Preface

Structural health monitoring (SHM) is a term coined several years ago within the research community; however, it has only recently received increased attention when it comes to practical implementation. Although certain pronounced failures in large civil structures might be considered as a trigger for this turning point, it was more so the realisation of an ageing and severely deteriorated infrastructure demographic that has shifted the focus to a pro-active approach towards infrastructure management. Infrastructure operators in developed countries are currently more and more concerned with the number of structures approaching their design lifespan, and are faced with decision-making processes for the proper maintenance, repair and future use of structural systems.

For infrastructure systems, SHM aims at exploiting sensory feedback from short- or long-term deployments towards extraction of information that is tied to performance. SHM provides a set of both tools (hardware) and methods (software) able to turn data into effective knowledge on structural integrity, durability and reliability. When exercised throughout the structural life cycle, SHM may form part of advanced decision-making schemes, ensuring optimal maintenance planning and safe operation of infrastructure components and networks. Naturally, such a task poses challenges at different levels, from the configuration of the deployed instrumentation grid, all the way to the actual design of a structural health evaluation system. More recently, the significant progress in sensor development has allowed for the deployment of dense sensor arrays at a relatively low cost, able to generate large bulks of heterogeneous data arrays.

As a result, advanced computational methods are required in order to handle the wealth of information as well as to translate this in an effective system representation, which may serve for tracking structural performance from “cradle-to-grave”. The proper combination of hardware resources and theoretical tools can ultimately lead to an automated framework, where structural assessment no longer merely depends on sporadic visual inspections that have been proven inadequate. Instead, the assessment process may benefit from the latent knowledge to be harvested from data. The latter is relevant not only for existing and already deteriorated systems but also in improving the design and simulation of newly engineered systems. However, the task of transitioning from raw data into salient indicators that are indicative of current and future performance necessitates adoption of appropriate data processing, identification and uncertainty quantification methods.

Within the framework of life cycle assessment and structural integrity evaluation, the 2013 CISM course on "Identification Methods for Structural Health Monitoring and Residual Lifecycle Assessment" had a two-fold objective. First, to provide a critical overview of well-known and established system identification methods on SHM; and second to introduce more advanced, state-of-the-art tools, able to tackle the challenges associated with actual implementation. This course volume summarises the content of the lectures provided within this context and is organised in the following chapters.

The chapter, titled "Implementation of Identification Methodologies on Large Scale Civil Structures", opens this volume with the first identified goal, i.e. the overview of existing SHM and system identification schemes for civil infrastructures. This chapter focuses on the techniques dealing with linear time-invariant systems; an assumption widely adopted for the case of civil structures. A selection of case studies highlights the benefits and drawbacks of these widely utilised methods when it comes to real-world and large-scale implementations. At the same time, the potential in incorporating tools from the information and computational technologies (ICT) domain in structural engineering problems is demonstrated along with key issues relatede to the integration between collection of measurements, data analysis and assessment.

The chapter, titled "Efficient Data Fusion and Practical Considerations for Structural Identification", moves one step further by touching upon the methodologies that are adept in the handling of the challenges identified in Chapter "Implementation of Identification Methodologies on Large Scale Civil Structures". Specifically, schemes for the fusion of data gathered from multiple sources of different types are overviewed, primarily relying on filtering tools, such as the well-known Kalman filter. Options for the handling of noise and uncertainty in both linear and nonlinear systems are presented with a focus on real-time implementations. Finally special considerations, and in particular the highly challenging issue of damping estimation, are overviewed with proposed remedies.

The chapter, titled "Implementation of Parametric Methods for the Treatment of Uncertainties in On-line Identification", builds on the concepts discussed in Chapters "Implementation of Identification Methodologies on Large Scale Civil Structures" and "Efficient Data Fusion and Practical Considerations for Structural Identification" and illustrates these via an exemplary implementation on simple numerical case studies. Two classes of time domain schemes are herein visited, namely the state space and autoregressive class. The examples provided demonstrate in detail how to effectively tackle diverse sources of uncertainties including input, measurement and modelling uncertainties for both linear and nonlinear systems. Finally, as a link to the decision-making framework discussed earlier, this chapter additionally overviews a metamodelling approach for the simulation and the tracking of nonlinear, dynamically evolving engineered systems. On the basis of the latter, appropriate indices may be devised that are indicative of structural performance.

The chapter, titled "Bayesian Parameter Estimation", introduces the Bayesian inference approach to uncertainty quantification with a focus on the estimation of model parameters. In this approach the plausibility attributed to the values of uncertain parameters is represented by suitable probability density functions (PDFs). A prior PDF reflects the prior knowledge on these parameters, i.e. the knowledge before any observations are made. Using Bayes' theorem, the prior PDF is transformed into a posterior PDF, accounting both for uncertainty in the prior information as well as for uncertainty in the experimental data and numerical model predictions. The theory behind the method is elaborated, and all steps in the Bayesian parameter estimation procedure are discussed and illustrated using a simple running example in the domain of structural vibration-based parameter estimation.

The chapter, titled "Bayesian Operational Modal Analysis", utilises the fundamental theoretical framework elaborated upon previously, and customises this to the problem of operational modal analysis. This is known to comprise a highly challenging task, primarily due to the multiple sources of uncertainty tied to identification of a system, where the monitored response amplitudes are low, close to the sensors' noise thresholds. The input excitation to the structure is in this case not measured but assumed to be "broadband random". A Bayesian system identification approach provides a fundamental mathematical framework for quantifying the uncertainties and their effects on the identification results. Rather than inferring the deterministic estimates of the modal parameters, the Bayesian approach yields their joint distribution, which is a function (though implicit) of the data and the modelling assumptions. This chapter overviews the main assumptions and resulting formulations of Bayesian operational modal analysis.

Finally, the chapter, titled "Bayesian Uncertainty Quantification and Propagation (UQ+P): State-of-the-Art Tools for Linear and Nonlinear Structural Dynamics Models", utilises the Bayesian framework for uncertainty quantification and propagation in the context of complex structural dynamics simulations using vibration measurements. The framework covers uncertainty quantification techniques for model selection and estimation, as well as techniques for robust prediction of output quantities of interest towards assessment of reliability and safety. Bayesian computational tools, such as asymptotic approximation and sampling algorithms, are presented for linear and nonlinear dynamical systems. This chapter additionally overviews the incorporation of high-performance computing techniques that drastically reduce the excessive computational demands arising from complex/detailed system representations. An application, employing identified modal frequencies from a full-scale monitored bridge, demonstrates the use of the proposed framework in parameter estimation of numerical models.

Eleni N. Chatzi
Costas Papadimitriou

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