models have usually limited their scope to individual deterioration mechanisms. Level 3 is the most advanced level, where the modeling of the deterioration profile is based on fundamental physical, chemical and mechanical principles. Detailed information on concrete microstructure and applied environmental loading is required, and multiple coupled deterioration processes are taken into account.

A few examples of multi-physics degradation modeling, namely carbonation and chloride penetration (Level 2), and sulfate attack (Level 3), are described next for the sake of illustration.

Carbonation

Unlike physical deterioration processes such as the heat transfer and moisture transport, carbonation of concrete is essentially a chemical process. As the hydration product of Portland cement, calcium hydroxide in concrete may react with carbon dioxide dissolved in pore solution, neutralize its high alkalinity environment, and finally result in depassivation of the passive layer and initiation of reinforcement corrosion — one of the major deterioration mechanisms for reinforced concrete structures. On the other hand, as the main product of the carbonation reaction, calcium carbonate will not dissolve in water but precipitate in the pores of concrete, thus decreasing the porosity of concrete and altering its microstructure. In this case, carbonation reaction may be favorable to maintain the durability of plain concrete. Thus carbonation has opposing effects on different constituents of the material.

Based on an assumption that the carbonation front advances after the alkaline material (i.e., calcium hydroxide) has been neutralized completely, the carbonation process is dominated by the diffusion of carbon dioxide through the porous microstructure of concrete, where the concentration gradient of carbon dioxide acts as a driving force. As a neutralization reaction, the carbonation process generates a specific amount of moisture, which may affect the temporal and spatial distribution of moisture content in concrete and should be considered in the simulation of previous moisture transport process. To develop a numerical model for carbonation, several coupled processes, namely the diffusion of carbon dioxide, moisture transport, heat transfer, formation of calcium carbonate, availability of calcium hydroxide in the pore solution etc., need to be considered. A popular approach is the multifactor equation, where the diffusivity of CO_2 is assumed to be dependent on the pore relative humidity, temperature and the carbonation-induced reduction of porosity as

$$D_c = D_{c,0} \cdot F_1^*(h) \cdot F_2(T) \cdot F_3(\xi) \tag{1}$$

where F_1, F_2 and F_3 represent the effects of humidity, temperature and carbonation, respectively. Refer Saetta et al (1995) for details of models for F_1, F_2 and F_3. Saetta et al. (2004) also proposed a similar numerical model for the carbonation reaction rate as

$$\upsilon_r = \upsilon_0 \cdot f_T \cdot f_h \cdot f_c \cdot f_R \tag{2}$$

where υ_0 indicates an ideal carbonation rate at which the carbonation reaction takes place in specified ideal conditions, and f_T, f_h, f_c, and f_R represent the influences of temperature, relative humidity, concentration of free CO_2, and degree of carbonation respectively, on the reaction rate.

Chloride Penetration

Chloride-induced reinforcement corrosion is one of the major deterioration mechanisms for reinforced concrete structures exposed to marine environment, deicing salts or underground environment. It leads to a series of structural degradations, such as loss of the concrete-steel interface bond, reduction of the cross-section area of reinforcement, and cracking and spalling of the concrete cover, thus severely reducing the load carrying capacity of the structure. Considering its unique significance, substantial studies have been carried out on the chloride-induced reinforcement corrosion process for several decades.

Based on Fick's second law, the governing equation of chloride penetration in concrete is expressed as:

$$\frac{\partial C_{cl}(x,t)}{\partial t} = D_{cl} \cdot \frac{\partial^2 C_{cl}(x,t)}{\partial x^2} \tag{3}$$

where $C_{cl}(x,t)$ is the chloride content at spatial coordinate x and time t, and D_{cl} is chloride diffusivity. Chen and Mahadevan (2008) proposed the modeling of chloride-induced deterioration through a multifactor equation as

$$D_{cl} = D_{cl,0} \cdot F_2(t) \cdot F_3(C_{cl,f}) \cdot F_4(T) \cdot F_5(\rho_{local}) \tag{4}$$

where $D_{cl,0}$ is the reference or nominal chloride diffusivity when all influencing factors assume values of unity. F_2 denotes the influence of the age of concrete, which reflects the cement hydration-induced reduction in the concrete porosity with time t. F_3 represents the influence of the free chloride content $C_{cl,f}$, which reflects the hindering effect of high chloride content on the chloride diffusion. F_4 indicates the influence of temperature T, which reflects the

thermodynamic effect of high temperature on the chloride diffusion. F_5 reflects the influence of local relative crack density ρ_{local}. Chen and Mahadevan (2008) implemented this approach through a finite element-based computational methodology to link the diffusivity change to structural degradation expressed by the local relative crack density.

