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# A novel DDDAS architecture combining advanced sensing and simulation technologies for effective real-time structural health monitoring

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**Abstract.** A still open question is how to design smart and autonomous mechanical structures able to perform online monitoring of their integrity and take anticipated actions during service before downtime of failure occur. To address this question, we present in this Chapter some innovative physics-guided numerical techniques for effective data assimilation and control. These techniques are integrated into a global feedback loop where the mechanical structure in service continuously and dynamically interacts with a digital twin which is updated and enriched on-the-fly for further command synthesis, as per the Dynamic Data Driven Applications Systems (DDDAS) paradigm. The overall strategy is unified around the concept of modified Constitutive Relation Error (mCRE) for enhanced robustness. The strategy also involves multidisciplinary numerical tools, such as Kalman filtering, adaptive modeling, deep learning, or Model Predictive Control, in order to accommodate real-time, accuracy, and portability constraints. The interest of the DDDAS approach is illustrated on several applications with evolutive mechanical systems, and with various sources of data obtained with advanced experimental devices.

**Keywords:** Structural Health Monitoring, Data Assimilation, Constitutive Relation Error, Model Predictive Control, Physics-Augmented Machine Learning, Real-time Applications, Dynamical Systems, DDDAS-based Digital Twin, Dynamic Digital Twin, Virtual Twin

## 1. Introduction

### 1.1 Basics on structural health monitoring

The detection, analysis, and monitoring of damage in mechanical engineering structures are perpetual and critical engineering issues to ensure durability and safety. Structural damage, initiated locally and at small scale due to manufacturing defects, impacts, excessive loading, or other unexpected events, may indeed be precursor of an overall structural performance decrease (e.g., through ageing or cyclic loading) and lead to failure with dramatic consequences. It is thus of paramount interest to make early and regular diagnosis on the internal state of materials of various critical operating structures employed in activities such as energy (wind turbines, nuclear power plants) and transport (aircrafts, bridges) to control damage evolution and increase structural life. This is the context of Structural Health Monitoring (SHM), which is both an active research topic and a major industrial challenge [1, 2, 3].

Nowadays, beyond well-trained but limited engineering visual inspection, effective damage tracking on engineering structures (subject to various operational conditions) is made possible with cutting edge developments on non-destructive evaluation (NDE) sensing techniques, which permit to inform on the internal material state [4]. The most advanced NDE sensing techniques allow for high accuracy and spatial resolution on structures in service, such as optic fiber sensors [5, 6, 7, 8] which are becoming more and more popular for *in situ* SHM applications and will be discussed later. Such sensing devices have a rapid deployment, and they are progressively playing an active role by permitting health recovery for large-scale structures in operational conditions, with report on any change in material properties before the structure potentially develops into a critical issue. In addition, the rich experimental information can be used to feed and complement elaborated computational damage models, which may be physics-based (white-box) models inheriting from a rich history of engineering sciences and computational mechanics [9], or data-based (black-box) models obtained from learning algorithms, e.g. Machine Learning and Neural Networks [10, 11]. The link between sensing and modeling permits to interpret data for damage diagnosis, assess the current structural behavior and stiffness, e.g. through inverse analysis and parameter identification [12, 13], perform simulation-based prediction of damage initiation and growth by exploiting all available knowledge, and eventually make appropriate decision. The DDDAS-based methods discussed here will advance over such approaches through continuous feedback control between sensing and an executing model representing the damage in the system as discussed next.

## 1.2 DDDAS paradigm for the design of smart structures

The synergy between experimental and modeling information can be pushed forward with the Dynamic Data-Driven Applications Systems (DDDAS) paradigm. In this context, the coordination between numerics and measurements is exploited by means of a continuous connection between on-board sensing devices and a customized high-fidelity simulator (virtual twin), for:

- on-the-fly inference of *in situ* observations, online updates, and ultimately enrichment of the digital twin;
- real-time damage diagnosis and prognosis;
- safe decision-making, e.g. by adapting the operational plan to prevent the structure from operating outside a safety regime and preserve structural integrity (for example by decreasing the load or applying dampening forces)

faced with the presence of stress conditions and the decrease of structure capabilities.

Implementing such a DDDAS process with global feedback loop on real mechanical structures in service would constitute a powerful SHM technology leading to modern self-aware engineering systems (see Figure 1). Such an approach would exploit and benefit from all available knowledge stored in data and models. If it may lead to increased foresight, more accurate damage analysis, optimized maintenance, and potential continuing operation even in a degraded mode, it would also alleviate the shortcomings of data science alone, by including physics-informed assessment for relevant management and interpretation of sensor information. The updated model would be used for prediction of the structural behavior involving localized multiscale and highly nonlinear damage phenomena, and would alleviate shortcomings of physics-based simulation alone to enable more dependable prediction within an uncertain and changing environment.

