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Digital Twin: a Hybrid Approach for Structural Health Monitoring

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Abstract

The scope of this work is to illustrate the advantages that can be obtained in the context of structural health monitoring (SHM) when data-driven and model-based approaches are combined through the construction of a numerical twin of the structure. While the strategy isn't entirely novel per se, the use of wholly integrated technologies and software developed by the same company for all parts of the workflow, preventing data loss and ensuring interoperability, is where the originality lies. ASDEA S.r.l. provides products designed to perform each part in the SHM cycle, spanning from data acquisition to alert emission and damage management. The paper describes how the pieces are put together inside the coherent environment provided by the STKO software, initially designed as a powerful interface to the OpenSees solver for finite element methods (FEM). Data is acquired through a network of MonStr sensors (produced by ASDEA Hardware), managed using artificial intelligence (AI). The data is then exposed to near-real-time analysis to obtain an accurate picture of the structural conditions, and the numerical model is updated continuously to reflect present conditions. When anomalies are detected by the AI-based classifier, they are compared to the output provided by the FEM analysis to ensure reliability.

Keywords: structural health monitoring, digital twin, FEM modelling, model updating.

1 Introduction

Over the last few decades, many automated methods for SHM have been introduced [1], [2]. The underlying algorithms for anomaly detection relate to the two main categories of data-driven and model-based approaches. In the data-driven paradigm, sensors are installed on the structure being monitored and are set to register dynamic and environmental data. These data are transmitted to a central node and then processed to provide a near real-time response about the structural conditions. Conversely, model-based monitoring techniques provide for the construction of a numerical model of the structure [3] (Figure 1). Numerical simulations of the dynamics are performed after the domain is meshed, and the equations governing the structure's motion are time-discretized. Such equations are solved by inputting several boundary conditions. Many scenarios should be considered to obtain the system response for several types of loads under different environmental conditions in a "what-if" approach. Furthermore, if a sensor network is available, experimental data can be exploited for the ongoing calibration of the parameters defining the numerical model for more reliable previsions (model updating). Both approaches are extensively used for structural condition assessment. Nevertheless, they both contain inherent limitations when considered alone, i.e., the data-driven approach is dependent on the quantity and quality of data, and the model-based approach's reliability decreases as the system complexity increases. However, the latter can perform better than the former when a suitable model is provided. Accordingly, a hybrid approach using both techniques can greatly improve the performance of the monitoring system in terms of execution time and overall reliability [4]. Specifically, when a data-driven approach detects anomalous states in the data flow, the data recorded by the sensor network can be treated as input conditions for the corresponding FEM model to check the validity of the anomaly, hence preventing the emission of false alarms.

Herein, we present our proposal for a comprehensive hybrid approach to the problem of SHM, as sketched in Figure 2. Each method developed is embedded within the common environment provided by ASDEA Software's [5] STKO (the Scientific ToolKit for OpenSees [6]). All the scripts are editable and then combined to get the desired algorithm, even though our purpose is to use the FEM solver of STKO to filter the outputs obtained from the AI-based APIs where necessary.

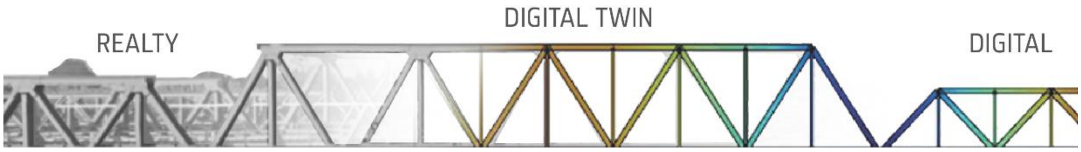

Figure 1 - From real structure to the numerical model.

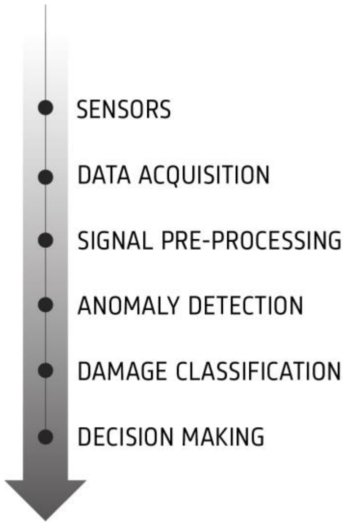

Figure 2 - The underlying levels defining the SHM process.

