- FORESEE -

Future proofing strategies FOr RESilient transport networks against Extreme Events

– Deliverable 4.4 –

Assessment and review of the different SHM algorithms

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1 EXECUTIVE SUMMARY

A State-of-the-art review has been done of the existing techniques for bridge monitoring, where special focus has been put on Vibration-Based Structural Health Monitoring (VBSHM). VBSHM founds on fact that the presence of damage in a civil engineering structure will affect its dynamic response, which can be measured through the acquisition of vibrational data from the structure. The general conclusion of this review is that there is no single method able to solve the problem of early damage detection in real practice, so different approaches need to be combined. Thus, the FORESEE approach is to combine model-based and data-driven methods with several selected algorithms. The proposed methodology distinguishes between an alert system for damage detection and, once the alert is triggered, a subsequent procedure for damage location and quantification.

2 INTRODUCTION

Condition of the existing structural systems is subjected to a constant degradation process due to several mechanisms, including aging, harsh ambient operation, or natural and man-made hazards, among others [1]. Thus, controlling the global state of structures and guarantying users' safety has become a key issue for today's civil infrastructure managers [2].

In this context, the idea of implementing Structural Health Monitoring (SHM) arises from the need to improve the rational basis for decision making for the design, construction, operation and maintenance. This helps to strengthen and complement subjective information provided by traditional visual inspections [1].

Damage in civil engineering structures results in a reduction of their capacity to withstand service conditions during their operative life [3,4]. Typical types of damage include cracks, fatigue, corrosion and deterioration due to environmental or loading effects [3]. The most widely applied technique over the years for controlling the condition of structural systems and components is visual inspection, which requires the subjective judgement of experts and can be difficult or dangerous to apply in hardly accessible parts of the structure [4,5].

This has driven researchers and engineers towards the investigation and development of more objective evaluation approaches such as non-destructive testing techniques, including the use of acoustic emission, ultrasound or thermography, among others [6,7]. Such an evaluation approach consists of scheduled field trips for periodical evaluations, regardless of the real condition of the structure. They can result in unnecessary expenditures or the emergence of late interventions which may pose hazard to public safety [4,6]. This has led to the implementation of more sophisticated assessment approaches for the lower cost, yet continuous and effective identification of structural changes that can provide early warning of unsafe conditions or malfunctions in operating structures (asset or component level) using monitoring data [4,8,9]. Monitoring systems provide raw time series records from different sensors, including acceleration or strain measurements [10]. Adequately exploiting this information in SHM requires the identification of proper damage sensitive features [10,11]. Among these features, we may highlight modal properties, such as natural frequencies, mode shapes and modal curvature [10,12] and strain-related features [13,14], due to their strong relationship with damage effects. The statistical parameters that define the measured time signals are also robust features to characterize the behaviour of structures [13,15].

One of the most significant developments in the SHM field for civil engineering structures pertains to the well stablished Vibration-Based Structural Health Monitoring (VBSHM) [4,16,17]. An extensive literature review regarding the different types of bridges has been developed in [10], based on this approach. They include several relevant references that help to frame the most insightful developments in the field.

VBSHM relies on the fact that the presence of damage will induce modifications in the stiffness, mass or energy dissipation properties of the structure and, thus, affect its dynamic response (natural frequencies, mode shapes and damping ratios). This response can be measured through the acquisition of vibrational data from the structure, mainly accelerations [9,12,18]. There are two main approaches to transform acceleration time series into dynamic damage sensitive features, namely Experimental Modal Analysis (EMA) and Operational Modal Analysis (OMA) [10,19,20]. The decision of which of these two techniques to use depends on the pattern recognition problem to solve and the excitation employed when measuring the structural response [10,20]. EMA corresponds to forced excitation methods such as shakers or impact hammers commonly used for small-scale structures tested in laboratories with a controlled environment [21–23] or for load testing in operational ones [85].

However, EMA becomes extremely challenging for large civil engineering structures under service as it would require massive loads and specialized diagnostic vehicles, and hence OMA techniques prove more actionable and rationally cost-effective [20]. Indeed, OMA practices employ environmental and operational phenomena (wind, temperature, live loads, etc.) affecting the structure as the excitation for modal analysis and identification [20,24–26]. The main advantage is that the excitation of the structure is effectuated from the environment where it operates, thus alleviating the need for employing large artificial excitation systems that, in addition, could affect structural integrity [24,26]. On the other hand, signal levels are considerably low (special sensors are required to capture the response), and the excitation has a limited bandwidth that may prevent the identification of higher order modes (which are, indeed, more interesting) [9].

