WG2 – SHM Technologies and Structural Performance

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Abstract

This factsheet summarises the activities of Working Group 2. Notwithstanding the wide and diverse nature of presentations and factsheets produced by WG2 members, it has been possible to create a framework through which SHM technologies can be categorised with regard to the performance state of interest in making asset management decisions. Moreover, the treatment on uncertainties, in terms of appreciation, modelling and propagation within decision-support tools, is investigated by collecting information from case studies in which WG2 participants have been involved.

Introduction

Structural Health Monitoring (SHM) has been researched extensively worldwide in the past 20-30 years, using different sensors and strategies to monitor the response of structures and from that infer their performance against a variety of safety and functionality criteria. During the same period, the investments made by infrastructure owners / operators in the development of SHM have been significant. As a result, not only have many scientific publications appeared, but also many structures, both new and aged, have been equipped with SHM systems, including bridges, buildings, wind turbines, offshore structures, nuclear plants, dams, tunnels, etc. In principle, the observations / measurements from SHM systems can provide more detailed and more relevant information regarding the response of a structural system compared to traditional inspections and spatially limited non-destructive evaluations; in turn, this can translate to more effective performance indicators that can be used improving decisions associated with life-cycle asset management. As might be expected, the wide range of applications in different parts of the world investigating structural systems at various stages of their service lives and subjected to a variety of environmental and manmade actions, coupled with the rapid development of sensing and communication technologies, has posed significant challenges: how are we to categorise available SHM strategies bearing in mind the type of decisions that need to be made in asset management? How can we compare different SHM options available and select optimum strategies for different situations? Is a performance indicator that may be estimated using different SHM strategies on a specific structure subject to the same precision and accuracy level? These questions appeared relevant at the outset of this COST action and the work undertaken in Working Group 2 was aimed at providing some answers within the general framework of TU1402 and the sub-division of tasks to different working groups, as outlined in the Memorandum of Understanding [1].

1 Aims

The general purpose of SHM is the collection of information that is used for the re-assessment of structural performance. The monitoring technology, the gathered information and the structural performance of interest vary considerably depending on the type of structures considered and the decision context that is being pursued. The activities in this Working Group were aimed at providing a categorisation of the available SHM technologies in regard to the quantity that is indicated (e.g. crack length (steel), chloride concentration (concrete)) and to the structural performance that can be related to the corresponding measurement (e.g. remaining fatigue life (steel component), corrosion state (concrete re-bar). The working approach involved collecting and representing best practice technologies and applications in the context of life-cycle asset management. Due to the rather diverse and fast developing field of SHM in civil infrastructure, this was a challenging task, even though the COST framework is very well suited to arrive at a good representation of relevant best practice approaches.

Quantifying the relationship(s) of the quantity/ies measured with SHM technologies and the structural performance of interest is of utmost importance for the effective application of SHM in practical situations. However, any estimation, and even more so prediction of structural performance, based on measured quantities is associated with uncertainties. The formulation of a link between the measured quantities and the estimated and/or predicted indicator value for the structural performance of interest with consistent treatment of uncertainties was a further aim of this working group.

2 Achievements

2.1 Categorisation framework

Since the start of the action, members of WG2 have made over 20 presentations on the implementation of SHM strategies (and produced a similar number of factsheets). Many structural types were covered and different aspects of performance were considered. In general, a widening of research interest in SHM challenges from bridges and offshore structures to other types of structures, e.g. renewable energy infrastructure, can be identified. As highlighted in [2], in which a succinct appraisal of more than thirty review papers on SHM was attempted, the evolution of research objectives in investigating SHM for different types of structures often reveal a similar sequence: initially sensing technologies are trialled/evaluated, then data acquisition and basic processing from different types of sensors is addressed, and lastly condition identification for different damage types or different structural component/assembly/system is undertaken. The different structural condition identification methods can be broadly grouped as physics-based and data-driven, with some innovative integration methods using advanced data analytics algorithms also emerging in this field. VoI analysis is not explicitly formulated, confirming the fundamental premise at the outset of the action, though the potential of cost-benefit analysis is often mentioned as a key driver in gaining industry acceptance for various SHM schemes proposed by researchers.

Moreover, the presentations revealed that structural response can be monitored at different levels in an expanding framework: structural component – structural system – infrastructure network. However, although there is consensus on the need to consider the widest possible framework in order to understand the potential of SHM (and be consistent with VoI analysis needs), the majority of presentations focused on the first level (component), with only few going beyond to a structural system level.

A similar picture emerged for performance indicators, with component-based indicators being most common. It is believed that this is related to the way in which development and implementation of SHM in civil infrastructure is evolving: namely, as an additional tool in structural integrity management rather than as a more holistic approach to life-cycle management. As is well known, structural integrity management surmises that the engineers are able to identify ‘critical’ members or details (such as cracks in welds). Thus, in many cases, the SHM application domain appears quite constrained since SHM is viewed as an additional tool to traditional inspections.

However, it is also evident that the community is increasingly aware of the potential of SHM even in cases where such critical locations are not readily identifiable. In this respect, approaches in which appropriate input or response parameters based on experience are measured, without a specific damage or defect case in mind, are also gaining ground. The justification for SHM is this case appears to be an effort to improve prior and/or generic models so that the performance of a given structure is better estimated/predicted using site-specific information.

Another salient point from the presentations lies in the range of temporal and spatial scales associated with different SHM strategies: from multi-year measurement aimed at revealing long-term trends and changes, to single-day measurement aimed at establishing correlations between extreme loads and associated response; from assessment of performance using global strategies and measures to methods applied in order to quantify localised damage.

In an effort to improve the impact of studies on the application of SHM strategies and to encourage cross-fertilisation, the framework was proposed by WG2 which has the following characteristics:

- It promotes the use of common language/terminology.
- It is proposes common ‘start’ and ‘end’ points so that greater transparency is achieved – in the proposed framework these points are *‘performance’* and *‘decisions’.*
- The paths joining these points should be sufficiently generic so as to cover the wide range of efforts made by practitioners and researchers in introducing SHM into the asset management process.
- It should be linkable to the conceptualisations proposed by WG1 and WG3.
- It should be developable to a greater level of detail.