2 Methods

Although data-driven and model-based approaches for damage identification and decision-making for SHM are available, data-driven algorithms are usually preferred. This is due to the fact that they allow for the manipulation and processing of real, effective data registered from sensors and then provides a current health status by means of robust multivariate statistic tools. However, such a task requires dependable and optimally arranged equipment and high-performing CPUs to manage the relevant datasets. Our solution overcomes such potential limitations through the use of a network of optimally-placed MonStr devices for data acquisition and the adoption of suitable GPUs for parallel computing. Nevertheless, some inaccuracies may still affect the overall reliability of the results, which is where the hybrid model comes into play. The data analysis algorithms work under the pattern recognition paradigm in an output-only approach. After a baseline characterizing the structure is obtained through the continuous monitoring of the structure in a healthy operative state, machine learning programs identify underlying trends, patterns, and correlations within the dataset, statistically comparing the output with the baseline scenario. Although well realized in theory, the detection system may still fail in diagnosis for many reasons and, if damage actually occurs, additional techniques have to be introduced for damage classification, localization, extension, and prognosis (concerning the remaining useful lifetime of the structure). Issues of this type can be resolved through the construction of an accurate digital twin of the structure, in the following manner:

- The initial baseline pattern can be integrated with a damage pattern obtained by running FEM simulations with several critical boundary conditions as inputs.

- The number of false alarms can be reduced by double-checking the FEM model using current data as input conditions.

- The corresponding FEM analysis helps classify the damage avoiding (or integrating) signal triangulation.

Although some digital-twinning experiments have been implemented, they greatly suffer from a lack of a common environment for the analysis. In fact, the various siloed software used to cover different parts of the analysis typically require incompatible data formats. Many problems arise in managing such large, heterogeneous datasets, including a slowdown of the algorithm, and part of the data may be lost in the process. Such issues are completely bypassed using our proposed system since the entire analysis is performed in the STKO environment, and the HDF5 data format is adopted for all steps that produce outputs.

3 Results

Among the various aspects characterizing the complex process which defines the digital twin strategy as a whole, at this stage, we will focus on the STKO software and, in particular, on the tools it provides for model updating. STKO plays a central role in our approach, hosting all the different stages of the SHM process and managing the HDF5 datasets produced at different levels. This guarantees a complete interfaceability among SHM algorithms, which is a true innovation in this field.

STKO was initially created to provide an advanced interface for the OpenSees software for finite element analysis to make it accessible to a broader range of users. What makes STKO even more useful as a unified environment for SHM is that individual users are able to create their own Python scripts according to their specific needs. Thus, the already powerful pre and postprocessors can be customized as required by the end-user.

Even though efforts are still being made to refine the FEM modelling aspects, like introducing new constituent elements and materials, new tools have also been made available especially for digital twinning purposes. In order to manage the workflow described as follows, a dedicated Python framework was developed and it supports the:

- Preprocessing of data acquired through the MonStr device network
- Data selection and feature extraction for model calibration
- Updating the numerical model by means of genetic algorithms to match the experimental data [7].

Once the FEM model is updated, dynamic simulations can be performed for “what-if” forecasting or to numerically reproduce near-real-time scenarios to check the reliability of the outputs produced by the data-driven part of the algorithm for structural monitoring. It is worth stressing once again that what holds all the pieces of the algorithm together within STKO is the consistent database formatting and the Python language itself that acts as a glue for the different scripts.

Figure 3 schematically illustrates how the entire process works, including the interdependencies among the various steps.

