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## IN SITU STRUCTURAL DAMAGE TRACKING AND MONITORING FROM ADVANCED SENSING TECHNIQUES AND HYBRID TWINS (DISTINGUISHED LECTURE)

Ludovic Chamoin <sup>1,2</sup>

<sup>1</sup> Université Paris-Saclay, CentraleSupélec, ENS Paris-Saclay, CNRS, LMPS, ludovic.chamoin@ens-paris-saclay.fr

<sup>2</sup> Institut Universitaire de France

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In a digital world with the expansion of connected systems, a still open question is to design smart and autonomous mechanical structures able to perform online control of their health and take anticipated actions during service before downtime of failure occur. This is a critical need in several areas such as transport of energy, for more reliability but also more performance and durability of the employed structures (aircrafts, wind turbines, bridges. . .). Implementing such an advanced structural health monitoring (SHM) technology would permit optimized maintenance and capability to operate in degraded mode, managing the decrease of loading capabilities by adapting the operating plan.

Tracking structural damage and predicting its evolution has been a perpetual engineering issue during the last decades. It was the topic of intensive research works, with both experimental and numerical advances. On the one hand, on-board sensing techniques nowadays permit accurate in situ measurements on displacement or strain fields and thus provide very rich experimental information on the internal damage state of materials. In particular, the technology using standard optic fibres coupled with Rayleigh backscattering (see the recent review [1]) is very attractive as it delivers a real-time distributed characterization of the strain field with unmatched spatial resolution (thousands of measurements per meter). On the other hand, sophisticated physics-based tools now permit to simulate damage phenomena with high-fidelity and give a relevant virtual image of the material state. They involve predictive models with macro- up to micro-scale damage descriptions, with increasing complexity and computational cost [2]. They constitute a rich history of simulation-based engineering sciences and they are now commonly used as numerical twins for design and optimization. These computational models are classically fed and a posteriori compared with experimental data in order to ensure simulation reliability.

The scientific bottleneck for going from smart materials to smart structures is in the monitoring of large complex engineering systems. A shortcoming of data science alone is in the management and interpretation of sensor information with large noisy data sets, and in the prediction of the structural behavior involving localized multiscale and highly nonlinear damage phenomena. Moreover, from complex physics-based simulations alone, it is difficult to perform safe command within a changing environment and with real-time requirements in order to be reactive and avoid instabilities faced to damage evolutions. As a matter of fact, high-fidelity simulations are very costly, requiring hours of parallel computing in practical applications, and they remain an imperfect representation of reality.

In this context, and in order to cross the gap, an ERC project called DREAM-ON started in 2021 [3], in which the innovative concept is a synergistic dialog between advanced structural sensing (from embedded optic fibres) and command (from the structure actuators) on the one hand, and the most powerful modeling and simulation tools of computational mechanics on the other hand. This dynamical connection between the mechanical structure in service and an on-board physics-guided simulator, seen as a real-time feedback loop (Figure 1), aims at making benefit of all available knowledge, from rich data and high-fidelity simulation, and to exploit the best of each to perform early damage detection, precise diagnosis, and appropriate decision-making. It is such that (i) the physics-based model is continuously updated and enriched from in situ observations which are assimilated on-the-fly; (ii) damage diagnosis

and predictive command are performed from the simulation in order to drive the system accordingly. This refers to the Dynamic Data Driven Application Systems framework (in short DDDAS) which is a visionary paradigm in which a continuous exchange between simulations and in situ observations is implemented [4]. It constitutes one of the most challenging applications of simulation-based engineering sciences. The DDDAS concept combining data and physics-based models is not new, but its practical implement for damage monitoring remains limited to toy problems due to computationally intensive procedures. Consequently, the richness of data which is nowadays available on real-life structures is not exploited to its full extent for SHM. Achieving a manageable feedback loop for large-scale structures, with highly nonlinear models, numerous data, and various uncertainty sources, entails major research challenges to accommodate real-time, robustness, but also portability issues (merely exploiting modern supercomputing facilities, with limited accessibility, is not an option). The objective of the project is to develop, implement, and test a light digital platform that combines all these features. DREAM-ON thus addresses key challenges, by designing innovative and effective approaches to build the numerical core (central system) of DDDAS, from sensing to command.

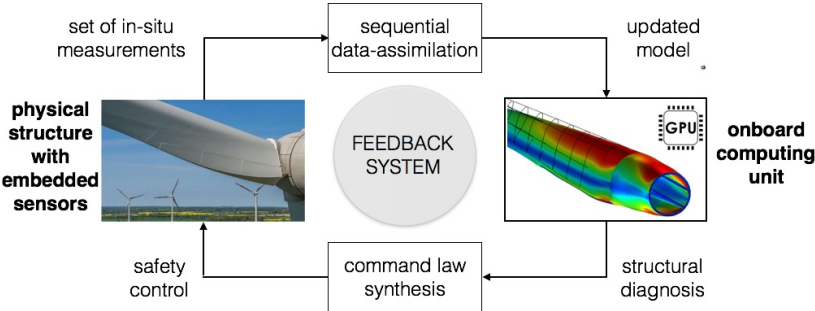


Figure 1: DDDAS concept applied to SHM.