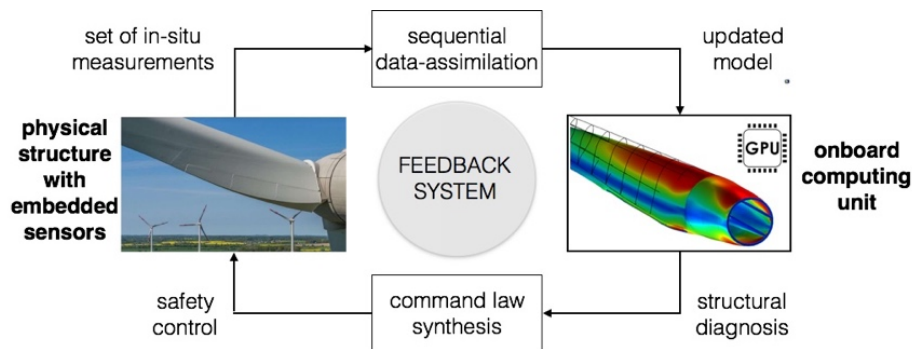


Fig. 1 Scheme of the targeted DDDAS feedback loop for SHM.

The development of DDDAS architectures for structural damage monitoring has been the topic of several research works, e.g. [14, 15, 16, 17, 18] to cite a few. It is also the topic of a current European (ERC) project called DREAM-ON (2021-2026) [19], with first achievements reported hereafter. Scientific progress in this context is supported by the expansion of powerful simulation tools and underlying computational infrastructures (e.g., GPUs), but also by the flourishing development of cyber-technology associated with a new generation of connected and autonomous systems fostered by artificial intelligence [20, 21]. These latter use integrated computational and physical capabilities provided by micro-sensors, micro-processors, and micro-controllers.

### 1.3 Challenges & objectives

Dynamically combining data and models is not a new idea [22, 23], but its practical implementation for damage monitoring currently remains limited to experimental problems due to several technical difficulties listed below. Consequently, the richness of data and models which are now available for real-life structures is still not exploited to its full extent for SHM. Indeed, applying the DDDAS paradigm with manageable procedures for damage monitoring on large-scale engineering structures entails major

research challenges to accommodate real-time (for reactivity faced to damage evolution, with time scale depending on the application), accuracy and robustness, but also portability issues; merely exploiting modern supercomputing facilities, with limited accessibility, is not an option.

First, damage propagation in composite materials (e.g., laminates, concrete) which are widely used in high-tech structures is a local evolutive nonlinear phenomenon. Such a complex behavior, associated with uncertainties on the operating conditions, induces modeling bias which needs to be taken into account (even though unknown *a priori*) for relevant data assimilation and decision-making. Model bias could be addressed by using purely data-based approaches (e.g., deep learning) as a substitute to physics-based models [24] but these require a huge amount of data in various structural configurations, which is hardly feasible in practice, and also inadequate to support dynamically changing (structural) conditions for real-time or near real-time decision support. Another option, which will be considered in next sections, is to resort to the *hybrid twin* philosophy, also referred to as DDDAS-based Digital Twin or Dynamic Digital Twin (e.g., see [25, 26, 27, 28, 29, 30, 31]) which promotes a data-based enrichment of the initial knowledge on physics fundamentals, in order to make the virtual representation and resulting predictions closer to reality with a limited dataset.

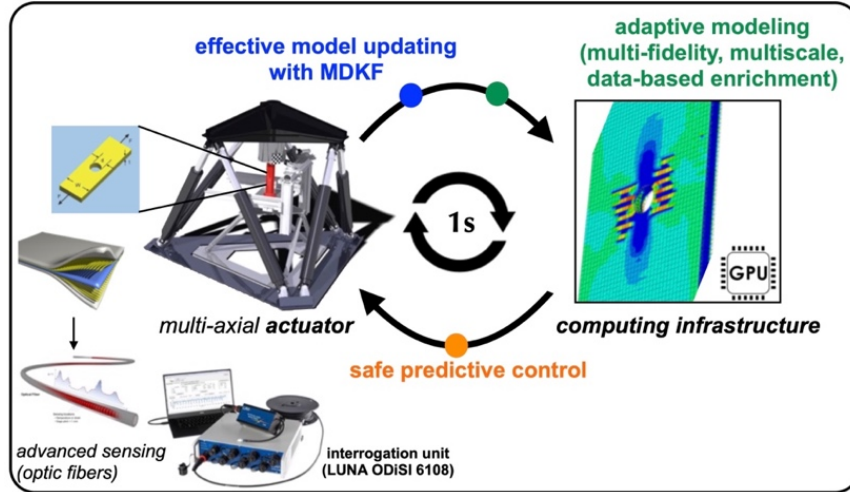
Second, when associated to large-size structures and multi-query simulations, the material complexity may lead to computationally-intensive tasks which are not compatible with DDDAS computational or communication requirements, so that reduced and adaptive modeling with smart dynamical management of computing resources is requested (to compute right at the right cost).