The above two modeling approaches use semi-empirical multifactor equations, whose parameters are calibrated using experimental data. These are Level 2 approaches using averaged parameters. An example of a Level 3 approach based on multi-scale modeling is illustrated below for sulfate attack.

Sulfate attack

When sulfate ions diffuse through a cementitious structure, they react with the cement hydration products to form expansive products. This induces strain leading to cracking and eventual failure. Sarkar (2010) developed a probabilistic computational model of concrete durability under sulfate attack that considers three processes – diffusion of ions, chemical reactions and mechanical damage accumulation due to cracking. The three processes were modelled through basic differential equations, chemical reactions and mechanics models respectively, based on continuum first principles.

There are several inputs and model parameters in the three parts of the model. Sarkar et al (2012) pursued a hierarchical Bayesian calibration approach where the parameters of each model component were calibrated using tests that progressively added the processes (i.e., first chemical alone, then chemical and diffusion, then all three). In the geochemical speciation modeling, many mineral sets are possible; their relative proportions were calibrated using experimental data.

The effect of chemical reaction products on mechanical properties such as elastic modulus and strength was computed through multi-scale modeling. Four scales were considered for homogenization and calculation of macro-level structural properties and strength degradation. These were: calcium silicate hydrate (CSH), cement paste, cement mortar, and concrete. The macro-level crack density was then connected to effective elastic modulus and diffusivity.

In summary, the above examples of concrete deterioration modeling show attempts at modeling the interactions among multiple chemical, physical and mechanical processes that operate simultaneously across multiple spatial and temporal scales. This presents unique challenges for concrete structures health monitoring. Sensing of physical, chemical and mechanical quantities is one challenge. In addition, since multiple processes are interacting in a coupled manner, it is difficult to link any observed damage to a particular deterioration process or to estimate the proportion of damage contributed by different processes.

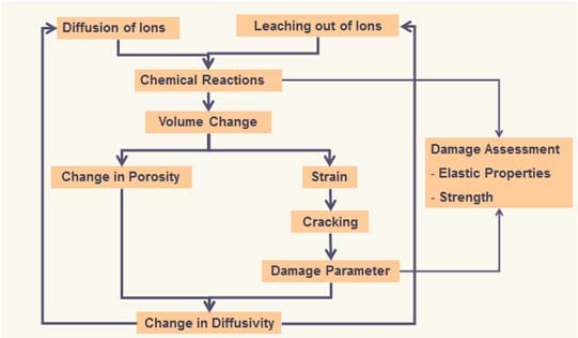

Figure 2. Multi-physics modeling of sulfate attack

3. HEALTH MONITORING

A variety of non-destructive evaluation (NDE) techniques have been studied for concrete structures. While some studies have investigated embedded sensors in concrete, we restrict this discussion to external sensing considering that the structures are already built. In a recent study led by the Oak Ridge National Laboratory, five NDE techniques were assessed for damage detection in concrete, namely shear-wave ultrasound, ground penetrating radar, impact echo, ultrasonic surface wave, and ultrasonic tomography (Clayton 2014). The techniques were compared in terms of ease of use, time consumption, and defect detection capability, and different techniques showed different advantages and disadvantages. For example, ultrasonic tomography appeared to have the best detection especially at larger depths under the surface, but was very time consuming. The first two (shear-wave ultrasound and ground penetrating radar) were found to have above average performance but some disadvantages as well.

For larger structures (e.g., containment structure in a nuclear power plant), the use of full-field imaging techniques appear promising. Some of these techniques are briefly discussed below (infrared imaging, digital image correlation, and velocimetry).

By using infrared imaging, it is possible to identify the thermal load path in a material. By tracking this thermal signature longitudinally in time, the onset of changes in the load path and hence changes in the composition of a material as well as mechanical damage in the material can be identified. Infrared imaging can also be combined with excitation techniques such as standoff acoustic sound pressure. By insonifying a material with an acoustic source, full-field vibro-thermography measurements can be made to characterize changes in the material over time. Such a methodology falls into the class of active structural health monitoring sensing methods (Mares et al, 2013).

A second approach to structural health monitoring for full-field infrared imaging is to measure the thermal response under an applied uniform heat flux. By analyzing thermal gradients in the material, regions of non-uniform material

composition such as due to the formation of defects can be identified and tracked (Sharp et al, 2014)..