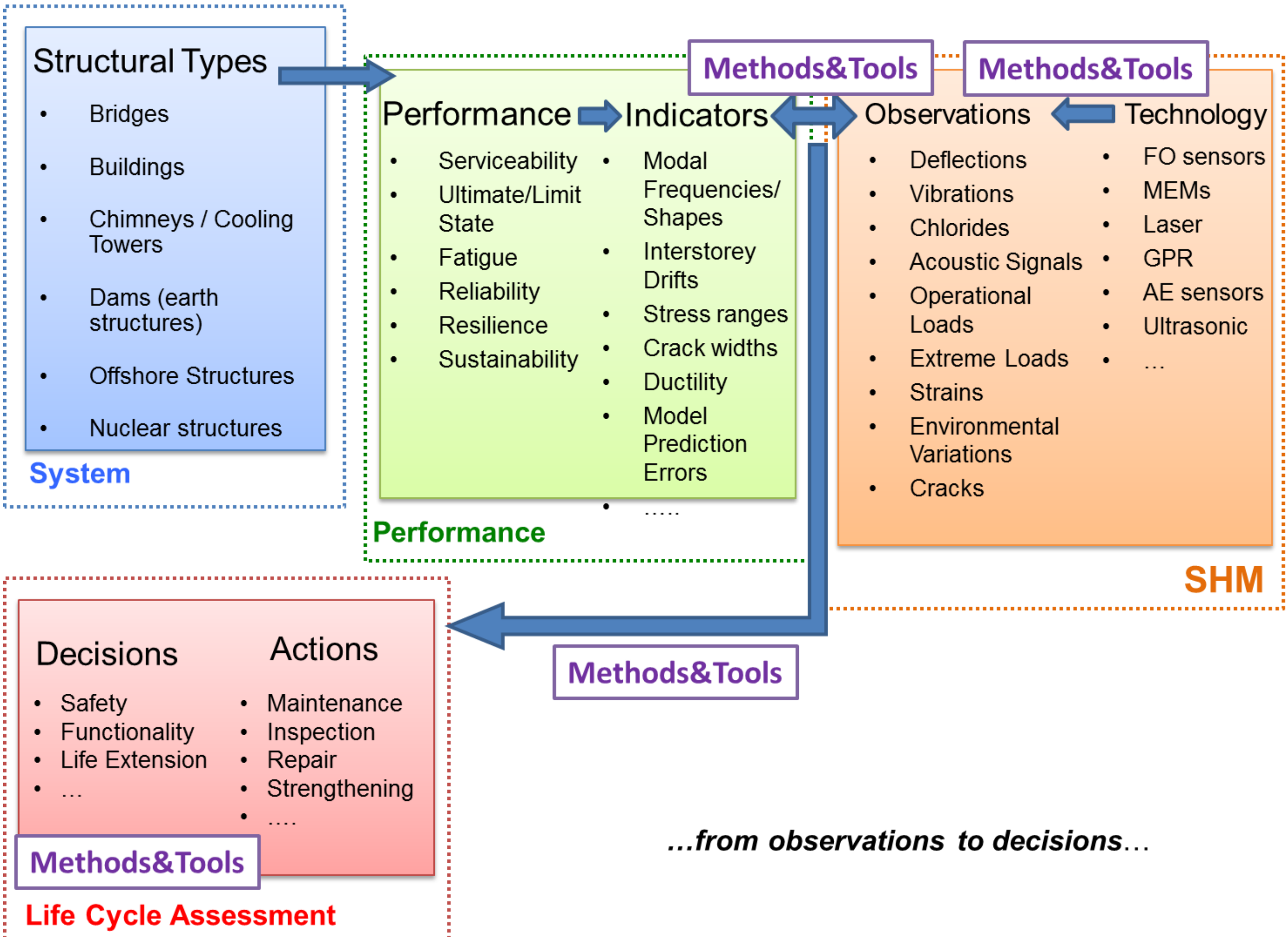

Figure 1: Categorisation Framework

The proposed framework is shown schematically in Figure 1, initially presented at the 2nd workshop in Istanbul and subsequently improved through discussions with the action members. Here an additional box has been added to the left to indicate the range of structural types that have been the subject of presentations by WG2 members. The boxes labelled “Methods and Tools” indicate the interfaces with other working groups in the action, particularly WG3 but also WG1 with respect to a decision framework in a life-cycle context.

The proposed categorisation framework is intended as a classification system, facilitating the choice of keywords in describing a problem and its proposed solution, and exposing the critical interfaces that need to be integrated in order to move “from observations to decisions”. For example, Bismut et al. [3] took basis on the proposed framework to further develop concepts for organizing and categorizing a value of information (VoI) analysis. It should be noted that the link between the observations from SHM and performance indicators is not always evident, and in some cases adequate methods taking into account also the statistical nature of SHM data are not sufficiently developed so far. Such a link can be direct, when the performance indicator or associated summary statistics can be computed from the measurements, e.g. the computation of modal parameters from vibration signals or test statistics indicating their change. Such a link can also be indirect, when structural performance models use SHM data by means of Bayesian updating, e.g. updating failure probabilities.

The framework is sufficiently generic to capture the wide range of contributions on different aspects of linking SHM with performance. However, it is envisaged that it can be refined with respect to attributes related to SHM technologies, performance of deteriorating structures and also with respect to the definition of system boundaries (from structural systems to infrastructure networks). An extensive overview of deterioration processes and performance indicators relevant to bridges that could be linked to the above framework is detailed in [4]. Also, a recent report from TU1406 [5] has provided comprehensive information regarding the definition of performance indicators for highway bridges throughout Europe. With respect to other structural types, aspects of performance modelling for wind turbines/parks are addressed in [6-8], and [9] provides a comprehensive risk-based methodology for performance assessment of levees. Performance indicators for heritage structures are presented in [10], whereas assessment of timber structures is covered in [11].