Given the need to assess the health condition of bridges and other large structures under varying environmental and operational conditions, researchers and engineers have intensively worked in the development of improved OMA techniques for the fast and accurate identification of modal parameters [24,27,28]. Some of the most widely used approaches include Frequency Domain Decomposition (FDD) [20,29,30] and Stochastic Subspace Identification (SSI) [20,24]. In [31–33], authors present automated versions of these approaches to continuously acquire the modal parameters of instrumented structures, where one of the most interesting techniques is the Automated Frequency Domain Decomposition (AFDD) approach due to its technical feasibility of automation. While these techniques are quite established, more specialized techniques exist for phenomena that involve environmental and operational variability [34].

Through modal analysis, we identify the dynamic response of the structure in terms of natural frequencies, mode shapes, and damping ratios [20]. Due to the global character of these features, vibration based SHM can provide overall insight on the structural condition even in those cases where damage is placed at inaccessible locations, in contrast to previous approaches [4,35]. However, although this technique has demonstrated to has been proved very powerful, it still presents some limitations, such as the low sensitivity of the lower modes to damage, the incomplete nature of the measured characteristics (total dependence on the sensor network density), or the effect that factors other than damage (environmental and operational conditions) can have on the damage-sensitive features [9,36].

The following section describes the main approaches to address a damage detection problem in large operating structures, using VBSHM.

3 VBSHM METHODS FOR DAMAGE IDENTIFICATION

The acquisition of damage sensitive information from monitoring data is a key aspect in the implementation of effective condition assessment [4]. However, some sort of intelligence must be applied in order to make that information predictive and able to evaluate the current state of the structure [37,38]. In this sense, there are two main approaches used in damage identification, namely model-based and data-driven [6].

This section presents the main particularities of both types of methods, including a brief description of some relevant case studies existing in the literature.

3.1 MODEL-BASED METHODS

Model-based techniques consist of building a physics-based model of the structure of interest, typically a Finite Element (FE) model, and then updating some parameters until the response of the model approximates enough the experimental response acquired through monitoring [39,40]. This procedure is known as Finite Element Model Updating (FEMU) [39]. Structural damage affects the stiffness and mass properties of the structure which are directly related to its dynamic response [41]. Hence, dynamic parameters obtained through modal analysis can be used as sensitive features to changes in the structural behaviour.

3.1.1. FEMU APPROACHES

We can consider FEMU as a two-step approach, depending on the pursued goal [42].

- Calibration: FE models are typically based on design specifications and empirical laws dictating material properties. However, they present significant discrepancies with respect to the real structure due to simplifying assumptions and inherent uncertainties [41]. If correct and accurate predictions want to be obtained, this mismatching must be addressed through model updating using experimental input from the structure during normal service [41,43]. As a result, the updated baseline model can be used to predict the structural response against extreme scenarios or expected load increases and evaluate the need for reinforcement or substitution actions as well as preventive service outage. In this step, the parameters to use during the updating must be those subjected to uncertainty, such as material properties, stiffness at joint connections or boundary conditions [41,44].
- Damage detection: once an accurate baseline FE model for the reference (undamaged) state of the structure is achieved, an updating strategy for damage detection may be implemented

[45]. If we feed the updating algorithm with new information corresponding to a damaged state, the values obtained for the updating parameters will be considerably far from those in the baseline model, since the experimental response has significantly changed due to the presence of damage [45–47]. The parameters here must be chosen based on the possible existent damage, such as cracks, pier settlements or corrosion. If the boundaries of these parameters are properly set, the resulting model will be representative of the damaged scenario and it will give insight on its location and severity.

3.1.2. FEMU PROCEDURE

There are essentially five main ways to address the Finite Element Model Updating procedure, being: manual tuning, direct methods, iterative methods, uncertainty quantification methods and artificial intelligence methods [36,48].

- Manual tuning: in this approach, the parameters of the model are modified manually to increase the agreement between the predictions of the FE model and the measured response. This can be understood as a trial and error procedure [29,86].

- Direct methods: here, the entire global stiffness and mass matrices of the FE model are updated, without accounting for the physical meaning of the final parameter values, until the model reproduces the measured response exactly [49]. Direct methods have a long history, but two main issues have restricted their use in practice [39,50]. Firstly, since measurements contain inherent errors, forcing the model to reproduce the experimental modal response causes these errors to be propagated to the parameters [51]. Secondly, since all the elements in the structural matrices are changed, a model updated this way may not be physically congruent, and it could be difficult or impossible to predict reliable responses. Another disadvantage is the need of high-quality field test data and a large amount of measurements for conducting the updating procedure [8].

- Iterative methods: in this case, the updating procure translates into solving an inverse problem where some local physical parameters, such as geometric or material properties, are iteratively changed by comparing the experimental and estimated responses at each iteration until a convergence criterion is reached [39,52]. This method can be very computationally demanding, but it allows to achieve robust models which are physically realistic and provide good predictions. There are some key aspects involved in the implementation of a robust iterative method for model updating, including (a) FE model definition and parametrization, (b) formulation of the cost function, and (c) implementation of the minimization problem [39].