Digital image correlation (DIC) has also been studied in recent years as a full-field structural health monitoring imaging technique. For example, DIC has been used to detect micro cracking in chopped fiberglass compression molded parts. The resulting image shows the principal strains in a region where a crack has formed. The strain field indicates the strains that occur under an applied static load. This method can also be used to detect localized residual strains (and stresses) after an applied load is removed. Furthermore, the method is applicable to tracking the strain that occurs under temperature or other types of environmental loading (wind, solar, etc.).

Velocimetry has also been studied as a full-field structural health monitoring imaging technique to detect subsurface nonlinearity due to material damage. For example, full-field velocimetry has been applied to monitor the ambient vibration of composite structures and data has been analyzed to detect subsurface damage in such materials. Damage indices quantify the degree of nonlinear stiffness/damping behavior that is observed locally at each measurement point in the grid. Using modern scanning laser technology, it is possible to perform these measurements for in-plane an out-of-plane vibration fields to achieve greater sensitivity to defects in composite structures. Using this technique, it has been demonstrated that the nonlinear dynamic behavior of heterogeneous materials such as the fiberglass sandwich material are indicative of subsurface damage, and that a higher frequency vibration provides for enhanced localization of the damage (Bond et al, 2013).

The aforementioned full-field measurement techniques have been applied to metallic and composite material structures. Their suitability for concrete structures is yet to be investigated. Full-field measurements also need to be supplemented by appropriate NDE and laboratory testing activities.

4. DATA ANALYTICS

Data analytics is a crucial step in processing the collected data and assembling the evidence for diagnosis and prognosis. A variety of data processing techniques have been developed during the past decades to analyze the data generated by the sensor systems. In general, health monitoring systems and sensors generate a large amount of data. For online monitoring, the amount of information grows very large, and this becomes a big data problem. A big data problem is characterized by volume, velocity and variety (heterogeneity) of data. When full-field imaging techniques are used, data analytics is challenged by the presence of heterogeneous data (numerical, text and image). The data becomes too large and complex to be stored, managed and processed by traditional database management techniques.

In recent years, several software frameworks for storage, management and retrieval of big data have been developed. The well-known Hadoop distributed file system for storing large amounts of data is scalable and fault-tolerant. MapReduce is a parallel processing framework for large-scale data processing. It consists of two segments -- Map function, where the task is subdivided and assigned to slave nodes, and Reduce function, where the results from slave nodes are aggregated to obtain final result (Prajapati, 2013).

Big data presents many issues such as data quality, relevance, re-use, decision support etc. In particular, uncertainty of inference due to data quality, and incompleteness need to be addressed. Sensitivity analysis leads to identifying the relevance of various data components, and helps to focus attention and collection efforts to the most relevant data. Additional challenges relate to data scrubbing and robust data management, as also the requirements for increased memory, storage and computing power.

Dimension reduction and data reduction are common steps in processing big data. Dimension reduction is achieved through feature selection and extraction. Two types of approaches are available for feature selection – filter approach and wrapper approach. In the wrapper approach, all possible subsets to predict the output variable are created, and the subset of variables, whose corresponding classification algorithm performs the best, is selected. In the filter approach, ranks are assigned to individual variables, and depending upon the accuracy required, the subset of variables is selected. In general, filter methods tend to be faster. In Feature Extraction, all the variables are mapped to a lower-dimensional space and models are constructed in this low-dimensional space. Principal components analysis (PCA) and factor analysis are well-known techniques that aid dimension reduction.

Prominent data reduction techniques include classification and clustering. Several different classification techniques such as decision trees, nearest neighbor classifier, neural networks and support vector machines are available. However, many of these are deterministic classifiers, whereas the Bayesian network is an uncertainty-based classifier where the available evidence is assigned to different classes with a quantified probability measure. Clustering can be either hierarchical or based on partition of the problem domain. Several different clustering techniques, such as k-means, DBSCAN, expectation maximization are available, and these need to be investigated for suitability in the present problem. For larger data sets, dimension reduction is possible through feature extraction and feature selection, in order to develop a low-dimensional representation of the available data.

After preprocessing and reducing the available data, the next step is PHM model building by learning the interrelationships. While doing this, it is advisable to use the data in a systematic manner that maximizes the information gain. An adaptive selection of data sources can be pursued, based on information-theoretic metrics. Various possible data sources are ranked based on the information gain potential and selected to train the model in decreasing order of information gain.