By way of example, Table 1 shows how SHM strategies employed in (a) the Great Belt bridge [12] and (b) the Z24 bridge [13] can be classified according to the diagram in Figure 1. Similar classifications can be undertaken in other cases.

System	**Performance**		**SHM**		**Life Cycle Assessment**	
	Category	Indicator	Observation	Technology	Action	Decision type
Great Belt	Serviceability LS	Strain	Strain Temperature Traffic	SG Thermocouples Cameras	Inspection Repair	Functionality
Z24	Ultimate LS	Modal parameters	Ambient vibration	Accelerometers	Inspection Repair	Safety

Table 1: Example of SHM strategies classified using Figure 1.

In the case of the Great Belt bridge, monitoring observations (taken over a number of years) consisted of two input (pavement temperature, heavy good vehicles) time-series and one output (strain) time-series. The effect of noise in measured strains and temperatures (from strain gauges and thermocouples respectively) was neglected and the model uncertainty in estimating the number of HGV vehicles from camera information (i.e. errors in correctly identifying HGV vehicles from camera information) was unaccounted. Moreover, the fatigue damage that is accumulated at a particular welded detail from vehicles other than HGVs was assumed to be negligible. On the other hand, physical and model uncertainties associated with S-N fatigue curves and the adoption of Miner’s sum were included in the structural reliability models and uncertainties in the stress-related fatigue indicator arising from the auto-regressive models for temperature and HGV traffic were also quantified and included in the analysis [12]. Referring to Figure 1, it can be seen that, in this study, uncertainties between SHM technology and observations (i.e. within the SHM ‘block’) were not dealt with, whereas uncertainties associated with the interface between observations and indicators were, at least partially, modelled. Uncertainties related to how performance (via an indicator function) is modelled for life-cycle assessment were also explicitly considered.

Within the frame of the Brite-Euram project BE-3157 SIMCES, a 3-span pre-stressed concrete highway bridge (referred to as the Z24 bridge), built in 1963, was monitored for about one year, followed by a progressive damage test, before the planned demolition. The aim of the test was to verify the feasibility of vibration-based structural health monitoring for a number of realistic damage scenarios and to check the influence of environmental variations. Data obtained from accelerometers on the bridge were converted into observations of natural frequencies, mode shapes, and damping ratios, involving statistical estimation (finite time duration) as well as model uncertainties (underlying assumption of linear time-invariant model). The observations of modal parameters have been used in many studies to construct indicators for monitoring of structural performance, and ultimately, structural safety. This requires, however, a separation of environmental from structural effects through, for example, data-driven model relating the environmental parameters to the observations. The estimation of such data-driven model will necessarily also involve estimation and model uncertainties.

The above exemplifies the idealisations that are made in developing SHM-based asset management strategies for specific problems. The information in the observations obtained through SHM is subject to uncertainties of different types or, more precisely, a formal quantification of the information content requires a consistent treatment of uncertainties. The importance of measurement inaccuracies and uncertainties has since long been recognized by craftsmen and engineers. An old English adage is “measure thrice, cut once”, whereas a Russian proverb, originally referring to carpentry and needlework, states “measure seven times, cut once” [16]. Notwithstanding the urge to debate whether 3, 7 or 37 measurements should be specified in any particular instance, the simple message is that measurements are subject to errors and uncertainties and it is therefore wise to develop an appreciation of their characteristics before taking the next, often irreversible, step. The proliferation of structural health monitoring (SHM) technologies and their implementation in various structural systems, principally during the past two decades, has brought a number of new challenges in relation to the measurement of quantities associated with system performance, be it input (such as loads or environmental parameters), system (such as model biases) or output related (such as deflections or vibrations). As part of the work undertaken in WG2, an effort was made to classify the sources of uncertainty in SHM-based life-cycle management and to understand the treatment of uncertainty in defining and estimating performance indicators. This work is summarised with reference to the above categorisation framework suggested by WG2. First, a brief recapitulation is made of the classification of uncertainty in the overarching framework of structural reliability. Next, statistical and model uncertainties are discussed for SHM in the framework of life-cycle asset management, followed by an assessment of their treatment in practice, using the questionnaire that was developed.

2.2 Classification and Treatment of Uncertainty in SHM-based life-cycle asset management

2.2.1 Classification of uncertainty in structural reliability assessment

Early work on quantifying the safety of structures through the birth and development of structural reliability theory [17, 18] focused on variability in strength of materials built to the same design; the distribution of strength in iron chains, castings and timber are examples where research in the first half of the 20th century led to the application of statistical analysis and the description of physical uncertainty in mechanical properties through probability distributions [19]. It is interesting to note that time-dependent effects attracted attention from those early days, such as the effect of load duration on the ultimate strength of timber or the variation of strength with time in the case of concrete cubes. At the same time, efforts were made to understand and categorise load variability by examining sources of uncertainty arising in the application of both quasi-static and dynamic loads on structures. The prediction of extreme loads in either category exercised the mind of those pioneering researchers, possibly spearheaded by the seminal monograph on statistics of extremes by Gumbel [20]. However, it is not until the late 1970's and early 1980's that a framework for categorising different types of uncertainty for the purposes of undertaking structural reliability analysis is beginning to be established. Ang and Tang [21] and Thoft-Christensen and Baker [22] introduce the distinction between uncertainty associated with randomness and uncertainty associated with imperfect modelling and estimation; the latter state explicitly that three types of uncertainty should be considered in any structural reliability problem: (a) physical uncertainty, (b) statistical uncertainty and (c) model uncertainty.