- Uncertainty quantification methods: Model updating has to deal with many uncertainty sources, namely (i) experimental noise due to the presence of noise in the measurements, sensor error, or variability of the environmental conditions, and (ii) model uncertainty resulting from simplification assumptions and modelling errors, mainly in the case of large and complex structures [41,53]. Uncertainty quantification methods try to handle this aspect by providing a probabilistic nature to the features under consideration [41,54]. They use Bayesian inference to identify the optimal probability distributions of the updating parameters to catch the measured response [54–56].

- Artificial intelligence methods: these techniques employ computational tools inspired by nature and the performance of biological systems to solve the inverse problem of minimizing discrepancies between experimental and model responses [57]. Some of the most commonly used techniques in the field of FEMU are genetic algorithms, particle swarm, fuzzy logic, neural networks and support vector machines [58], all of them showing a great capacity for automation.

3.1.3. SUCCESSFUL CASES OF APPLICATION IN CIVIL ENGINEERING

It is worthy to highlight some particular cases of study in the field of civil engineering.

In [59], a scale timber bridge is studied under laboratory conditions and its corresponding FE model is calibrated through FEMU reaching an accurate match with the real modal response. The experimental tests were carried out using an impact hammer and a set of accelerometers.

The study presented in [60] is focused on the optimization procedure involved the Finite Element Model Updating strategy and aims to improve it through an hybrid genetic algorithm together with Nelder-Mead’s simplex technique, where the optimization function is a linear combination of fitness functions on natural frequencies, mode shapes and static deflections. In this case, a simultaneous mass and stiffness updating procedure is pursuit. The method is validated in a simply supported bridge.

In [61], a continuous wavelet transform algorithm is used to identify the dynamic parameters of a cable-stayed bridge from the field vibration tests performed under normal traffic and environmental wind fields in order to calibrate an original FE model. The results confirmed a better fitting between the real structure and the baseline FE model regarding the first mode shapes and thus, the model could be subsequently used for damage detection.

In the recent study [62], authors introduce a computational procedure orientated to fatigue damage assessment through the combination of operational experimental measurements and a complex high-fidelity FE model of a linear steel lignite grinder structure. The FE model undergoes a FEMU algorithm to approximate the experimental dynamic response. This approach employs Bayesian parameter estimation to account for the presence of uncertainty by including probabilistic models for the parameters using Baye's theorem thanks to the availability of multiple experimental measurements.

In [63], the analytical FE model of a bowstring-arch railway bridge is calibrated by minimizing the difference between operational (output-only) modal parameters and the analytical results from applying modal analysis to the initial FE Model. This is achieved through a genetic algorithm and the optimal value of the involved parameters is used for redefining the FE model. This work presents an interesting approach for the complete calibration process following a scheme similar to the one presented in the following figure:

