Towards Integration of a Knowledge-Based Approach into SHM

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Abstract. Structural Health Monitoring (SHM), as a method to monitor structures continuously, is gaining increasing interest in the NDE community. Many SHM systems are currently using only one specific source of information to extract knowledge regarding the structural state. Moreover the output of many SHM systems tends to be black or white, often not taking uncertainties into account. This limits the reliability performance of these systems. In the area of Knowledge Management (KM) there are already many available techniques which may perform the reasoning under uncertainty and the decision-making by using different knowledge technologies and information sources. Such approaches might incorporate technological risks e.g. constraints on software or hardware development, and non-technological risk associated with economic factors of SHM, particularly cost, present value, and return on investment. Those risk parameters have an influence on maintenance programs, the advancement of SHM systems, and ultimately on decision-making. This contribution proposes to integrate the systematic approaches from KM into SHM in order to improve the reliability of SHM systems.

Introduction

The aim of Structural Health Monitoring (SHM) Systems is to monitor a variety of aero, civil or mechanical structures. SHM assesses the state of the structural health continuously or periodically in an automated way via direct measurements and through appropriate data processing and interpretation in a diagnostic system. In its basic form, the main objective is to detect one defined kind of damage in the area of inspection. Additional levels also perform the localization and classification of damage as well as the damage assessment and prediction. To achieve damage prognosis, attempting to forecast system performance, it is e.g. necessary to measure the current loading (usage monitoring) on the structure in some way, estimate the future loading environment, and deploy a damage evolution model. This way the remaining useful life can be predicted.

SHM features a variety of sensing and data evaluation techniques, based on different physical principles and mathematical approaches. But most of the time only one approach is used within an SHM system. This way many possible sources of information are not used. Reliability of SHM systems therefore highly depends on one approach.

Via data management and the combined use of multiple algorithms, already used in the SHM community, in a knowledge-based decision making toolbox, it is possible to achieve a higher level of information. In such a way, it fosters optimal usage of SHM algorithms developed for different aims, and therefore improve the reliability of the analysis result. Furthermore this concept also may enhance the SHM study, transforming it into more practical usages and promote condition-based maintenance.

In this context, the authors have established the collaborative research to investigate how KM methods and solution can be integrated into SHM systems. In [1] they have proposed a concept of knowledge-based SHM using the case study of force identification. In particular, a toolbox for the reconstruction of unknown forces on a high rise building (Canton Tower) is implemented.

This paper discusses the novel strategy and progressive research for merging the knowledge-based approach into an SHM system. Here, the term "knowledge-based" refers to the knowledge-intensiveness of the process of reasoning in SHM. Therefore one should consider that the principles of knowledge-based systems are not fully integrated into this approach while, in a same perspective, risk and economic factors are foreseen. In this paper, therefore, the term knowledge-based approach and in a broad sense KM are interchangeably used. The general integration of both fields is discussed at a conceptual level, highlighting the promising potentials of this merger. Afterwards, the 3-DOF-case study is taken to give a simple example for the successful application of KM on an SHM system.

1. Theory on the Knowledge-Based Approach

1.1 Background on KM

The objective of integrated technologies and components for Knowledge Management (KM) is to make information actionable and reusable. Developing a KM solution requires effective deployment of knowledge technologies (i.e. semantic technologies, information systems or Mindware and Software Engineering) towards the evolution of adaptive and intelligent systems for industrial applications. Here, the common attribute is "Knowledge" for reasoning (i.e. reasoning under uncertainty), and decision-making by discovering hidden relations between knowledge attributes, and improving reliability of decisions. Such an approach requires the assurance of reliability of the data via the prioritization of different sensing and data evaluation techniques up to the reasoning and final decision-making.

Several accounts are detectable for defining KM. This is due to the generic nature of KM and its use in various fields such as, but not limited to, (strategic) management, computer science, psychology, education, quality management, information technology, and organizational learning.