Classifying uncertainty can be helpful in modelling and accounting for it in specific problems and it is important to note that it can be classified in different ways. In quantitative risk analysis it is common to distinguish between uncertainty that captures the random variability of a repeatable experiment (aleatory), and the uncertainty due to lack of complete knowledge (epistemic). Inherent or natural variability associated with natural phenomena (e.g. in terms of seismic motion: future earthquake locations, future earthquake source properties, ground motion scatter about median value) or man-made processes (e.g. in terms of building construction: mechanical properties of materials) is classified as aleatory, and is typically modelled by stochastic (probabilistic) models. On the other hand, modelling assumptions and idealisations (e.g. fault geometry and capability, selection of ground motion models, simplified representation of real structure: 2D vs. 3D analysis) and parameter estimation through sampling are treated as 'epistemic' uncertainties. In principle, aleatory uncertainty is non-reducible, whereas epistemic uncertainty can be reduced by investing in additional data or information. In practical situations this statement should be viewed as a useful rule rather than an axiom. Moreover, the uncertainty split can change during the life of a structure. For example, the level of epistemic uncertainty may be reduced as knowledge and understanding of a particular situation increases with time, through targeted investigations or service-proven record (e.g. if a structure experiences an earthquake of 'known' characteristics). Der Kiureghian and Ditlevsen [23] appear to have laid to rest the discussion regarding the relevance of distinguishing between aleatory and epistemic uncertainties. They argue that the distinction is useful within a model, since it then becomes clear(er) as to which uncertainties have the potential to be reduced, especially in near-term, and in developing sound and transparent risk and reliability models. Issue of ergodicity and dependence between random events may not be properly accounted for if the nature of uncertainties is not correctly modelled. In codified reliability-based design, uncertainty and knowledge representation is described succinctly within the recently updated ISO 2394, where it is stated that the quantitative representation of uncertainties should be founded on probability theory and that the Bayesian interpretation of probability provides a basis for the consistent representation of uncertainties independent of their sources and facilitates the joint consideration of purely subjectively assessed uncertainties, analytically assessed uncertainties and evidence as obtained through observations [24].

2.2.2 Uncertainties related with the integration of SHM in life-cycle asset management

2.2.2.1 Statistical uncertainties in SHM

Any observations that are measured with SHM technology are subject to some measurement noise. Furthermore, observations are often the outputs of dynamical systems whose properties are never completely known in practice. When using the observations for the computation of indicators that are relevant for a particular monitoring problem, then the indicators are in almost all cases afflicted with statistical uncertainty since the information from the measurements is in general neither *perfect* nor *complete:*

- The measured observations are only noisy versions of the desired quantities to be measured due to measurement noise.
- Observations are obtained only in a finite time window, while the exact computation of some indicators would require infinite time series of data.
- In some cases, the exact computation of an indicator would be possible if some additional information was available which however is not measured or not measureable in practice, and only assumptions on its statistical properties are made.

Thus, nearly all indicators that are computed from data are random variables with some probability distribution and hence some statistical uncertainty.

Obviously, the knowledge of the statistical uncertainty of an indicator is crucial for monitoring in order to judge if a change of the indicator is just due to its natural statistical variability or if the change is (statistically) significant and hence indicates an abnormal behaviour of the monitored structure. So first, the uncertainty of an indicator needs to be *quantified*, and subsequently *treated* for a decision on a change of the indicator or for any further analysis of such a change.

Uncertainty quantification

In order to quantify the statistical uncertainty of an indicator, the parameters of its probability distribution are required. In the vast majority of cases, indicators that are estimates of some physical quantities (e.g. modal parameters) are assumed to be Gaussian distributed, hence only their covariance is required to quantify their uncertainty. The (approximate) Gaussian distribution of an indicator can often be justified through its *asymptotic Gaussian distribution*, i.e. its convergence to a Gaussian distributed variable when the number of measurements tends to infinity. Many indicators are functions of correlations of the measurement data. These correlations satisfy the central limit theorem (under standard assumptions like ergodicity) and are therefore Gaussian distributed. Then, indicators that are functions of these correlations also satisfy a central limit theorem under certain conditions (notably that their sensitivity with respect to these correlations is different from zero) and hence are asymptotically Gaussian distributed.

The quantification of the uncertainty can then simply be made through the computation of a sample covariance of the indicator, when several independent samples t_k of an indicator in the same structural state are available, as

$$\Sigma = \frac{1}{K-1}\sum_{k=1}^{K}(t_k - \overline{t})(t_k - \overline{t})^T \, , \; \overline{t} = \frac{1}{K}\sum_{k=1}^{K} t_k \, .$$

In other cases it is more difficult to obtain such a sample covariance directly, e.g. when the computation of the indicator is less straightforward from the measurement data, or when only one dataset is available. In this case, a sample covariance may be computed on the measurement data directly, and then propagated to the indicator with the statistical delta method, which requires the computation of the analytical sensitivities of the indicator with respect to data correlations. An example on the variance estimation of modal parameters is given in [25].

Other indicators are not directly estimates of physical parameters for monitoring, but some features computed from measurement data whose change indicates damage. For example, such indicators originate from statistical pattern recognition or other statistical time series analysis techniques [26]. These indicators should take into account the statistical properties of the measurement data directly in their computation, from which their probability distribution follows. An example on indicators for change detection and diagnosis in dynamic systems is given in [27].

Indicators that are not only computed from measurement data but that also involve sophisticated models (e.g., finite element models, reliability models, …) are subject to both statistical uncertainty related to the data and to model uncertainty. Furthermore, the model itself may have some data-based uncertainty when measurements are used to obtain it or to calibrate it. In this case, all sources of uncertainty should be considered. An example of uncertainty propagation from data to parameters of a finite element model in model updating is given in [28]. This case is discussed in more detail in the next subsection.