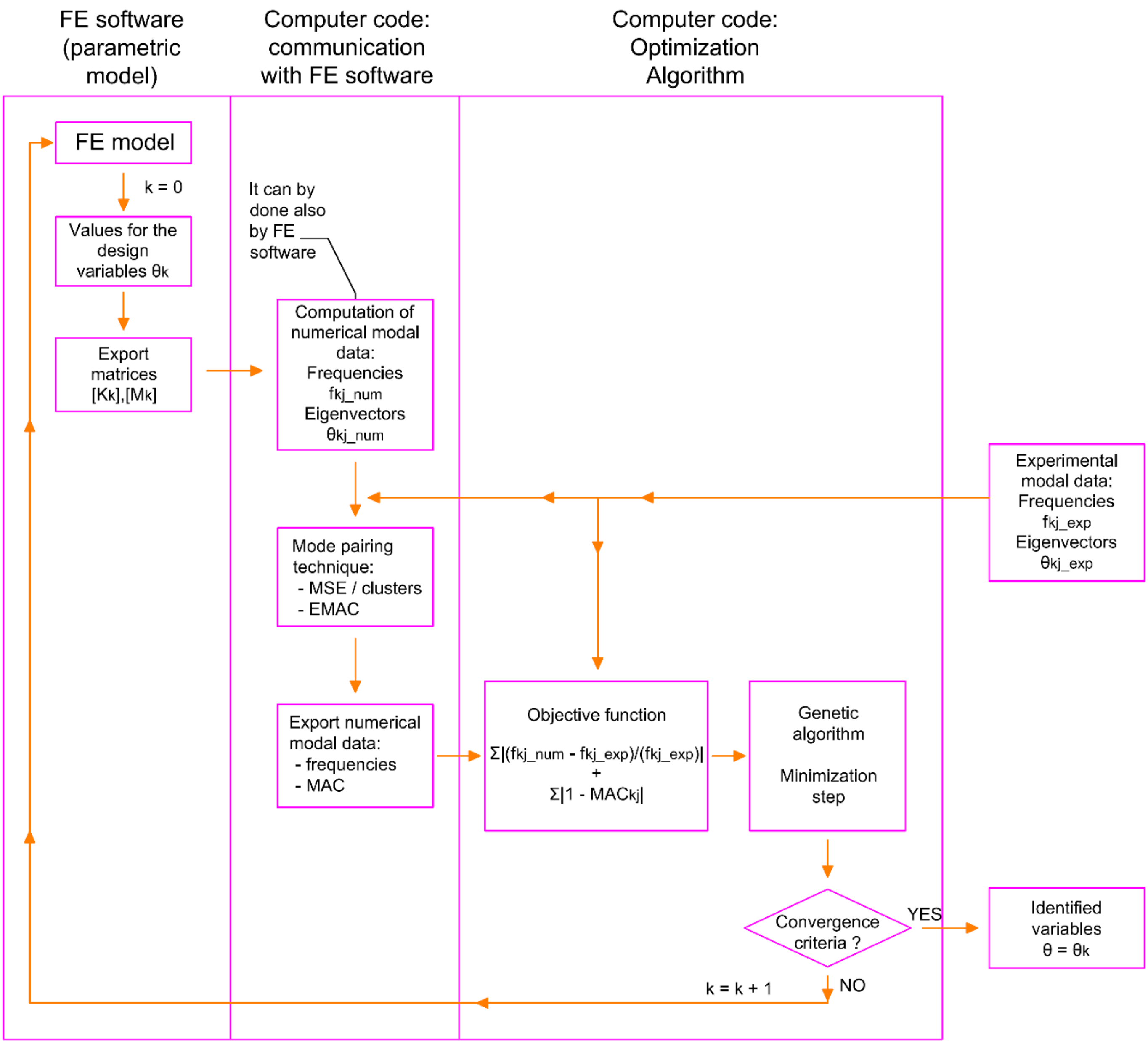


Figure 1 Flowchart of the methodology presented in [51]

3.2 DATA-DRIVEN METHODS

Given the difficulties of model-based methods to provide real-time diagnostics on the current state of structures together with the difficulties of finding good numerical models in the case of large civil engineering structures, new methodologies purely based on monitoring data have arose in the last decades to overcome these facts [4,64].

Data-driven methods do not require any a priori definition of accurate physical models of the structure but rely exclusively on the data obtained from the real structure [4]. In this kind of methods, damage sensitive parameters characterizing the structure must be identified by analysing the registered vibration data so as to define different patterns for classifying the possible states of the structure [65]. Hence, like the FEMU method, this approach also employs a model, but instead of a physical, a statistical one [4].

Advancements in sensor technologies have enabled the installation of affordable instrumentation systems for long-term monitoring of civil engineering structures [66]. The main objective of data-driven algorithms is to transform sensor data into useful information that can be used to improve managers' decisions [4]. In this way, if sufficient (and reliable) information is available, these approaches allow for the development of learning patterns from sensor data without any knowledge on the physical characteristic of the structure [67]. These approaches become more interesting when (a) large amounts of data are available, (b) the physical characteristics of the structure are difficult to model or unknown, or when (c) almost real-time evaluations are required without excessive computational resources.

Since this methodology is fully based on the data acquired during monitoring, there are various aspects to account for when implementing data-driven algorithms in real full-scale structures. According to [4], these are the key steps to be followed:

a) Operational Evaluation: this stage identifies the potential risks and requirements of a structure that make it a candidate for monitoring. The decision founds on some key aspects such as the economic justification, the potential damage that may happen given the type of structure and its ageing level, or the Environmental and Operational Conditions (EOC) affecting during service [68,69].

b) Data acquisition, normalization and cleansing: once it is decided to monitor a structure, an instrumentation system must be installed according to the characteristics of the structure in order to acquire useful information [6]. Normalization and cleansing are data pre-processing techniques required to filter unnecessary data and separate the variability due to damage from that induced by EOCs. One commonly used approach for sensor data management is Principal Component Analysis (PCA) [4,58, 87], a statistical multivariate technique that consists of projecting the original data onto a new coordinate system of uncorrelated variables [71]. It allows for the removal of environmental and/or operational variability present in the data and can be used to represent or characterize the reference structural state based on principal components [71]. For example, in

[70], PCA is used to detect damage in aeronautic structures for the calculation of a damage indicator (as a measure of the distance to the space defined by the principal components).

c) Feature extraction: this is a key step in the procedure, since it conditions the rest of the methodology. Damage-sensitive features must be obtained through the application of different data processing techniques [72,73].

d) Statistical model development: this step is related to the implementation of the algorithms that will finally work with the extracted features and will be able to detect, locate and/or quantify damage in a structure. These algorithms learn from the previously described features and can be divided into two main categories, being (i) Supervised Learning and (ii) Unsupervised Learning algorithms [74–76], depending on the availability or unavailability of data from the possible damage scenarios to identify. In general, Supervised Learning approaches are preferable as they allow to classify and quantify damage while Unsupervised Learning only reaches the first level (damage detection) in the Rytter's damage states of a system [77].