Third, experimental information often corresponds to local, indirect, and incomplete observations on the material state. It is transferred sequentially in time and it is inevitably plagued with measurement noise (or even corrupted sensors). The numerical processing of a (possibly large) data collection thus needs to be appropriately performed, with a fast and robust data assimilation procedure.

Eventually, feedback control needs to be performed to preserve integrity on systems having evolving properties and operational constraints. The controller requires fast online command synthesis, with guaranteed command and stability issues. An appealing tool in this context is Model Predictive Control (MPC) [32, 33], although it requires adaptation to address above-mentioned issues in large state dimension.

The overall objective of the work is to design a light and dedicated computational platform, constituting the DDDAS numerical core, that addresses the previously described key computational challenges. The solution is made possible by the development of innovative and effective numerical approaches, from sensing to command, which will be integrated within a unified architecture in this platform. A targeted representative and original application (which is the proof-of-concept of the DREAM-ON project), used to validate in practice the proposed DDDAS methodology, is shown in Figure 2. It consists in the real-time damage monitoring of a composite workpiece embedded with optic fiber sensors and submitted to a controlled multi-axial loading. High-resolution optic fiber data is acquired by the Luna ODiSI 6108 system (see Section 3.1). A Stewart platform (six-actuator parallel-kinematics) is used to perform active structural command, applying a multi-axial loading trajectory with

preserved structural integrity and possible operating range analysis over many instances of the initial damage state.



**Fig. 2** Illustration of the proposed DDDAS methodology on a laboratory proof-of-concept, with techniques described hereafter.

## 2. A new and enhanced framework for data assimilation

In the following, the mechanical structure is modeled by an uncertain nonlinear dynamical system of the form:

$$\dot{X}(t) = A(X, t; p) + C(t)$$

where  $X$  represents the system state,  $A$  is the operator describing the system evolution (defined by parameter vector  $p$ ),  $t$  is time, and  $C$  is the control law (set of external actions applied to the structure).

### 2.1 The mCRE concept

A task in DDDAS is model identification or updating, that is the calibration of some of the structural parameters  $p$  (related to material behavior, structural boundary conditions, etc.), from noisy and indirect observations. Some of the parameters describe the damage state and/or evolution, and they are recovered by solving an inverse problem. For this purpose, and among many numerical methods, we resort to the flexible *modified Constitutive Relation Error* (mCRE) framework. It was initially developed and analyzed for model updating in vibration problems [34, 35, 36] before being extended to a wider scope of structural mechanics problems. The mCRE approach is driven by reliability of information, that is the *a priori* level of knowledge on model and measurements, which is a fundamental aspect for addressing inverse problems effectively. Parameters are then sought alongside mechanical fields as the

best trade-off between all available information given by measured data and physics knowledge, without any further assumption.

In practice, information is split between a reliable part (e.g., balance equations) which is enforced in the process by means of an admissibility space  $A_d$ , and an unreliable part (e.g., material constitutive relations correlating applied forces with induced strains) which is released and satisfied at best. Considering for instance that only measurements (due to experimental noise) and the constitutive relation are unreliable, with parametrized potential  $\psi$  describing a hyperelastic state law between strain  $\epsilon$  and stress  $\sigma$  (i.e.,  $\sigma = \partial\psi/\partial\epsilon$ ), the mCRE procedure thus consists of a constrained minimization in the form

$$p_{opt} = \underset{p \in \mathcal{P}}{\operatorname{argmin}} [\min_{(\hat{\epsilon}, \hat{\sigma}) \in A_d} \mathcal{E}_{mCRE}^2(\hat{\epsilon}, \hat{\sigma}; p)]$$