Uncertainty treatment

A simple evaluation of an indicator can be based on its estimate and its confidence interval obtained from the properties of its probability distribution. In the case of (asymptotically) Gaussian distributed estimates, confidence bounds are easily obtained for a desired confidence level from the covariance estimate. For example, let t be unbiased Gaussian distributed indicator with standard deviation σ. Then, the probability that the true value that is estimated by t lies in the interval $[t - \sigma, t + \sigma]$ is around 68%, 95% that it is in $[t - 2\sigma, t + 2\sigma]$ and 99.7% for $[t - 3\sigma, t + 3\sigma]$.

For the monitoring of changes in an indicator, statistical distance measures are useful tools to decide if a change is significant or not. The statistical uncertainty of the indicator is naturally considered in the computation of such a distance. For a decision, the distance is usually compared to a threshold based on an acceptable type I error. There are several ways to define such distances. For example, a popular and simple way is the computation of the Mahalanobis distance [29], where an indicator t with covariance Σ is compared to a reference value μ:

$$d^2 = (t - \mu)^T \Sigma^{-1} (t - \mu)$$

When the indicator is asymptotically Gaussian distributed, then the Mahalanobis distance is asymptotically χ^2 distributed. Another popular way to analyse changes is the use of control charts [30]. A more general setting for the analysis of indicators is hypothesis testing with (generalized) likelihood ratio tests, where the likelihood is evaluated that the current estimate of an indicator is drawn from the probability distribution corresponding to the null hypothesis or to the alternative hypothesis. The definition of the hypotheses is hereby quite flexible and can be based on relevant system parameters. They usually correspond to certain states of the monitored system [26, 27].

2.2.2.2 Model calibration uncertainties in SHM

In model calibration, data obtained from a sensor network is used in either direct or indirect, processed form to calibrate or update a model, adjusting parameters representing unknown system properties. In a context of SHM, the data is often obtained from sensors which pick up the dynamic behaviour of the structure in operational conditions, e.g. by accelerometers or optical fibres, and the data is subsequently processed using system identification algorithms to yield modal parameters (natural frequencies, mode shapes, modal damping ratios) for model calibration. The model under consideration, on the other hand, is usually a finite element (FE) model of the structure, i.e. a physical model or model based on first principles. In civil engineering, the process of model calibration is most commonly referred to as FE model updating. Due to the indirect nature of the relation between the data and the model parameters, model calibration is usually formulated as a nonlinear least-squares problem and solved using gradient-based optimization algorithms. In SHM, model calibration can be applied 1) as a technique for damage detection, when the parameters characterize damage in the structure, or 2) as a way to improve the predictive qualities of the model.

Model calibration is an inverse problem, as the conventional forward relation between the parameters and the model output is reversed. In many cases, this inverse problem is ill-posed, meaning that the existence, uniqueness, and stability of the solution to the inverse problem are not guaranteed. Small deviations in the data or modelling errors may have a large impact on the estimated parameter values and, hence, predictions made using the model. It is therefore imperative to consider all relevant uncertainties in the model calibration process.

Uncertainty quantification through Bayesian inference

A first question that arises is what types of uncertainties are involved. When SHM is considered within the frame of engineering decision analysis [31], one can revert to the differentiation between inherent natural variability, model uncertainties and statistical uncertainties, which is conventionally adopted in this field. Uncertainties of the first type are often categorized as aleatory or irreducible uncertainty whereas the latter two types are considered as epistemic or reducible uncertainty. The epistemic uncertainties can be reduced as information becomes available, often by updating the corresponding probabilities in a Bayesian setting. The implementation of Bayesian inference for parameter estimation in structural dynamics and structural health monitoring was first considered by Beck at al. [32].

In the Bayesian framework, Bayes' rule is used to update a prior distribution of the model parameters into a posterior distribution through multiplication by a likelihood function that characterizes additional information that became available. It is important to note that the solution to the inverse problem is the full posterior distribution rather than a single deterministic solution. For this reason, Tarantola argues in his well-known book on inverse problems [33] that data should only be used to falsify models rather than validating them.

One of the most widely cited publications on parameter inference in the Bayesian framework is the work on the Bayesian calibration of computer models by Kennedy and O'Hagan [34]. They consider the following types of uncertainties: (1) parameter uncertainty, (2) model inadequacy, (3) residual variability, (4) parametric variability, (5) observation error, and (6) code uncertainty. Key in the framework presented by Kennedy and O'Hagan is the relation between the true process $\zeta()$ and the model output $\eta(x_i,\theta)$, with x_i known variable inputs and θ the calibration parameters [34]:

$$z_i = \zeta(x_i) + e_i = \rho\eta(x_i,\theta) + \delta(x_i) + e_i$$

where e_i is the observation error, which includes the aforementioned, inseparable residual variability, ρ is an unknown regression parameter and $\delta()$ is a model inadequacy function that is independent on the code output $\eta()$. By adopting probabilistic models for the error terms, this prediction error equation leads to the formulation of the likelihood function. Distinguishing between parameter uncertainty, model inadequacy, and observation errors may be difficult and prone to issues of identifiability, however [35]. In many publications presenting Bayesian calibration in a context of structural engineering, the model inadequacy is (implicitly) lumped into the observation error, implying that systematic errors or bias are disregarded. Apart from a few exceptions [36], a simple i.i.d. model is used for the complete observation error. Inadequate treatment of the model inadequacy and observation errors may jeopardize the interpretation of the estimated parameter values as “true values”, however, since any discrepancy not explicitly considered in the prediction error equation will lead to bias. Kennedy and O’Hagan warrant against this physical interpretation of the parameter values and argue that the model should only be used for predictions. This is of course violated in case FE model calibration is done with the purpose of damage detection [37]. It is noted here that the filtering techniques which have recently been proposed for on-line estimation of states, inputs, and parameters rely on a similar prediction error equation and can be cast into a Bayesian framework.