In summary, data about different physical quantities being measured is available in heterogeneous formats and fidelity, from multiple sources (e.g., test data, expert opinion, operational data, legacy system data, and model-based simulations). Data may be sparse about some quantities, while it may be abundant for other quantities. A systematic and rigorous approach is needed for data analytics that makes use of all available heterogeneous information. One promising approach is to use the Bayesian network (BN) machine learning approach as the organizing principle for connecting data in multiple different formats. The Bayesian network (discussed in the next section) allows the integration of various types of information that (a) occur at different times, and (b) combine in different ways (linear, nonlinear, coupled, nested, and iterative).

5. UNCERTAINTY QUANTIFICATION

Uncertainty sources in various components of the PHM model may broadly be classified into three categories: natural variability in the system properties and operating environments (aleatory uncertainty), information uncertainty due to inadequate, qualitative, missing, or erroneous data (epistemic uncertainty), and modeling uncertainty induced by assumptions and approximations (epistemic uncertainty). Much previous work has focused on variability, but a systematic approach to include data and model uncertainty sources within PHM still awaits development.

Data Uncertainty: On the one hand, sensor information may be inadequate, due to sparse, imprecise, qualitative, subjective, faulty, or missing data. On the other hand, one may be confronted with a large volume of heterogeneous data (big data), involving significant uncertainty in data quality, relevance, and data processing. In the context of a probabilistic framework, both situations lead to uncertainty in the distribution parameters and distribution types of the variables being studied, and the Bayesian approach is naturally suited to handle such data cases and update the description with new information. Flexible parametric or non-parametric representations can be developed within the Bayesian framework to handle such epistemic uncertainty (Sankararaman and Mahadevan, 2011). An important recent development is the extension of global sensitivity analysis to quantify and distinguish the relative contributions of aleatory uncertainty vs. epistemic uncertainty (Sankararaman and Mahadevan, 2013a).

Model Uncertainty: The challenges in developing a computational framework for concrete degradation modeling that mathematically represents the interactions among the multi-physics degradation processes and their relation to the quantities being measured by sensors were discussed earlier. The models for various processes could be based on first principles or regression of empirical data. For some components there may not even be any mathematical models available, but perhaps reliability data from past experience or literature. The Bayesian network offers a systematic approach to integrate such heterogeneous information. Quantification of the model uncertainty resulting from such heterogeneous information could be studied w.r.t. three categories, namely, model parameters, model form, and solution approximations; and the corresponding activities to quantify them are calibration, validation and verification, respectively. Model parameters are estimated using calibration data, and Bayesian calibration constructs probability distributions for the model parameters. Model form uncertainty may be quantified in two ways: either through a validation metric, based on validation data, or as model form error (also referred to as model discrepancy or model inadequacy). Model form error can be estimated along with the model parameters using calibration and/or validation data, based on the comparison of model prediction against physical observation, and after accounting for solution approximation errors, uncertainty quantification errors, and measurement errors in the inputs and outputs (Liang and Mahadevan, 2011)

Probabilistic graphical models for machine learning such as Bayesian networks (Jensen, 1996) have shown much effectiveness in the integration of information across multiple components and physics in several application domains. Dynamic Bayesian networks (DBNs) have been used for systems evolving in time, and recent work has extended DBNs to include heterogeneous information in diagnosis and prognosis (Bartram and Mahadevan, 2014). The Bayesian network is able to include asynchronous information from different sources. Also, Bayesian networks can be built in a hierarchical manner, by composing component-level networks to form a system-level network.

In summary, data and model uncertainty sources need to be systematically included in the PHM of concrete structures, and the Bayesian network offers such a systematic and comprehensive approach for the aggregation of uncertainty from multiple sources and heterogeneous information. The Bayesian network facilitates both forward propagation of uncertainty and the inverse problem of decision-making (e.g., sensor layout design) in order to achieve uncertainty reduction. The Bayesian approach has been used to quantify the uncertainty in each step of diagnosis and prognosis (Sankararaman et al, 2011; Sankararaman and Mahadevan, 2013b). Connection of these uncertainty quantification techniques to risk assessment and risk management

decisions through the use of structural reliability theory needs to be investigated (Naus, 2009).

6. CONCLUSION

This paper discussed challenges encountered in four elements of PHM for concrete structures – degradation modeling, sensor measurement, data analytics and uncertainty quantification. Illustrative techniques and ongoing challenges in each direction were briefly discussed. An important current need is the development of an effective framework for PHM of concrete structures that combines the state-of-the-art techniques in each of the four elements, overcomes challenges such as feasibility, complexity and scalability, and develops confidence in PHM result. Such a comprehensive approach will facilitate the development of a quantitative, risk-informed framework for structural health management.

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