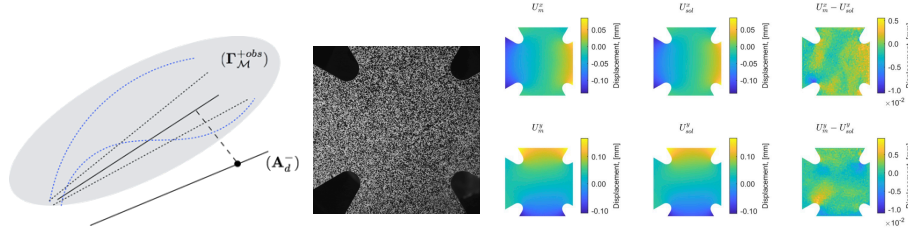
$$\mathcal{E}_{mCRE}^2(\hat{\epsilon}, \hat{\sigma}; p) = \int (\psi(\hat{\epsilon}; p) + \psi^*(\hat{\sigma}; p) - \hat{\sigma} : \hat{\epsilon}) + \alpha \|\Pi\hat{\epsilon} - \epsilon_{obs}\|^2$$

with  $\alpha$  a scaling factor (automatically tuned using appropriate techniques such as the Morozov discrepancy principle [37] linked to the measurement noise level and preventing from overfitting),  $\psi^*$  the dual potential derived from the Legendre-Fenchel transform [38],  $\Pi$  a projector on observed quantities, and  $\|\cdot\|$  the Mahalanobis distance. The definition of the mCRE functional is flexible and can be extended to other contexts, e.g. with uncertain boundary conditions [39, 40] or dissipation laws [41].

The nested minimization of the mCRE functional is performed in an iterative process where each iteration  $n$  is composed of:

- A first step performed with fixed parameters  $p^{(n)}$ , in which a new admissible field couple  $(\hat{\epsilon}^{(n+1)}, \hat{\sigma}^{(n+1)})$  is found to minimize the mCRE;
- A second step performed with fixed admissible fields  $(\hat{\epsilon}^{(n+1)}, \hat{\sigma}^{(n+1)})$ , in which parameters are updated with a gradient descent step (with adjoint state method).

The energy-based mCRE functional  $\mathcal{E}_{mCRE}^2(\hat{\epsilon}, \hat{\sigma}; p)$  is thus made of a regularizing first Constitutive Relation Error (CRE) term which accounts for modeling error, and a classical data-to-model distance term. The associated metric thus naturally considers and connects all error and uncertainty sources. The mCRE framework is naturally associated with a hybrid twin strategy, as optimal admissible fields are recovered from both the *a priori* physics-based model and data-based information. We add that the CRE term and its spatial contributions can be further used to localize and quantify modeling bias, to select the appropriate model (see Figure 3) in terms of constitutive law structure and complexity (which is *a priori* set in classical parameter identification), and to adapt the parameter space according to experimental information [42]; we will come back to this point in Section 3. A link between mCRE and Bayesian inference can also be exhibited [43], showing that mCRE involves a specific representation of the modeling bias.



**Fig. 3** Illustration of the adaptive selection of an appropriate constitutive model in the manifold  $\Gamma_{\mathcal{M}}^{+obs}$  through mCRE (left), and distribution of admissible fields and modeling error on a specimen with experimental data given by digital image correlation (center & right), from [44].

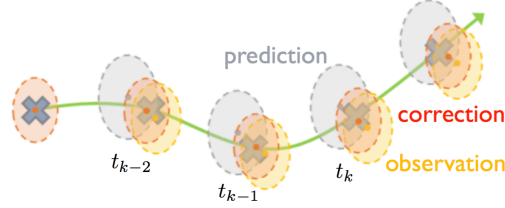
Numerous research works on mCRE have been conducted over the years, with several applications dealing with vibration dynamics [43, 45, 46, 47, 48], transient dynamics [49], nonlinear behaviors [41, 44], or goal-oriented parameter updating [50]. The mCRE minimization process was also coupled with reduced order modeling (ROM) to decrease the computational cost [43, 51, 52]. The mCRE-based inversion strategy has proven robustness to noisy or corrupted measurements [53, 54, 55], yielding higher identification performance as compared to some alternative inversion techniques [56, 57, 58], demonstrating excellent capability for spatial localization, e.g. to detect local defects [59, 45, 60], providing tolerance to incompletely specified boundary conditions [61], and improving convexity properties and lower sensitivity to initial guess through the CRE term [54, 61]; all these features are crucial advantages in the objective of addressing the DDDAS process for SHM.

## 2.2 Sequential data assimilation through enhanced Kalman filtering

In the DDDAS framework, data is acquired sequentially and iteratively in time through the executing model control. A dedicated numerical process should thus be used to infer noisy sequential measurement streams and recursively recover material state and model parameters. For this purpose, a modified version of Kalman filtering has been designed, coupling such a filtering with mCRE to gather benefits of both [62, 63]. It is described below.