Uncertainty quantification through non-probabilistic methods

In the last few decades, non-probabilistic models emerged for uncertainty modelling, in response to the inadequacy ascribed to the description of epistemic uncertainties by probabilistic models [38]. Probabilistic models are considered not well suited to capture uncertainty appearing in the form of poor data or linguistic expressions, which may be more straightforwardly described by ranges of possible values or intervals. This type of uncertainty is also referred to as impreciseness. Examples of non-probabilistic models include interval-based approaches, convex modelling, and fuzzy set theory. An example of the application of fuzzy set theory for damage detection through FE model updating can be found in [37]. One of the difficulties found herein is the inability of the method to consider dependency between fuzzy variables or quantifying dependency among multiple outputs, although some suggestions have already been made to remediate these shortcomings. A workshop on the treatment of epistemic uncertainties held in 2002 and sponsored by Sandia National Laboratories showed that that there was little or no consensus on the preferred approach for the modelling of epistemic uncertainties [39]. Participants with a background in probabilistic mechanics advocated the use of a purely probabilistic approach for treatment of all types of uncertainties, while most of the other participants felt the formal treatment of epistemic uncertainties introduced new considerations. Although the workshop was held over 15 years ago, it is fair to say that the debate is still ongoing and agreement on the subject has not been (and is probably not expected to be) reached.

2.2.3 Survey of current practice amongst COST Action TU1402 participants

The categorisation framework in Figure 1 illustrates the wide range of different asset types and performance issues, as well as the plethora of available SHM options and analysis methods. Introducing observations from SHM technologies in life-cycle asset management involves a consistent treatment of the relevant uncertainties as discussed in the previous section. A questionnaire was launched among the participants of the COST Action TU1402 to assess current practice in the treatment of uncertainties in the links between measured quantities and structural performance. In particular, it was intended to assess where the participants’ emphasis is placed with regard to consideration of uncertainties and their treatment in, e.g., system variables, performance indicators, SHM data and, finally, range of decisions considered. The following questions were asked:

(a) Context of the work
(b) What sources of uncertainties are present in this work?
(c) How are these uncertainties best described?
(d) Are these uncertainties currently taken into account in SHM data processing and/or the performance analysis in your work?
(e) What methods are used to quantify or to propagate the uncertainties?

Eighteen contributions were received, covering many different aspects in the proposed categorisation framework. The participants’ contributions within the respective context of their work are summarised in the Appendix. A recap and synthesis of the results of the questionnaire is given in the following.

(a) Context of the work

Five main areas regarding the context of the work could be identified:

1. Analysis of measurement uncertainties of the used SHM technology
2. Uncertainties in data-driven performance indicators (mainly linked to damage detection)
3. Model-based performance indicators with uncertainties due to unknown material characteristics
4. Fatigue/reliability analysis with performance model uncertainties and measurement uncertainties
5. Decision making

(b) What sources of uncertainties are present in this work?

The following principal sources of uncertainties have been mentioned:

- **Modelling uncertainties**: underlying the choice and computation of an indicator is often a model implying an idealized representation of the system's behaviour. Examples: unknown material properties; imperfect models for changing environmental and operational conditions; imperfect models for soil-structure interaction, etc.
- **Measurement uncertainties**: observations extracted from data by SHM technology are characterized by measuring (data processing/human inspection) uncertainties.
- **Estimation/statistical uncertainties:** an indicator computed from SHM observations is a random variable (measurement uncertainties, finite time window) with properties depending on the applied method.

(c) How are these uncertainties best described?

The majority of contributions used probabilistic models and statistical inference (random variables, random processes) for the characterisation of the present uncertainties. Few contributions mentioned fuzzy or interval based methods, and scenario based models. Overall, there is a tendency towards probabilistic methods, partly because the recognition/quantification of measurement and estimation uncertainties in statistical terms seems to be quite widespread. There is little evidence of the distinction between epistemic and aleatory uncertainties being made, not even from an identification point of view (i.e. in order to understand how uncertainties may be measured, updated or controlled).

(d) Are these uncertainties currently taken into account in SHM data processing and/or the performance analysis in your work?

The presence of different kinds of uncertainties is widely acknowledged, and in many cases some uncertainties are taken into account. However, there seems to be an overall lack of consistency on how uncertainties are classified and the methods for their quantification and treatment are adequate on a case specific basis. In particular, the uncertainty of indicators is often (at least partly) quantified, but in many cases not explicitly taken into account for monitoring. Furthermore, the measurement uncertainty of SHM data is widely acknowledged but few contributions have been made on the resulting statistical uncertainty of the indicators. As a result, the concept of confidence levels does not play the role that might have been expected, given the varied sources of uncertainty present in these case studies.

(e) What methods are used to quantify or to propagate the uncertainties?

The following general method classes have been mentioned:

- Quantification through statistical methods and Bayesian inference
- Propagation through structural reliability methods (probabilistic models)

- Practising engineers are used to cast uncertainties in bounds, though these are not strictly based on probabilistic principles (i.e. they seem ‘logical’ rather than being statistically quantified).

3 Dissemination

1. Working Group 2 has produced a large number of fact sheets that are collected in the proceedings of the different workshops of the COST Action TU1402: 6 fact sheets in the Proceedings of the 1st Workshop (publicly available), 13 fact sheets in the Proceedings of the 3rd and 4th Workshop (password protected). In addition, the leaders of WG have contributed to the organization of the following sessions at international conferences:
    a. 8th European Workshop On Structural Health Monitoring (EWSHM 2016), 5-8 July 2016, Spain, Bilbao, “Health monitoring and structural performance assessment”, organized by Michael Döhler (INRIA), Geert Lombaert (KU Leuven), Eleni Chatzi (ETH), Sebastian Thöns (DTU): 15 presentations.
    b. Fifth International Symposium on Life-Cycle Civil Engineering, IALCCE2018, October 29-31, 2018, Belgium, Ghent, “Special Session SS-10: Value of Structural Health Monitoring information for the Life-Cycle management of civil structures”, organized by Sebastian Thöns (DTU), Geert Lombaert (KU Leuven), Maria Pina Limongelli, (Politecnico di Milano): 9 presentations.
2. The categorisation framework shown in Figure 1 and included in the COST Action TU1402 brochure (http://www.cost-tu1402.eu/resources-downloads/action-documents) lends itself as an introductory web page that presents an overview of the activities within the working group. The different fact sheets could be linked to (parts of) the diagram for an appreciation of work contributed by the COST action participants, as has been demonstrated for a couple of fact sheets related to bridges in the above section. This would require making public those fact sheets that are currently included in password protected proceedings.

