Towards risk-informed decision-making for population-based structural health monitoring

A.J. Hughes, P. Gardner & K. Worden

Dynamics Research Group, Department of Mechanical Engineering, University of Sheffield,
Mappin Street, Sheffield S1 3JD, UK

email: ajhughes2@sheffield.ac.uk

ABSTRACT:
The prospect of informed and optimal decision-making regarding the operation and maintenance (O&M) of structures provides impetus to the development of structural health monitoring (SHM) systems. A probabilistic risk-based framework for decision-making has already been proposed. In order to learn the models necessary for a SHM system, measured data from the structure of interest are required. Unfortunately, these data are seldom available across the range of environmental and operational conditions necessary to ensure good generalisation of the model. Recently, technologies have been developed that overcome this challenge, by extending SHM to *populations* of structures, such that valuable knowledge may be transferred between instances of structures that are sufficiently similar. This new approach is termed population-based structural heath monitoring (PBSHM).
The current extended outlines a formal representation of populations of structures, such that risk-based decision processes may be specified within them. The population-based representation is an extension to the hierarchical representation of a structure used within the probabilistic risk-based decision framework to define fault trees. The result is a series, consisting of systems of systems ranging from the individual component level up to an inventory of heterogeneous populations.

KEY WORDS: population-based structural health monitoring; risk; decision-making; value of information.

1 INTRODUCTION

Structural health monitoring (SHM) systems are a technology that aims to detect damage within mechanical, civil and aerospace structures and infrastructure [1] for decision-support purposes. Recent works have explicitly framed structural health monitoring in the context of decision-making [2–6]. The approach to decision-making for SHM presented in [4], adopts a probabilistic risk-based perspective.

A critical challenge associated with the development of SHM systems is the scarcity of the data necessary for the learning and validation of models. Prior to the implementation of a monitoring system, there is often a lack of comprehensive labelled data across the health-states of interest for a given structure as obtaining data corresponding to damage states tends to be prohibitively expensive or otherwise infeasible. Population-based structural health monitoring (PBSHM), provides a holistic framework for overcoming data scaricity in the development of predictive models for SHM [7–10]. The core principal of PBSHM is that predictions about individual structures can be improved with the use of information transferred from other similar structures.

The current extended abstract begins to further the core principal of PBSHM, such that *decisions* about the operation of both individual structures and populations of structures can be improved via the transfer of information. This new perspective is realised by extending the hierarchical representation of structures, used to develop fault trees in the risk-based approach to decision-making for traditional SHM presented in [4], to hierarchical representations of populations of structures.

2 POPULATION-BASED SHM

The foundations of PBSHM have been presented in a series of journal papers, each detailing the fundamental concepts of the approach; homogeneous populations [7], heterogeneous populations [8], mapping and transfer [9], and the geometric spaces in which structures exist [10]. By adopting a population-based approach to SHM, such that knowledge and information can be transferred between similar structures, there is the potential for improved diagnostic and prognostic capabilities [11].

In the most general sense, a population can be considered to simply be a set of structures. Given the broad nature of this definition, in order to achieve useful transfer of knowledge and information between structures, it is discerning to consider specific classes of populations based upon the similarity of the constitutive structures. Thus, the notions of homogeneous and heterogeneous populations are introduced in [7–9]. For the context required to appreciate the contents of the current extended abstract, it is highly recommended that the reader's familiarise themselves with the work presented in [7–10].

3 PROBABILISTIC RISK-BASED SHM

The probabilistic risk-based approach to SHM is founded on the notion that monitoring systems should be designed and developed with consideration for the specific decision-support applications motivating their implementation. The approach to risk-based decision-making for SHM detailed in [4] relies on a hierarchical representation of structures – this representation, detailed in the following section, can be leverage to develop risk-based PBSHM.

4 STRUCTURES AS HIERARCHIES

A key assumption implicit in the development of the fault-tree failure models in [4], is that structures can be represented as a hierarchy, or, in other terms, as a system of systems of systems.