The proof-of-concept which is envisioned in the project is an original lab experiment that aims at preserving the integrity of a reduced-size composite structure under monitored mechanical loading (Figure 2). It involves two specific experimental facilities: a multichannel high-resolution optic fibre interrogator, based on the Rayleigh backscattering in the frequency domain (OFDR technology); a Stewart platform (six-actuator parallel-kinematic hexapod) with high multiaxial load capacity to perform active structural command.

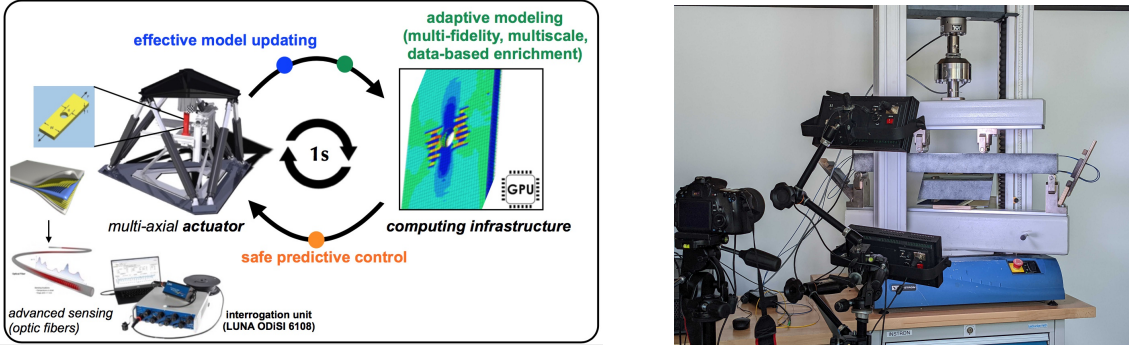


Figure 2: Envisioned proof-of-concept in the project (left), and typical experimental test (right).

The methodology which is followed in the project is cross-disciplinary, mobilizing skills embracing experimental mechanics, data science, mathematical modelling and simulation, applied mathematics, and computer science. Here, we focus on two important aspects of the project which employ the concept of modified Constitutive Relation Error (mCRE) developed in [5] and referring to reliability of information. The powerful and robust mCRE concept was used for model updating in many practical structural mechanics applications (see [6, 7, 8, 9] for some recent ones), with various physics-based models and noisy data.

A first aspect which is presented is effective and physics-guided data assimilation from distributed

optic fiber sensing (DOFS), in order to update damage information on-the-fly for concrete or composite structures (Figure 2). For this purpose, a modified version of Kalman filtering is employed, with specific regularization from the thermodynamics of continuum media, in order to infer noisy sequential measurement streams and recursively recover material state and model parameters [10, 11]. Also, optimal experimental design and adaptive modeling with local higher accuracy in regions where damage occurs (using the modeling error indicator provided by mCRE [12], and a hierarchical list of possible models with increasing complexity) are performed in this context, in order to manage computing and experimental resources at best.

A second aspect which is presented is data-based enrichment of the model structure using AI learning tools coupled with a sharp a priori knowledge on the physics fundamentals and specific features of studied damage phenomena. The idea is to efficiently complement pre-existing models, with data-based correction of model ignorance, and thus make the virtual representation and resulting predictions closer to reality. This refers to hybrid twins and physics-constrained neural networks which have recently received much attention in the recent years [13, 14, 15]. Here, a method using neural networks for learning constitutive laws in the form of thermodynamic potentials is proposed [16]. The associated loss function is derived from the mCRE functional, and the architecture of the network is built so that it satisfies thermodynamic principles owing to convexity properties [17, 18], as shown in Figure 3.

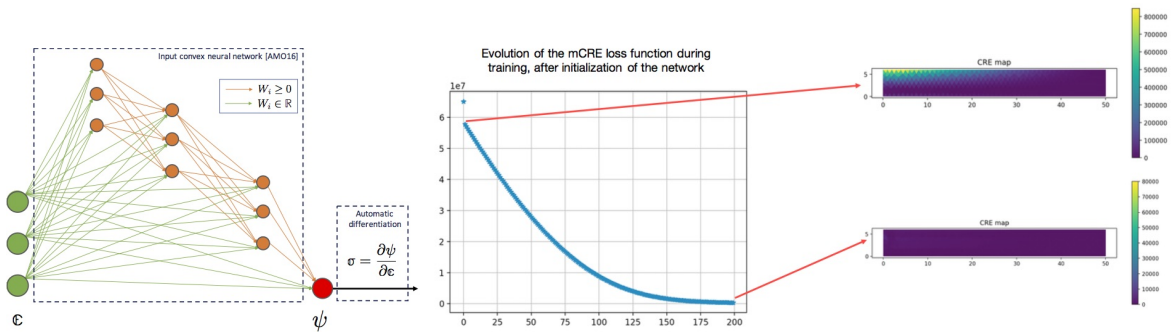


Figure 3: Structure chosen for the neural network (left), and decrease of the modeling error with iterations (right).

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