Not only in academia but also in practice the variety of accounts on KM is visible, where e.g. managers interchangeably use Information Management (IM) and KM. The reason for this is that definitions of knowledge, itself, can differ, comparing application domains and sectors or even branches of a sector. Therefore, for instance, one can define an entity as information while at the same time it is used as knowledge by others. The definition of Groff and Jones explains KM more comprehensively [2]:"KM is taken as the tools, techniques and strategies to retain, analyze, organize, improve and share organizational expertise". This is also addressed by Wijnhoven [3], Eppler [4] and Maier [5]. Despite the diversity of accounts, KM is generally defined in computer science as an iterative, life cyclic, dynamic and systematic process which encompasses the creation, acquisition, extraction, storage, retrieval, discovery, application, review, sharing and transfer of the knowledge captured and stored in databases. In this context, several components should be integrated to manage e.g. databases (including non-homogenous types of documentations and data), soft/hard competences, human resources, experiences, quality and change of processes, and associated risks.

The term knowledge refers to a certain typology for distinction between tacit, explicit and latent knowledge. Tacit knowledge is a person-dependent knowledge (personal knowledge). This type of knowledge is not and cannot be expressed. Explicit knowledge "is or could be expressed without attenuation" [3]. Latent knowledge "could be expressed but it is difficult to express it without attenuation" [6]. In practice, knowledge is mostly seen as explicit or implicit. In this way, knowledge is classified into two major categories by identifying whether knowledge is represented, documented and codified or not. Particularly, undocumented or non-codified knowledge is considered as implicit i.e. tacit or latent that needs to be extracted, documented or discovered using certain methodologies like experience management, observation, interview, etc. The given definition of KM only addresses the major aspects, and in turn KM needs to be redefined or adopted for each application domain e.g. SHM.

1.2 KM approaches

The various approaches of KM can be summed up in three ways: (1) Mechanistic, (2) Cultural, and (3) Systematic approaches. Mechanistic approaches apply technologies as well as resources aiming at improving the whole business processes. The main assumptions of this approach come from a better accessibility to information which also includes access and reuse of documents, i.e. hypertext linking, databases, full-text search etc. The main advantage of these kinds of approaches is the possibility of a relatively easy implementation. This is caused by the circumstance that the technologies and techniques are common and easily implicit [6, 7].

Cultural approaches have their roots in process re-engineering and change management [6, 7].They treat the "knowledge problem" completely as a management issue. Although they do not forget that technology is essential for managing explicit knowledge resources, they think that technology cannot be the solution. Actually such an approach focuses on innovation and creativity (the "learning organization") instead of leveraging existing explicit resources or making working knowledge explicit [8]. The main assumption of these kinds of approaches is that organizational behaviours and culture need to be changed [6, 7]. Another key assumption is that it is still possible to change organizational behaviours as well as culture, although traditional technologies and methods of attempting to solve the "knowledge problem" have reached their limits of effectiveness [7, 6]. As a result a "holistic" view is required.

Systematic approaches to KM try to keep the traditional faith in rational analysis of the knowledge problem [5]. In other words, they know that all problems can be solved, but they also know that new thinking of many kinds is required. Finally they tend to view KM as an important management component, but it is not an activity or discipline that belongs exclusively to managers [5].

Besides, a single approach does not necessarily deal with all aspects of KM lifecycle. For example, knowledge discovery from databases is a component for extraction of knowledge from structured or unstructured documents (e.g. csv files or text based reports). In the broad perspective, KM is to effectively and efficiently conduct the knowledge life cycle especially to utilize knowledge assets for operational and strategic endeavours such as decision-making.

Decision-making ultimately effects on quality of products, processes or services [9], [10]. It is, in most of cases, a complex, time consuming, problematic activity, and requires simultaneous and systematic consideration of decision-parameters, risk factors, customer preferences, priorities and associated cost/benefit ratios [9], [10]. In the context of SHM, decision-making is a critical endeavour due to reliability and safety requirements of the structures. For instance, using algorithms of damage detection isolatedly is not an optimal solution and could not coherently consider all influential factors of decision-making in a right time and place. In this context, knowledge-based approaches to decision-making can improve the situation through utilizing and integrating various knowledge sources, combining SHM algorithms, and deploying learning and intelligent methods for detection of semantics between instances and parameters of decision-making.