Basically, Kalman filtering (KF) is a Gaussian recursive state estimate (through mean and covariance statistics) based on measurements and a state evolution model. The KF acts with a prediction/correction scheme (see Figure 4), new measurements being involved in the correction step alone through an innovation term with optimized (Kalman) gain (in the sense that it minimizes the trace of the covariance matrix of error estimates). Initially introduced for linear models [64], it was later extended to nonlinear models, e.g. by means of statistical regularization; the sigma-points Kalman filter [65] permits to sample *a posteriori* statistics on state by propagating a set of well-chosen samples (so-called sigma-points) through the nonlinear operators of the filter. A popular filter of this kind is the unscented Kalman filter (UKF) based on the eponymous transform introduced in [66]. When considering both state and parameter estimation [67, 68, 69], dual Kalman filtering combining two Kalman filters is a classical approach. In practice, the Kalman filter on mechanical state is hidden within the observation update equation of Kalman filter dedicated to parameter estimation.





**Fig. 4** Sketch of the Kalman filtering recursive scheme (ovale shapes correspond to confidence envelops of Gaussian distributions).

For increased robustness with respect to modeling bias and measurement noise, we proposed a new version (called Modified Dual Kalman Filter algorithm - MDKF) of the dual Kalman filtering for sequential data assimilation, in which the mCRE is integrated as a new observer [62, 63]. Therefore, by enhancing the classical Kalman filtering, the correction of model predictions is achieved through the mCRE functional itself, corresponding to a change of metric in the observation space compared to classical  $L^2$ -norm metric. The MDKF dynamical system reads:

$$p_k = p_{k-1} + w_k$$

$$\nabla_p \mathcal{E}_{mCRE}(x_k; p_k, y_k) + v_k = 0$$

where  $x_k$  is the state in terms of admissible mechanical fields,  $y_k$  is the set of observations, and  $w_k$  and  $v_k$  are Gaussian noises. The chosen optimality condition with mCRE gradient permits to get around the mCRE value that depends on the features of the studied problem (size of the domain, energy level, measurement noise, etc.).

There has also been improvements to achieve real-time data assimilation with MDKF without losing accuracy, in particular by performing parallelized mCRE computation and sigma-points propagation, using a scaled spherical simplex Kalman filter structure [70], much like the randomized UKF (RUKF) [71], and developing of CRE-based clustering to restrict the amount of structural parameters to be estimated and consequently the number of sigma-points to consider [42].

### 2.3 Application on a typical industrial case

This section illustrates the relevance and robustness of the MDKF strategy for sequential data assimilation on damageable structural systems [63]. It deals with a practical industrial application in the context of earthquake engineering.

The EMSI laboratory of CEA Saclay (France) is equipped with shaking tables that allow to assess the seismic performance of civil engineering constructions by applying low-frequency dynamic loadings (Figure 5). Currently, the control laws of the hydraulic actuators that drive these shaking tables do not directly integrate the health condition of the tested structures, which can suddenly deteriorate and lead to unstable tests. Here, by implementing the DDDAS feedback loop shown in Figure 6 as a digital twin, the objective is to monitor in real-time and from sparse acceleration measurements the changing modal signature of a complex reinforced concrete specimen, placed on the

shaking table and undergoing nonlinear damage phenomena, for further automated command of the shaking table (Figure 6).

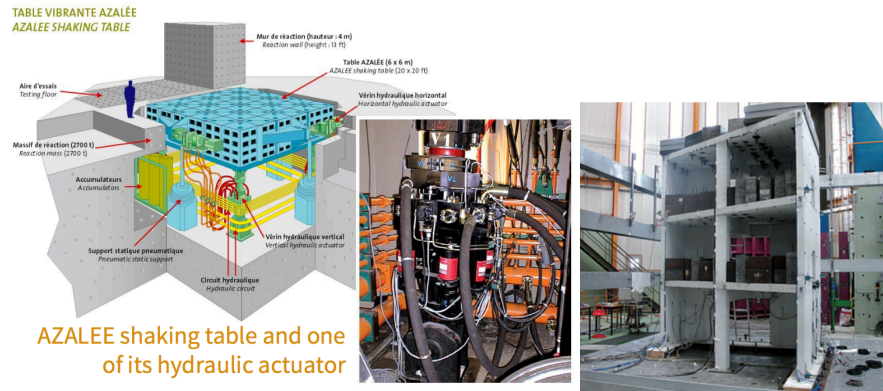


Fig. 5 Details on the studied shaking table system with concrete building clamped on it.