Consider a structure of interest S. To obtain a hierarchical representation for S, one must first decompose S into a discrete number of constituent elements, which are referred to as *substructures*. Substructures are considered to be entities which may, in principle, be assembled remotely or available for independent testing prior to incorporation into the full-scale structure. Within the hierarchical representation, some substructures may be further decomposed up until the stage at which it would no longer be meaningful or useful to do so. Substructures at this stage are referred to as *components*. As such, components are considered to be substructures which cannot (or need not) be decomposed further; these are the smallest element of a structure one might reasonably monitor. A notable sub-class of component is the *joint*. Joints are considered to be the physical mechanisms by which substructures are joined together.

A diagram illustrating the hierarcical representation of a structure is shown in Figure 1. The levels in the hierarchy that specifies the system of systems of systems shown are denoted as $\mathcal{S}^1$, $\mathcal{S}^2$, and $\mathcal{S}^3$ – corresponding to the component, substructure and substructure levels, respectively. Within each level of the hierarchy, elements can be listed.

The hierarchical representation of structures facilitates the specification of the decision process that motivate the development and implementation of SHM technologies. This facilitation is achieved by decomposing structures into constituent substructures and components which can then be used to define failure modes of the structure. Given a finite set of failure modes of interest, one can then specify critical components, and therefore health states, to be targeted by a monitoring system.

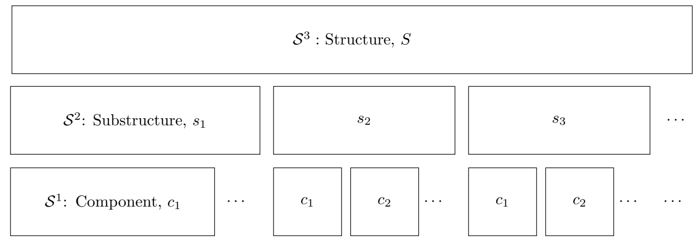

Figure 1: A structure as systems of systems.

5 POPULATIONS OF STRUCTURES AS HIERARCHIES

A natural method for incorporating decision-making into PBSHM, is to extend the hierarchical representation of structures to hierarchical representations of populations. The number of levels required in a hierarchy is of course dependent on context. However, it is deemed that an additional three levels provide sufficient generality for most PBSHM applications.

The additional levels necessary to extend the hierarchical representation to populations of structures can be summarised as follows:

- $\mathcal{S}^4$ – Type/Model Inventory: This level of the hierarchy corresponds to the lowest population level and represents an organisational grouping in which all individual structures in the population are of the same type/model and can be considered to be nominally identical. Thus, populations at this level in the hierarchy are homogeneous.
- $\mathcal{S}^5$ – Group Inventory: This next population level corresponds to a set of $\mathcal{S}^4$ inventories for which it is necessary or convenient to consider as a group for operational reasons such as asset management. As a group inventory may be formed of disparate type/model inventories, in general, group inventories are heterogeneous populations.
- $\mathcal{S}^6$ – Inventory: This level of the hierarchy corresponds to the total set of structural assets operated or owned by an organisation or company. Again, this level will generally represent a heterogeneous population.

Figure 2 depicts the continuation of the hierarchical representation from $\mathcal{S}^3$ to $\mathcal{S}^6$. In Figure 2, an inventory I is considered as a system of systems of systems of systems. Once again, a list can be formed of the constituent elements for each level in the hierarchy.

As is the case for traditional SHM, the hierarchical representation of structures and populations of structures can help faciliate decision-making for PBSHM in several ways. These decision processes are discussed further in the following section.

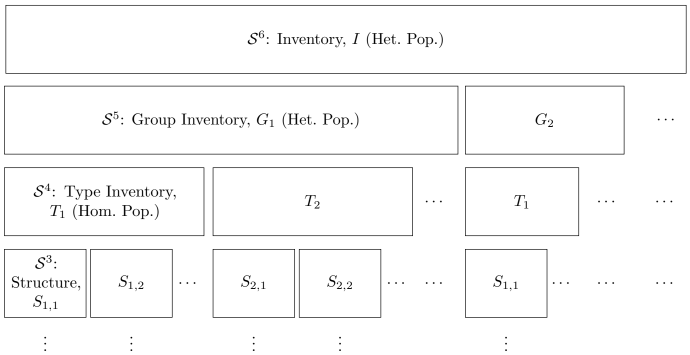

Figure 2: An inventory as a system of systems of systems of systems.