3.2.1. Supervised Learning algorithms: these techniques require large amounts of data for their training and validation, including information on the potential damage to be identified [4]. In civil engineering, there are two main sources of damage data: experimental tests (small-scale lab models or full-scale controlled scenarios) and physics-based modelling (FE models). Some of the most commonly used algorithms are [78]:

a) Response Surface Analysis (RSA): this method approximates the relationship between the resonant frequencies and other damage parameters (i.e. location and size). As an example, in [57], authors present an integrated damage identification system, where the updating problem employs Response Surface (RS) models instead of Finite Element (FE). They validated the method using a numerical beam, a tested reinforced concrete (RC) frame and an experimental full-scale bridge with natural frequencies as the output responses. In addition, [79] employs this method to distinguish crack types with eddy current inspection of metal fasteners.

b) Fisher's Discriminant (FD): FD applies a linear transformation to the original multivariate distributions of the data to obtain univariate distributions whose means are as far apart as possible, while the variances of those transformed distributions are kept as small as possible [80,81].

c) Neural Networks (NNs): this methodology is widely used in SHM applications for the identification, localization and quantification of damage in structures [81]. The structure of these algorithms founds on the biological neural behaviour and they are used to estimate or approximate functions that can depend on a large number of parameters based on known input output pairs [78].

d) Evolutionary algorithms: these techniques have been extensively investigated for various applications [82–84]. Similar to NN, these methods solve a minimization problem to obtain the model parameters that best approximate the real experimental data. They have a random component in the search for convergence, what makes them more robust to local minima. However, as the structural complexity increases either in size or geometry, this optimization can become prohibitive [4]. In [83], authors applied Simulated Annealing (SA) technique and eigen-sensitivity analysis to identify several synthetic damage scenarios in a FE model of a frame structure.

e) Support Vector Machines (SVM): this methodology constitutes a powerful tool for general classification and regression problems, as those of predicting the damage state of a structure [81]. It can employ various discriminant functions, such as linear, nonlinear or radial-basis, depending on the problem to be solved [85,86]. For example, in [87], a SVM algorithm is applied for solving damage classification problems in ball bearings and truss structures; and in [88], nonlinear Principal Component Analysis based on the unsupervised SVM is introduced for data normalization.

3.2.2. Unsupervised Learning algorithms: Unsupervised Learning algorithms are widely used for full-scale structural condition assessment to bias the problem of unavailability of data from damage scenarios. Their main drawback results from the maximum level of damage characterization according to Rytter's damage states [4,77]. These methods seek for the characterization of a reference or baseline condition of the structure, covering different possible EOCs during service and trying to identify departures from that reference by measuring the distance from the new condition with respect to the baseline [4].

a) Control charts: this statistical process control tool has been used over years in the machine industry to track the production process and identify malfunctions or failures in the constructed products. Although this technique is not such efficient in the field of civil engineering (due to the uniqueness of each structure), it can provide an early warning tool to control certain parameters and ensure a correct behaviour [78,79,88]. This methodology was applied in the well-known Z24 bridge [31]. This structure constitutes a benchmark for testing SHM algorithms and has been widely used since data from some damage scenarios was acquired before its demolition. The modal parameters of the bridge were used as the damage sensitive features to be tracked automatically through the control charts.

b) Outlier detection methods: these algorithms provide insight from the statistical distributions of the measured or derived features for complementary damage identification purposes [91]. The basic principle behind Outlier detection is that a model of the system is built using information from the normal state of the structure, including various EOCs [4,81,92–94]. Then, when a new monitoring event takes place, the acquired data are compared with the model and, in case that significant deviations are found, the algorithm indicates novelty. An interesting work is presented in [95]. Here, authors generate regression models to relate displacements at the joints with two EOC variables, being temperature and traffic load. Once these models are defined, an outlier detection algorithm based on a measure of the probability of new data to belong to the baseline or reference models is implemented and used to detect abnormal behaviour [4].

c) Neural Networks: NNs can also be applied in unsupervised learning contexts. An example of application is presented in [96], which uses a feedforward architecture and a modified backpropagation algorithm to adjust the learning rate over iterations. The method is tested with a model of a suspension bridge and verified experimentally, providing considerably small errors in the predictions of the modal response. One interesting full-scale case study is presented in [97], where Artificial Neural Networks and Gaussian Processes are applied to modal data obtained from acceleration measurements in the historic San Michele Bridge in Northern Italy during operation to characterize a reference state or baseline of the bridge. The ANNs are then used to predict the accelerations for certain EOCs and an assumed state of preservation of the bridge, with successful results compared to previous studies.