4 Lessons learnt

The vast amount of research devoted to SHM has led to a wide variety of possible monitoring technologies (sensors, algorithms, etc.) with different levels of technology readiness. Notwithstanding the pressing need for condition assessment of a large number of structures in practice, the practical implementation of these monitoring technologies is lagging behind. Within Working Group 2, the following challenges were identified that need to be dealt with in order to facilitate a wider deployment of SHM:

- Undertaking successful field testing, reaching the appropriate level of technology readiness level for different SHM options.
- Establishing robust links between monitoring data and performance indicators with appropriate treatment of uncertainties.
- Defining suitable thresholds / targets for performance indicators.
- Assessing the benefits of SHM beyond a component level, in the first instance to a structural system level.
- Quantifying the confidence levels with which performance indicators can be estimated and predicted, given the propagation of uncertainties from various sources.

5 Conclusions

Notwithstanding the wide and diverse nature of the collection of fact sheets produced by Working Group 2, they only represent a few samples from ongoing research and implementation of Structural Health Monitoring. An exhaustive categorization of monitoring technologies, including their relation to performance indicators and targets, is therefore prohibitive. Instead, Working

Group 2 has focussed on providing a categorization framework which can have a wide applicability and provide a common reference point to the community.
In order to quantify the value of information brought by the observations provided by monitoring technologies, a formal, holistic and consistent treatment of the corresponding uncertainties is needed. This involves the identification of the uncertainties directly related to these observations, as well as their propagation, be it in forward relations between observations or indicators, or in inverse relations e.g. occurring when observations are used for model calibration. A questionnaire among the participants of the COST TU1402 Action shows that the importance of the various types of uncertainties is widely recognized. Although probabilistic models and statistical inference are mostly used to quantify these uncertainties, it is felt that interval or fuzzy based methods or scenario based methods can also be appropriate in some cases. The move towards more formal decision theory tools (such as VoI), as opposed to the current less formal judgement based decision framework, will have a positive impact on uncertainty quantification and treatment. This is to be welcomed, provided it does not lead to an unnecessarily higher degree of complexity and loss of transparency. In this respect, there is scope for well documented case studies to be developed and presented so that practitioners can see the benefits that can be accrued from the adoption of new tools and associated criteria.

6 Outreach

A feasible option for outreach activities is via mobilisation of industrial partners who have both the incentive and the resource to develop such material from real projects with which they are involved. The factsheets provide information on current activities of several industrial partners who engaged with WG2 and who might be approached for this purpose.

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Appendix: Summary of participants' contributions

Part I: Fact sheets from the participants of WG2

1st workshop

Contributors	Title
M.P. Limongelli, M. Domaneschi, L. Martinelli, M. Dilena, A. Morassi, A. Zambrano and A. Gecchelin	The interpolation method for the detection of localized stiffness losses
F. Hille	Subspace-based detection of fatigue damage on a steel frame laboratory structure for offshore applications
M. Maślak, M. Pazdanowski, J. Siudut and K. Tarsa	Probability-based durability prediction for corroded shell of steel cylindrical tank for liquid fuel storage
J. Markova, M. Holicky and M. Sykora	Monitoring of bridges for calibration of load models
A. Mandić Ivanković, Jure Radić and Mladen Srbić	Finding a link between measured indicators and structural performance of concrete arch bridges
A. Zornoza, T. Grandal, R. de la Mano, L. Blanco, F. Rodriguez, A. Asensio, P. Rey and E. Rodriguez	SHM with fiber optic sensors at AIMEN technology center

3rd and 4th workshop

Contributors	Title
C. Andrade, J. Fullea, J. Sanchez, N. Rebolledo, F. Pedrosa, L. Saucedo	On-site corrosion rate
C. Andrade, J. Fullea, F. Tavares, J. Sanchez, N. Rebolledo, F. Pedrosa, L. Saucedo	Permanent corrosion sensors

H.Sousa, L.Oliveira Santos	Long-term performance of prestressed concrete bridges
A.Žnidarič, M.Kreslin, J. Kalin	Weigh-in-motion and traffic load monitoring
I.Farreras Alcover, M.K. Chryssanthopoulos, J. Egede Andersen	Outlier detection based on Structural Health Monitoring of welded bridge joints
K.Radzicki, S. Bonelli	Thermal monitoring of leakages and internal erosion in dams and levees
R. Szydłowski, M. Maślak, M.Pazdanowski	Monitoring of the prestressed concrete slabs with unbonded tendons during erection and in service
W.M.G. Courage, A.J. Bigaj-van Vliet, W.H.A. Peelen, G.T. Luiten, R. Drieman	Smart Structures for Smart Maintenance
M.G. Masciotta, J.A.C. Matos, L. F. Ramos	The Value of SHM for the Structural Behaviour of Masonry Structures under Varying Environmental Effects
M. Sykora, J. Markova	Assessment of cooling towers and industrial chimneys based on monitoring
A.Strauss, A. Mandić Ivanković, H.Sousa	Performance indicators for road bridges
A.Tavares de Castro, I. Ferreira, J. Mata	Monitoring and structural safety assessment of large concrete dams
P. Omenzetter, M. P. Limongelli, U. Yazgan	A pre-posterior analysis framework for quantifying the value of seismic monitoring and inspections of buildings