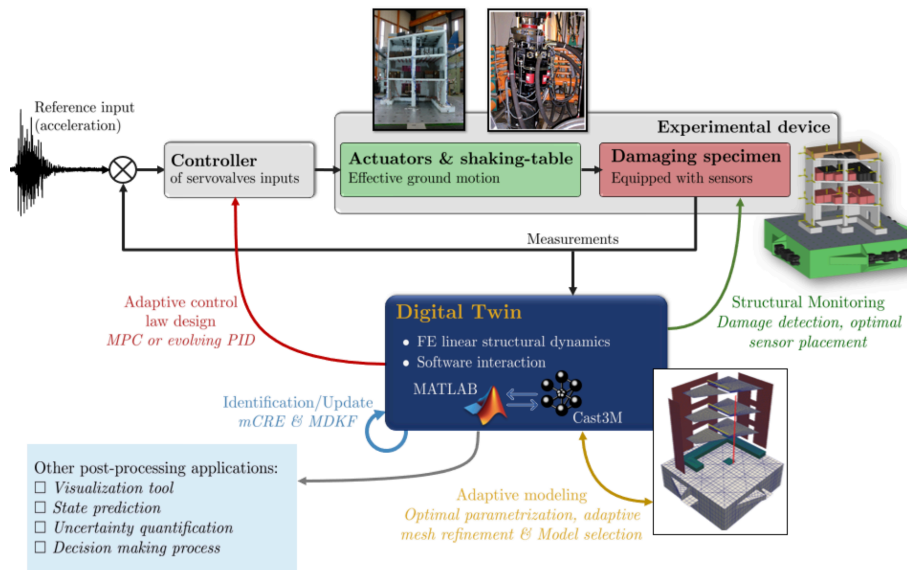
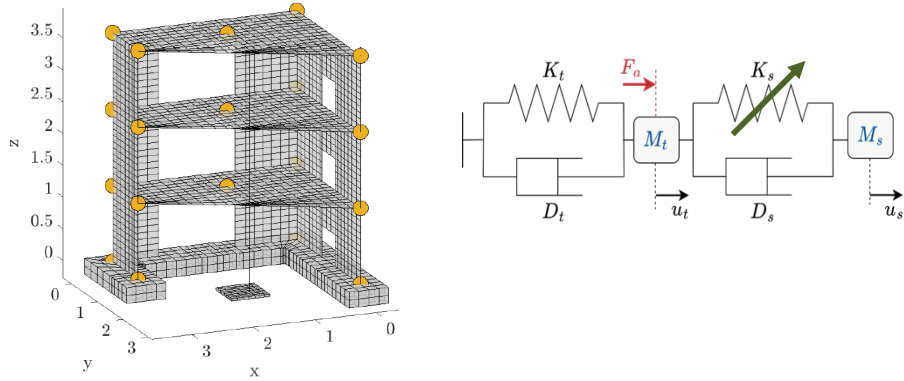


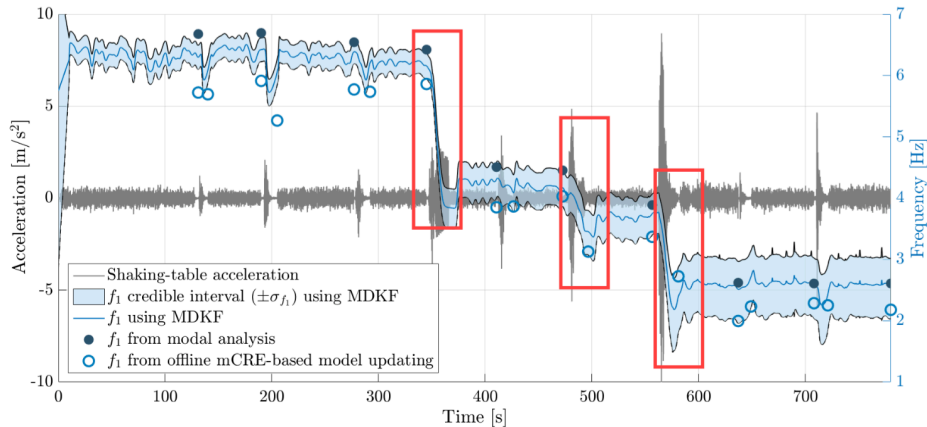
Fig. 6 Envisioned DDDAS feedback loop to monitor the command on the shaking table system.

The experimental database is taken from the SMART2013 test campaign, that consisted in a sequence of gradually damaging tests. Data are obtained by some accelerometers placed on the structure (see Figure 7) with a high noise level.