2. The Knowledge-Based Approach in SHM

2.1 General Remarks

The knowledge-based approach in SHM as a general integration scenario is depicted in Fig. 1. It consists of three major components for generating a decision. The data layer for gathering and storing data in the database (DB) builds the first component, the analysis layer using the SHM Analytical Toolbox builds the second and the decision layer using a knowledge-based approach for logical modelling of the rules and reasoning i.e. rule based decision support, builds the third component.

The first component can be divided into the external database, which can include e.g. current maintenance schedules, baseline measurements for different temperatures and physical models of the monitored structure or its parts. This information is combined within the Data Management, which also transforms data to the adjacent format for the following component, the SHM Analytical Toolbox. Within the Knowledge-Based Approach in SHM it is possible to include different algorithms and measurement systems. This way the same data can be used for several calculations as well as the same algorithms can be used for data of different sources to extract most information of the raw data. This information already contains most knowledge for domain experts, but only within the third component, consisting of knowledge-based decision making, makes this knowledge accessible for stake holders, like the operator of the structure. An example for a data evaluation in this context is the usage of rules, which are structured in a form of “IF-THEN-ELSE”. The conditions and consequences, within these forms are defined by the domain experts. Therefore the rules represent the domain specific knowledge for decision-making. In general the rules can be represented as:

IF A [first condition] AND B [second condition] OR C [third condition] THEN D [Consequence]

The main advantage of such an approach is the adaptivity of the decision modelling for updating the existing rules, based on conditional changes, and generating of new rules, based on new requirements. However, increasing the number of rules may raise a need to optimize the decision-making process and in turn use learning approaches for automatic adjustment and updating of parameters and preferences. Such a challenge can be resolved using e.g. the concept of Fuzzy Control, and involving domain experts within the development of the inference logic.

This approach can be included e.g. for the development of a draft of a new maintenance schedule, taking into account costs of maintenance, risk of failure and consequences of failure. Decision alternatives can be developed and either the decision is made automatically or domain experts and the operator of the structure can finally decide, e.g. on a new updated maintenance schedule.

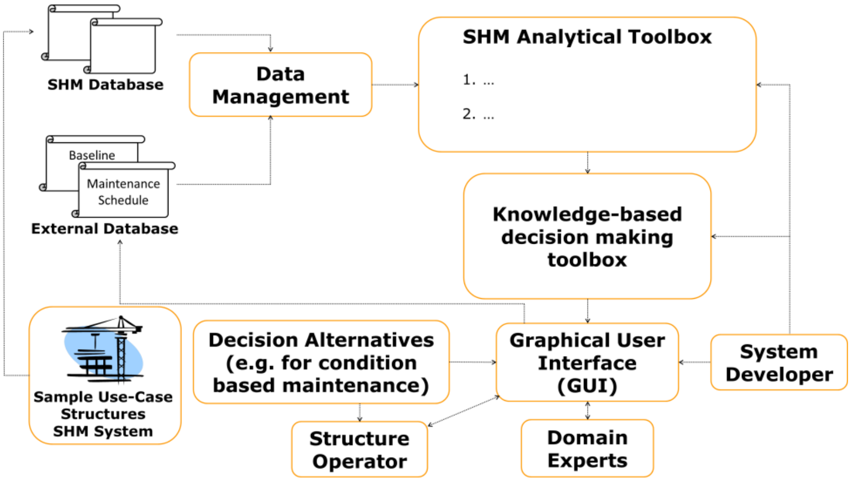

Fig. 1. General concept for a Knowledge-Based Approach on SHM

2.2 Case Studies

A simple example, including the data of a 3-dof-numerical model (Fig. 2), visualizes the use of the Knowledge-Based Approach in SHM on a very simple level. The external data base consists of the calculated system answer as displacement of one of the masses after white noise excitation on the second mass.

The SHM database consists of data of the undamaged system, as well as of three different scenarios, which have been modelled. These include a temperature change, resulting in a slight stiffness change of all included springs, a sensor fault, modelled as a bias on the calculated displacement as well as a damage of the structure, modelled as stiffness reduction of the spring between the second and the third mass. All different scenarios are not visible in the time domain data, but with the help of different SHM algorithms knowledge about the structures state can be extracted.