Part II: Summary of the participants' responses to the uncertainty questionnaire

1. Analysis of measurement uncertainties of the used SHM technology

Contributors	Title	Context of work	Uncertainty types	How quantified/treated?
Barrias & Casas; BarcelonaTech	Distributed optical fiber sensing for the SHM of concrete structures	Analysis of measurement technology	Measurement uncertainty due to strain transfer between the monitored structural component and the optical fiber itself	Regression error analysis by comparing the performance of distributed optical fiber sensing with other sensing techniques
Schoefs; University of Nantes	Uncertainty of measurements on the on-site quality of detection	Analysis and treatment of inspection uncertainties in general	Measurement (and inspection) uncertainty	Establishment of probabilistic model

2. Uncertainties in data-driven performance indicators (mainly linked to damage detection)

Contributors	Title	Context of work	Uncertainty types	How quantified/treated?
Masciotta, Ramos, Lourenço & Matos; Minho	Development of key performance indicators for the structural assessment of heritage buildings	Monitoring of crack opening rate, towers tilting, modal frequencies	Measurement uncertainties, change of ambient conditions (temperature, humidity)	Sample variance of static and dynamic parameter estimates; no quantification related to ambient condition changes
Moughty & Casas; BarcelonaTech	Damage sensitivity evaluation of vibration parameters under ambient excitation	Damage detection using vibration measurements	Ambient excitation	Sample covariance of damage features in outlier analysis

Hoell & Omenzetter; University of Aberdeen	Optimal damage sensitive feature projections for enhanced damage identification in wind turbine blades	Damage detection using vibration measurements	Estimation uncertainty of damage features (due to ambient excitation + measurement uncertainty); uncertainty due to choice of model describing the data	Statistical hypothesis tests
Reynders, Chatzi, Döhler, Lombaert	Monitoring the structural health of the Z24 Bridge	One year ambient vibration monitoring	Estimation uncertainties due to ambient excitation and measurement noise, model uncertainty of baseline model describing range of environmental conditions	Variance estimation of modal parameters, damage indicator definition through Polynomial Chaos Expansion approach using the distribution of temperature parameters
Omenzetter & de Lautour; University of Aberdeen	Vibration-based structural damage detection via statistical pattern recognition	Damage detection using vibration measurements	Estimation uncertainty of damage features (due to ambient excitation + measurement uncertainty)	Statistical hypothesis tests

3. Model-based performance indicators with uncertainties due to unknown material characteristics

Contributors	Title	Context of work	Uncertainty types	How quantified/treated?
Sienko, Howiacki, Maslak & Pazdanowski; Cracow University of Technology	Structural Health Monitoring for Kościuszko Mound in Cracow	Monitoring of soil behavior in combination with numerical model	Uncertainty of soil properties (heterogeneous soil structure), change of ambient conditions (humidity), measurement uncertainties	Sample variance of estimated parameters
Omenzetter; University of Aberdeen	Analysis of in-situ strain and temperature data from post-tensioned bridges	Strain monitoring, calibration of creep and shrinkage models	Estimation uncertainty due to ambient excitation + measurement uncertainty; model uncertainties after calibration from measurements	Sample statistics, analysis of model errors

Pakrashi, O'Donnell, Wright & Cahill; University College Dublin and Cork	Instrumentation and Modelling of the 'Shakey Bridge' in Cork, Ireland	Vibration monitoring due to concern of bridge performance	FE model uncertainty due to existing damage in bridge and unknown material strength	
Rizzo & Gaggero; University of Genoa	A posteriori monitoring of still water hull girder loads	Estimation of shear forces and bending moments	Data (weight and position of cargo are very roughly recorded), model uncertainties	Statistical hypothesis testing

4. Fatigue/reliability analysis with performance model uncertainties and measurement uncertainties

Contributors	Title	Context of work	Uncertainty types	How quantified/treated?
Leander; KTH	Monitoring and fatigue assessment of a critical railway bridge in Sweden	Fatigue assessment in combination with numerical model	Estimation uncertainty of load effect through stress range spectra, uncertainty of material resistance (physical)	Variance analysis of measured response for fatigue analysis; FORM to consider uncertainties in service life estimations
Strauss, Slovik, Novak, Novak; BOKU Vienna, Univ. Brno	Shear resistance of prestressed girders	Probabilistic design of precast structural members	Measurement uncertainties, modelling and model uncertainties, material uncertainties	Probabilistic inverse analyses techniques and neural network approaches
Sykora, Markova & Diamantidis; CTU Prague, OTH Regensburg	Structural health evaluation of heritage structures	Update of performance models with monitoring results	Uncertainties in resistance parameters, dimensions, loads, model uncertainties, measurement uncertainties	Bayesian techniques for treatment

Zonta, Verzobio, Cappello; Univ. of Trento	Parameter estimation based on Bayesian inference: Application to a constitutive model for intact rock	Measurement of radial strain and axial stress of quartz phyllite due to axial strain	Measurement uncertainties, material inhomogeneity, model uncertainty	Bayesian inference, taking into account the estimated covariance of the likelihood functions
Alcover, Andersen & Chryssanthopoulos; COWI, Univ. Surrey	Outlier detection and fatigue life prediction based on structural health monitoring of a long-span bridge deck	Development of data-based models for asset integrity management	Data-based uncertainties due to variation of temperature and traffic, fatigue model uncertainties	Autoregressive model to quantify uncertainties in de-seasonalized time series, Monte Carlo simulation for evaluation of failure probability

5. Decision making

Contributors	Title	Context of work	Uncertainty types	How quantified/treated?
Zonta, Tonelli, Cappello; Univ. of Trento	Determination of a decision rule concerning the temporary closure of Colle Isarco Viaduct based on the Expected Utility Theory	Detect possible excessive deflections of the main span	Measurement uncertainties of prisms (also influence of temperature), structural model uncertainties	Bayesian inference, taking into account the estimated covariance of the likelihood functions
Smith, EPFL	Uncertainty estimation for asset-management decision support	Static or dynamic monitoring	Measurement and model uncertainties	Estimations from practising engineers