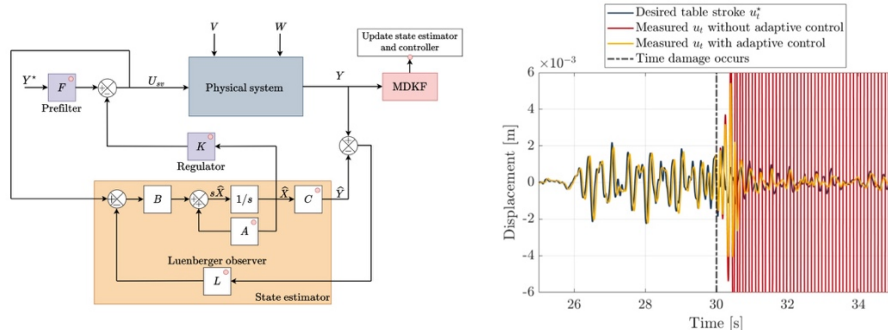
**Fig. 7** Finite element model with location of accelerometers on the concrete structure (left), and rheologic model of the overall system (table+structure).

From sequential and real-time updating of local material stiffness through MDKF, with mCRE written in the frequency domain, eigenfrequencies of the building are effectively tracked during the whole duration of the test. A typical result is given in Figure 8, showing the predicted evolution of the first eigenfrequency. From Figure 8, one can clearly observe the frequency drops due to progressive structural damage during the dynamics test.



**Fig. 8** Predicted evolution of the first eigenfrequency using MDKF.

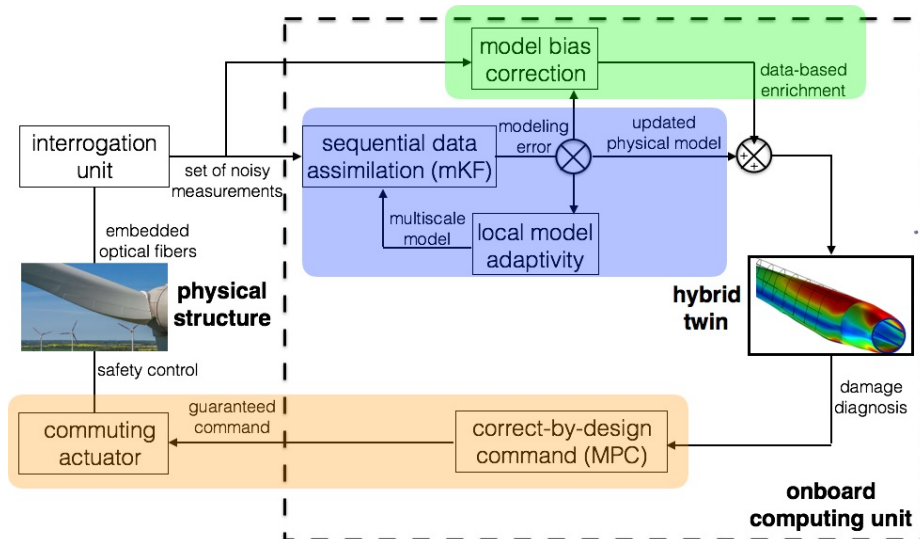
The real-time constraint, which is successfully achieved here when using MDKF, further enables an appropriate evolving online command on the shaking table, taking into account the interaction between actuators, table, and the damaging specimen. The dynamic-data-driven and model-based control is here performed by inserting the MDKF algorithm within a state feedback control strategy (as a proof-of-concept). The control architecture is shown in Figure 9, as well as its interest for stabilizing simulated shaking table tests in real-time.



**Fig. 9** Control strategy using MDKF outputs (left), and typical stability result obtained from such a control (right).

### 3. Ongoing research works

This section presents some research works in progress as part of the DREAM-ON project, utilizing the mCRE/MDKF concepts. They focus on effective data assimilation and model selection from distributed optic fiber measurements, on model enrichment by means of data-based learning techniques, and on robust and guaranteed online command synthesis for control. Considering the DDDAS feedback loop of Figure 1, the overall methodology which is proposed is detailed in Figure 10.