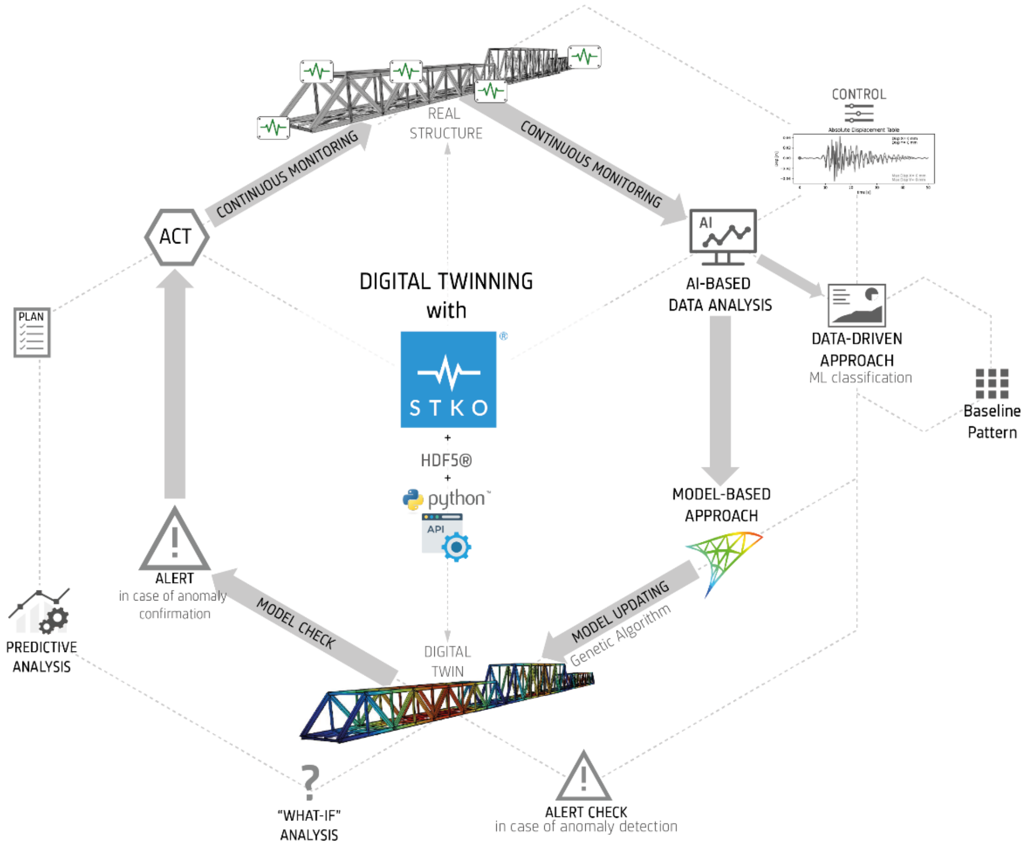

Figure 3- Scheme of the workflow as explained in the text.

4 Conclusions and Contributions

The approach presented here has many features that make it very innovative compared to the strategies currently available. To guarantee complete interoperability and optimal management of all phases, from data acquisition to anomaly detection and data management, ASDEA's various companies have collaborated to provide the necessary products. This crucial aspect was made possible by adopting a suitable, common format for databases and developing a robust software environment in the form of STKO that hosts the Python codes needed for data analysis and feature classification. Contrary to what the reader may assume from such a rigid workflow, the system's organization inherently supports its adaptability. Each script featured can be easily customized, and the various moduli arranged as desired for the purposes of each specific case under examination.

The workflow's clarity also improves the readability of the underlying codes, makes the data portable, and increases the speed of simulations.

Furthermore, substantial technical innovations have been made regarding the sensors themselves. The novel, high-performing MonStr device designed by ASDEA

Hardware for data recording has extremely competitive features: signals can be sampled at an effective rate of 1 kHz, while the entire network can be synched to less than 1 ms. Moreover, MonStr device networks can support up to 1000 channels, meaning hundreds of units can be optimally placed and arranged on a single structure for highly reliable analysis. Furhermore, the MonStr device belongs to the A class performance for accelerometers and B class performance for all the remaining equipment according to the ANSS guidelines.

Another key innovation of the system is that it takes already existing extremely powerful machine learning-based algorithms for data analysis and redirects some of the heavy calculations to dedicated GPUs that run in parallel to the CPU, thus increasing speed and efficiency. Python's TensorFlow and Apache Spark API libraries on related topics support such computations by default. Tests performed using random forests as feature classifiers showed that the running speed of the algorithms can be increased up to a factor of $O(10^4)$ using average GPUs rather than average CPUs. Finally, the FEM modelling phase capitalizes on the well-known advantages of using OpenSees solvers via the powerful STKO software.

Thus, we believe our digital twinning strategy for SHM is well-positioned to become the standard for predictive engineering problems in the near future.

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