4 CONCLUSIONS AND FORESEE PROPOSED APPROACH

The previous literature review gives insight on the different SHM methods, and their applicability in the field of civil engineering.

In the case of model-based approaches, their main advantage relies on the fact they account for the physical properties of the system under study, enabling to provide more meaningful information towards the structural condition [29]. In addition, these models also allow the synthetic simulation of damage scenarios, which are often unavailable in real full-scale cases. However, the application of these techniques is strongly restrained by the computational cost implied, mainly to solve the problem of system identification to detect a damage state [98]. In addition, the solution of the inverse problem is not unique.

On the other hand, data-driven approaches are much less time consuming and more efficient in computational terms, since they do not require to solve any direct problem for convergence [99,100]. But despite this great advantage, we must bear in mind that these methods rely exclusively in the data acquired during experimental measurements on the real structure. This makes them dependent on the quantity and quality of the instrumentation and the effectiveness of data-processing systems, which will always contain some uncertainty. In addition, in most full-scale cases, experimental information about the possible damage and degradation scenarios that may happen over time is unavailable, thus restricting the input information to train these algorithms and resulting in unsupervised learning-based diagnostics for novelty detection.

This situation suggests and motivates the research on the implementation of combined approaches for SHM practices in the field of civil engineering. A balanced proposal with effective automation possibilities (customized to a particular bridge) is the implementation of an unsupervised learning data-driven method to detect damage (in a real time alert system) and, if damage is detected, the subsequent application of FE model updating for damage location and quantification. Since FE model updating is computationally inefficient and hard to automate, supervised artificial intelligence algorithms are proposed to support this process as later explained. In this task, we want to address the development of such a combined method for damage identification in full-scale bridges under service.

One of the key aspects behind this proposal is the implementation of a model-based method (FEMU) to adjust some uncertain parameters in parametric FE model using the experimental modal response (natural frequencies and mode shapes) of the structure. The goal of this calibration step is to achieve numerical simulations that accurately reproduce the real structural response without using extremely complex and computationally demanding models. Next, this updated FE model is employed for the simulation of damage scenarios that normally are not available in a real full-scale context. The modal response of these damage scenarios provides synthetic information to complement that given by the monitoring on the real structure and enables the generation of a more complete database to train and test data-driven algorithms for damage location and quantification.

Another important aspect to consider when working with structures under service (instead of controlled laboratory environments), is the presence of environmental and operational variability.

These phenomena, such as temperature, wind or traffic loads, may induce additional variation to the response of the structure and mask the presence of damage. For this reason, it is important to clearly distinguish both sources of variation. Properly addressing this issue strongly depends on the availability of experimental data.

In this task, we propose a structural monitoring system which can be separated in two main parts: (a) a real-time alert tool, with statistical and/or machine learning methods based fundamentally on undamaged data for outlier detection only (level I SHM [77]), and (b) a damage location and quantification tool based on Supervised Artificial Intelligence algorithms trained with synthetic damage scenarios.

The alert system characterizes the normal behaviour of the structure (including environmental variability) and, thus, it will detect changes in the structural response caused by the presence of damage.

In the case that an alert is triggered, a more complex supervised learning algorithm is activated to locate and quantify damage. This algorithm has been trained with various databases, each one corresponding to a FE model calibrated at a different temperature level to account for environmental variability. Hence, when the alert appears, a temperature parameter is measured to indicate which of the trained supervised learning algorithms must be used to identify damage. Due to the uniqueness of each bridge, which do not respond to an industrial production, this second part for damage location and quantification needs the algorithms to be customized for the case.

However, behind these particularities, a general scheme of the methodology including the chosen algorithms to apply at each phase is defined in figure 2. The selected algorithms are:

- Genetic Algorithm (GA),
- Principal Component Analysis (PCA),
- Support Vector Machine (SVM) and
- Neural Network (NN).

These algorithms can be implemented in different variants if required. GA, PCA and NN are chosen because of their capability of adaptation and wide successful use for SHM applications as reported in the state-of-the-art review. SVM is chosen because it is an interesting solution for damage classification (an intermediate step between detecting the presence of damage and the location-quantification of the damage) that offers good results even with a reduced amount of data. Particularly for outlier detection, other alternative algorithms could be considered if required. In addition, we will employ an Automated Frequency Domain Decomposition (AFDD) algorithm for the automatic identification of the structural modal properties (natural frequencies and mode shapes), since it is relatively simple to automate compared to other more complex methods, such Stochastic Subspace Identification (SSI), which require the interpretation of the stabilization diagrams and thus its real-time automatization is harder to implement [32,101].

In summary, the output of the proposed methodology and algorithms is a particularized assessment of a bridge based on its structural dynamic response, including damage detection, location and quantification (level 3 SHM).