Simple algorithms have been included in the SHM toolbox, using statistical values, like mean, variance, using AR coefficients and eigenfrequencies extracted from the time domain data. For all three algorithms, the obtained features were combined with the help of Principal Component Analysis in a Damage Index [11]. Afterwards these three damage indices are used in the Knowledge-based Decision Toolbox to extract knowledge from the information included in these Damage Indices. A graphical User Interface makes this accessible for a wide audience, already giving some interpretation of the data but also supplying all necessary information for an own interpretation of the data.

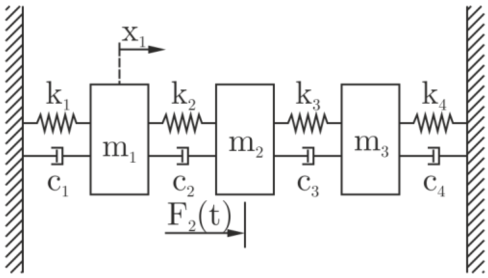

Fig. 2. Numerical 3-dof-model, used as structure for a simple case study.

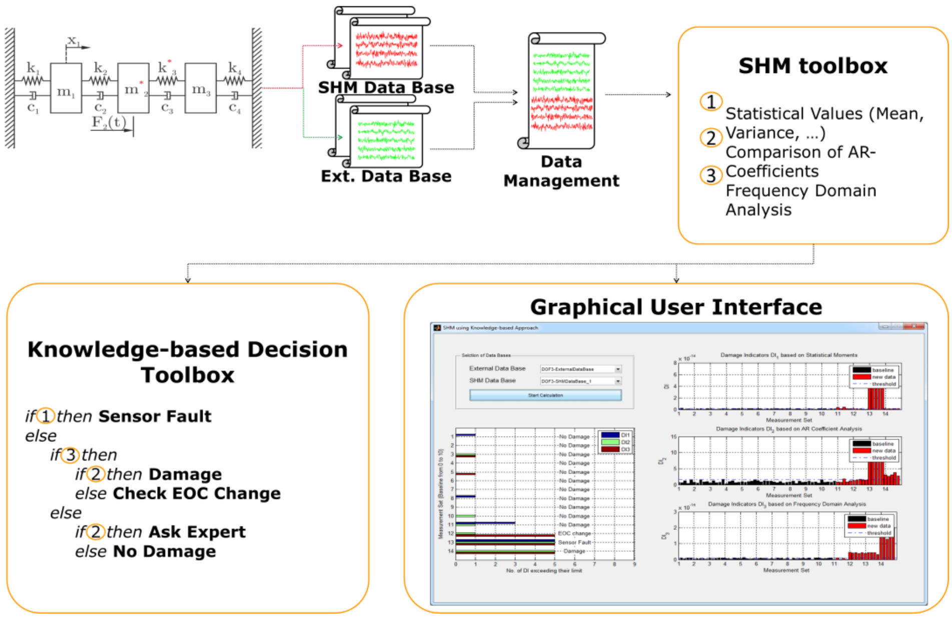

Fig. 3. Integration of a Knowledge-Based Approach in SHM of a simple 3-dof-structure (EOC=environmental and operational conditions).

With the use of this knowledge-based approach all modelled scenarios can be identified, while none of the algorithms alone would be able to identify these, because the single algorithms respond differently to data of various system states like sensor fault or damage. A visualization of this example is given in Fig. 3.

In a similar way one can use the load identification, which is a key-information for the estimation of the remaining useful lifetime, when a structural model and a damage evaluation model is agreed on. The aim is to assess the current health status of the structure, including maintenance schedule optimization. The Knowledge-based Decision Toolbox combines the information of the actual maintenance schedule, risk and reliability information as well as the input of the SHM algorithm toolbox to gain knowledge about the structures state and make a draft for a new maintenance schedule. The 600 meter tall Canton Tower is located in a typhoon active area, and a long-term SHM system has been designed and integrated into this tower [12]. These two points make the Canton Tower an ideal test-bed for the wind load reconstruction study using the field measurement data from the SHM measurement system. This example approach is visualized in Fig. 4 [13].