6 RISK-INFORMED PBSHM

Numerous decisions must be made throughout the life cycle of a PBSHM system. Most obvious are the operation and maintenance decisions an organisation may have to make, following the installation of a monitoring system, such as inspections and repairs. Equally important, however, are the decisions that must be made prior to implementation such as those made in the operational evaluation stage of PBSHM.

6.1 Operational evaluation

One significant way in which adopting a hierarchical risk-based approach to PBSHM faciliates decision-making occurs very early on, in the operational evaluation stage. By considering specific failure modes and constructing fault trees for individual structures, one can decide the key elements of a structure which should be modelled in IEs and AGs.

The extension of the hierarchy to represent populations of structures via the inclusion of levels $\mathcal{S}^4$ to $\mathcal{S}^6$ prompts one to consider how failures may be defined at the population level. One possible way to approach the failure of a population would be to consider the critical missions for the operating organisation. Depending on the nature of the organisation – whether they are non-commercial or commercial – these missions may be related to performance measures such as availability and/or profitability. Defining failures at the population level within the hierarchy allows one to assign costs during the operational evaluation stage. Following on from this, population-scale actions can be also be defined.

6.2 Inferences and decisions

A fundamental process of decision-making for PBSHM is reasoning under uncertainty. This is typically achieved via inferences. Within the hierarchical framework for PBSHM, different types of inferences can be defined:

- I-inference: This type of inference corresponds to those usually made in traditional SHM, and occur within the individual structure levels $\mathcal{S}^3$ to $\mathcal{S}^1$. An example of an I-inference is the process of determining a probability distribution over the health states of an individual structure using data acquired from that structure.
- L-inference: This type of inference occurs between levels in the hierarchical representation of structures. These may also be types of I-inference, for example determining the probability of failure for a (sub)structure given local component health states. Other L-inferences may include those relating to the validation and verification of predictive models (V&V). For example, one may be able to validate a predictive model for a structure at the $\mathcal{S}^3$ level with data measured from substructures or components at the $\mathcal{S}^2$ and $\mathcal{S}^1$ levels, respectively.
- P-inference: This type of inference occurs across populations. If the inference is across a type inventory in $\mathcal{S}^4$, i.e. a homogeneous population, they can be denoted as HomP-inferences. These inferences across populations may utilise technologies such as forms [7]. An example of a HomP-inference is inferring the health state of a member in a population using data aggregated across all members in the population. On the other hand, if a P-inference is between populations containing different types of structure, such as within a group inventory in $\mathcal{S}^5$, then the inferences can be referred to as HetP-inferences. HetP-inferences may involve using transfer learning techniques such as domain adaptation [9].

These inferences within the hierarchical representation of populations, facilitate reasoning under uncertainty using PBSHM systems; this can naturally be extended to decision-making under uncertainty, by considering the following types of decision:

- I-decision: This type of decision is made at the individual structure levels in the hierarchy, $\mathcal{S}^1$ to $\mathcal{S}^3$. Again, this type of decision corresponds to decisions one may make with a traditional SHM system. An example of an I-decision is selecting a maintenance strategy for an individual structure, substructure, or component for repair. Unlike in traditional SHM, in the risk-informed PBSHM approach, I-decisions can be informed by I-, L- and P-inferences alike.
- L-decision: The actions selected via this type of decision operate between levels of the hierarchical representation. As with L-inferences these decisions may pertain to the V&V of predictive models. For example, deciding whether can one proceed with using a structural model validated on substructures. Another example of this type of decision relates to resource allocation. Suppose one has a limited budget to carry out some structural testing to acquire data for mode updating. Under these circumstances, one should aim to decide on a set of tests, and the levels at which these tests are carried out, such that the largest improvement in model performance is obtained for the given budget.

- P-decision: This type of decision is made at the population levels in the hierarchy, S^4 to S^6. These actions may pertain to resource management. For example, one may decide to send a team of engineers to perform inspections on a type inventory based on the probability of failure for a population rather than the probability of failure of an individual structure. Scheduling inspections in this manner could save both time and expenditure. Again, these decisions may be informed via I-, L- and P-inferences.

To summarise, the hierarchical representation of populations of structures facilitates both making inferences and making decisions for PBSHM, by allowing for the definition of specific types of inferences and decisions.

7 CONCLUSIONS

To conclude, the current abstract extends a hierarchical representation of structures to representations of populations, such that decision processes can be defined over populations of structures.

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