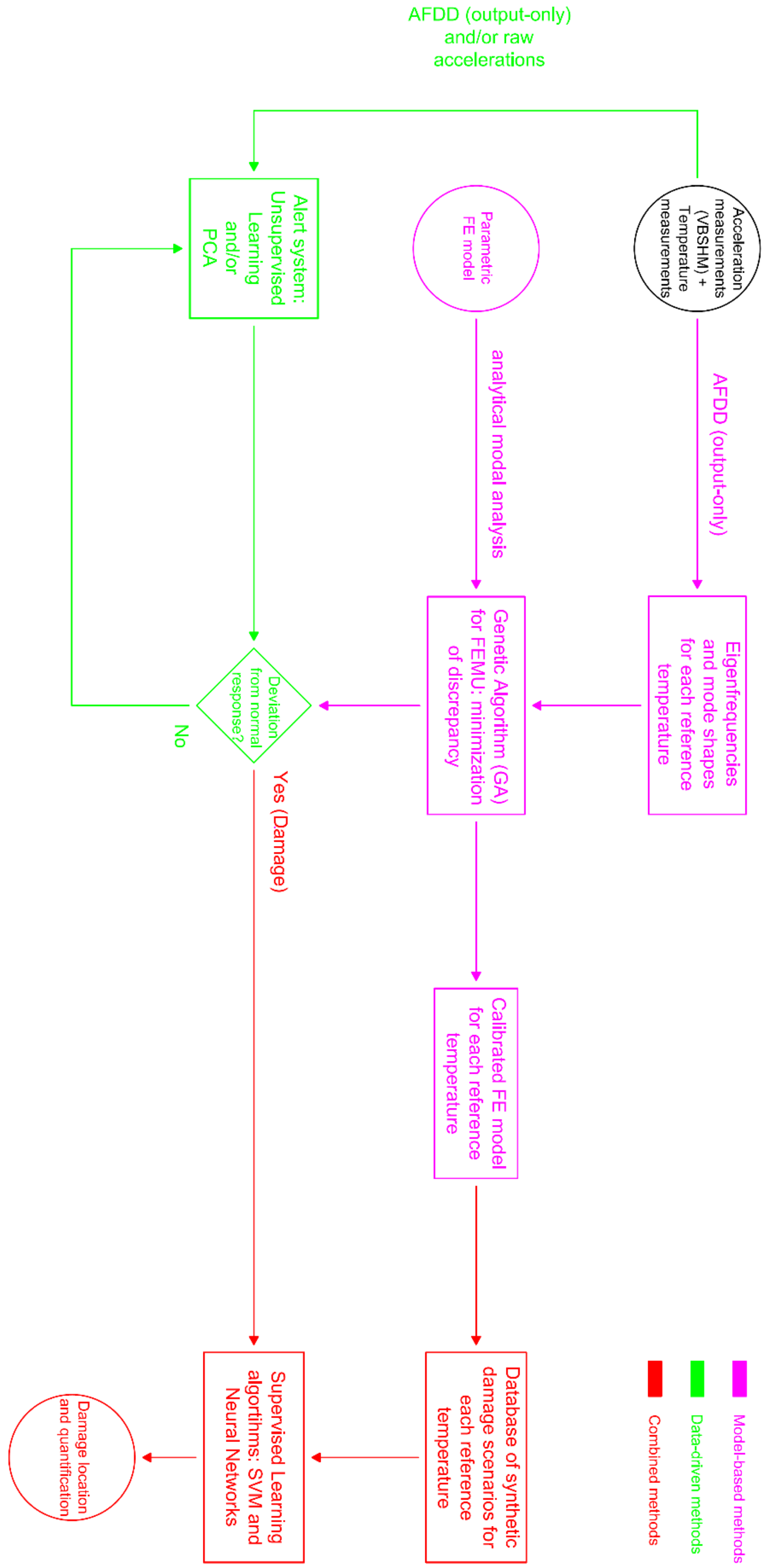


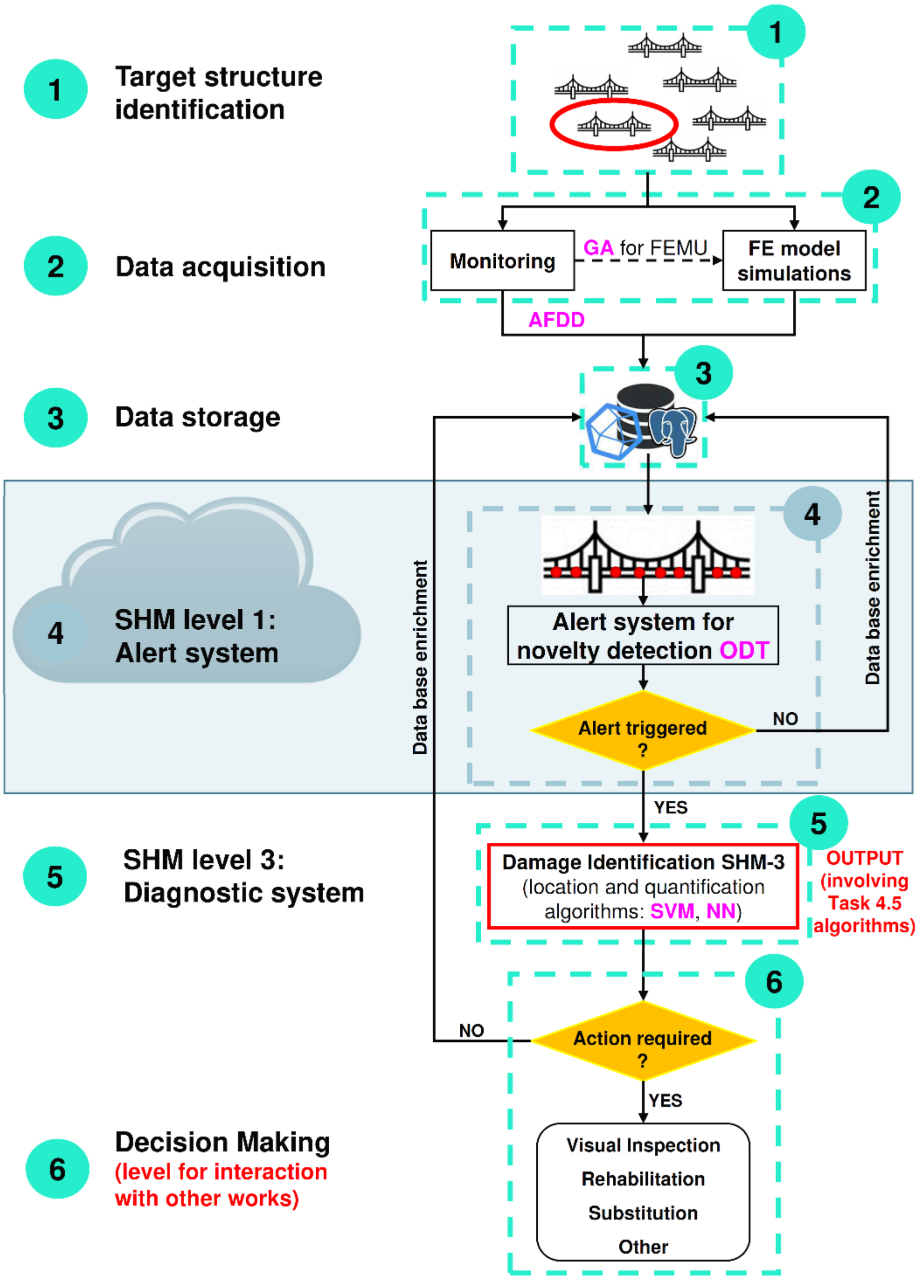
Figure 2 Scheme of the proposed methodology

5 FURTHER WORK AND INTERACTION WITH OTHER DELIVERABLES

D4.9 will be the continuation of the present deliverable D4.4 in Task 4.5, where the selected algorithms will be further reviewed, programmed and tested as the result of Task 4.5.

The information provided by the methodology and damage identification algorithms of Task 4.5 can generally interact with other works as shown in the flowchart in figure 3.

In addition, as a suggestive future line, the output of damage assessment particularized to a bridge could be employed in a tool for civil infrastructure management at the network level (developed in T4.4 by ETHZ and connected to the FORESEE Toolkit through T5.2). This management tool founds on a deep risk evaluation using historical information about failure types and other hazards to define probabilistic models for decision making. The results obtained from the algorithms proposed in Task 4.5 provide isolated insight on the structural condition of a particular monitored structure. Although it is out of the scope of this project, we understand that the referred probabilistic models could somehow incorporate this quantitative information (at structure level) as an additional indicator to evaluate risks and prioritize actions at the network level. It is important to mention that a post-processing procedure would be required to adapt the results provided by the particularized damage identification algorithms to the network management tool.



Algorithms* developed in Task 4.5:

GA → Genetic Algorithm. *MATLAB/ANSYS optimization routine for FEMU.*

AFDD → Automatic Frequency Domain Decomposition. *MATLAB code.*

ODT → "Outlier Detection Techniques". Including Principal Component Analysis (PCA) + an algorithm between: One-class SVM **or** One-class NN **or** Clusterization algorithm. *Python codes.*

SVM → Support Vector Machine. *Python web based tool.*

NN → Neural Network. *Python code.*

***All the algorithms require an offline configuration stage. The machine learning algorithms require specific training and validation.**

<u>Note</u>: The computer architecture (database, cloud computing, communication protocols…) is NOT developed within Task 4.5, which is centered in the implementation of the damage identification algorithms. Always refer to Task 4.5 deliverables for detailed information of the work.

Figure 3 T4.5 Algorithms flowchart and possible interaction with other FORESEE outputs

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