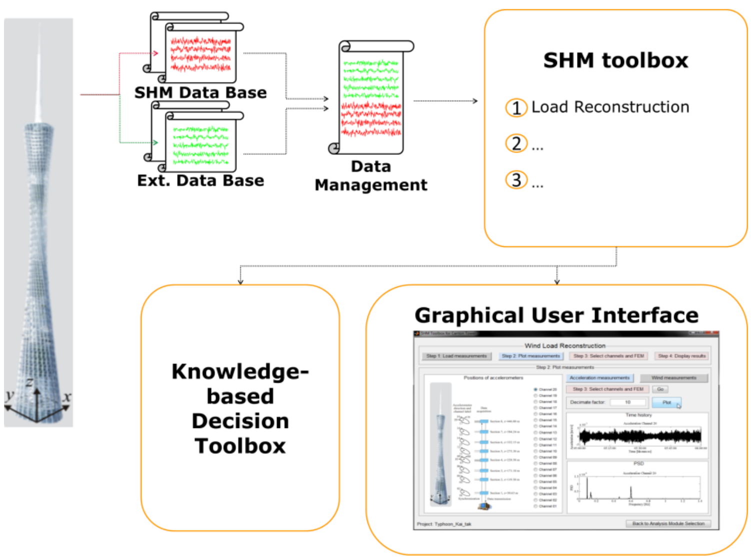

Fig. 4. Integration of a Knowledge-Based Approach in SHM for the application scenario "Canton Tower".

3. Prospective Knowledge-Based Decision Support in SHM-Systems

The concept for integration of knowledge-based approaches in SHM can be extended and further developed in the future. The potentials are employing knowledge-based approaches in decision-making, reinforcing of data management, and using a feedback component. In particular, the knowledge-based decision toolbox can be advanced using major principles of decision support (i.e. identifying decision models, internal and external preferences and disturbances as well as decision and feedback mechanisms), instead of only employing logic rules in the reasoning process. A decision is derived through management of data including data quality control, analysis of data using SHM toolboxes like load reconstruction, calculation of damage indicators and finally by fulfilling certain predefined conditions defined by the domain expert, which might also be a physically based model comparison.

Decision models provide the structure for problem-solving and decision-making considering risk, financial, environmental, legal factors and customer preferences. In addition, the Graphical User Interface (GUI) is required so that the users, with different access levels e.g. operator, engineer, manager, can communicate with the system. In this way, the communication of the domain expert with the system is managed and the system developer can improve the algorithms, based on their feedback.

The advanced toolbox should include sub-systems for incorporating decision models and automatic generation of decision alternatives. In this way, identification of dependencies between parameters and prioritizing them is essentially important. The decision models can be developed considering condition and environmental changes as well as risk and economic factors. Using the described components, the system should in turn deploy a Learning Algorithm e.g. Artificial Neural Network (ANN) or Bayesian Network (BN) for automatic learning of the decision instances and related preferences. This is, in fact, strengthened through gathering feedbacks e.g. from sensors, servicemen and clients regarding the consequential or actual condition of the structure after selecting a certain decision alternative. The feedback component plays a major role as a watchdog of the system especially to evaluate the effectiveness of selected decision alternatives and provide potential recommendations for improving SHM algorithms and preferences of decision-making.

4. Conclusions and Future Work

SHM practitioners deal with a considerable amount of data gathered via sensors and inspection. Accumulation of data provides opportunities for elaborating the analyses and outlining a knowledge-base consisting of certain semantics between entities. The semantics relate the entities in a meaningful form to be (re)-usable in reasoning and decision-making. A promising case study of a 3-dof model highlighted the potential for integration of knowledge-based approaches in SHM.

This paper commences the collaborative research for the integration of KM techniques and methods, and knowledge technologies in SHM. The proposed concept foreground potential future research especially dealing with aggregation or hybrid usage of SHM algorithms for discovering and extracting new knowledge in e.g. damage detection and predictive health assessment. Also the feedback component needs to be studied using knowledge visualization and data mining methods to discover improvement potentials for developing new sensors or materials. In addition to technological risks, the promising research theme is to investigate how economic and risk sensitive parameters of SHM should be moderated to decrease cost and assure return on investment. The influence of economic factors should be further studied in the context of maintenance programs towards advancing SHM systems, and sustaining reliability of decision-making.

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