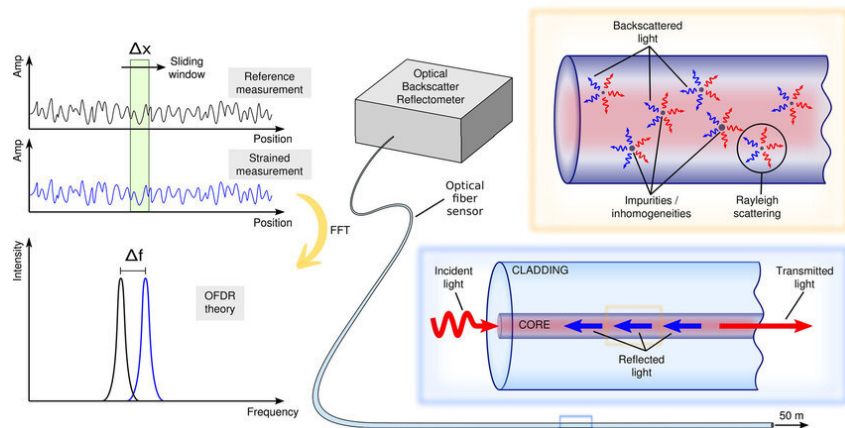
**Fig. 10** Description of the numerical methodology within the DDDAS feedback loop.

### 3.1 MDKF strategy with optic fiber measurements

Distributed Optic Fiber Sensor (DOFS) technologies are increasingly used for SHM in composite structures of various engineering fields (e.g., see [72, 73, 74, 75, 76]). A classical optic fiber, bonded on the structure or embedded during manufacturing, can indeed be used as a sensing element and provide for *in situ* experimental information, which then acts as both transducer and transmitter. In addition to unique sensing capabilities in terms of measurement density and rate to capture localized phenomena as damage, DOFS offers many other inherent advantages compared to alternative sensing technologies [77]; we may list the flexibility in installation and use (portable, electrically passive, remote sensing), the large range of applications with capability to operate in harsh (radiative, corrosive) environments and immunity of the signal to electromagnetic interference, or the large spatial extension of the monitored area. A recent review on the various DOFS technologies can be found in [8].

In the DREAM-ON project, we focus on DOFS sensors based on elastic Rayleigh backscattering (caused by interaction of light with natural density fluctuations within fibers, see Figure 11) analyzed in the frequency domain (optical frequency-domain reflectometer (OFDR) technique), which permits to recover local and high-resolution material strain information [78, 79]. Indeed, local modifications of fiber features lead to variations in the magnitude of the backscattered multi-frequency signal analyzed with Fast Fourier Transform FFT; an accurate measurement of longitudinal strain along a network of optic fibers, with sub-millimeter resolution and high-frequency scan, can then be obtained before being converted into a map of damage over the entire structure. Consequently, DOFS is a technology of choice when tracking early damage in mechanical structures.

The sensing equipment is made of an active opto-electronic unit or interrogator (including laser and interferometer) that sends light signal into one or several fibers then collects and processes the backscattered signal to retrieve measurement information. For the purpose of the DREAM-ON project, a Luna ODiSI 6108 equipment has been purchased and is extensively used.



**Fig. 11** Illustration of the equipment and backscattering phenomenon used for sensing with optic fibers, from [80].

A mCRE-based inversion method was first applied with DOFS measurements in [58]. Here, the method is enhanced by using the MDKF strategy with such high-resolution measurements in the context of SHM [81, 82]. Let us recall that MDKF, which is a modified version of Kalman filtering, only requires to store current data in the sequential process, avoiding keeping in memory the whole history of measurements. We report below a typical application, in which experimental data is collected from an optic fiber embedded inside a cement-based mortar beam undergoing a quasi-static 4-point bending test with increasing loading until failure (see Figures 12 and 13). Additional image-based data (from digital image correlation-DIC) is also recorded on a local area of the beam surface for validation purposes. Such data is then analyzed to identify parameters of an isotropic material model and detect damaged zones along the mechanical test.

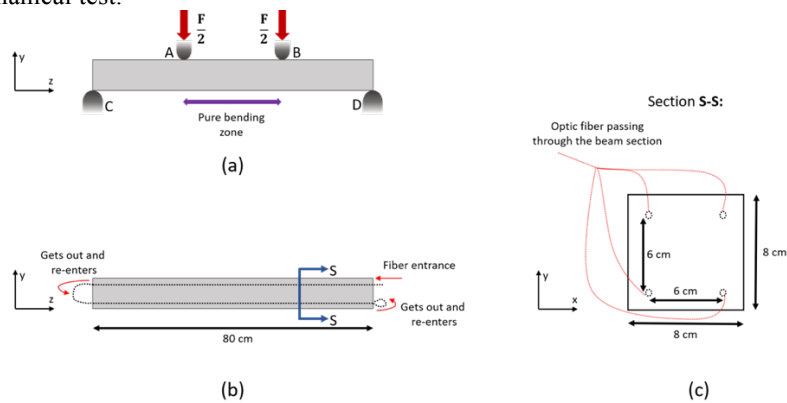


Fig. 12 Considered configuration for the bending test on a concrete beam.

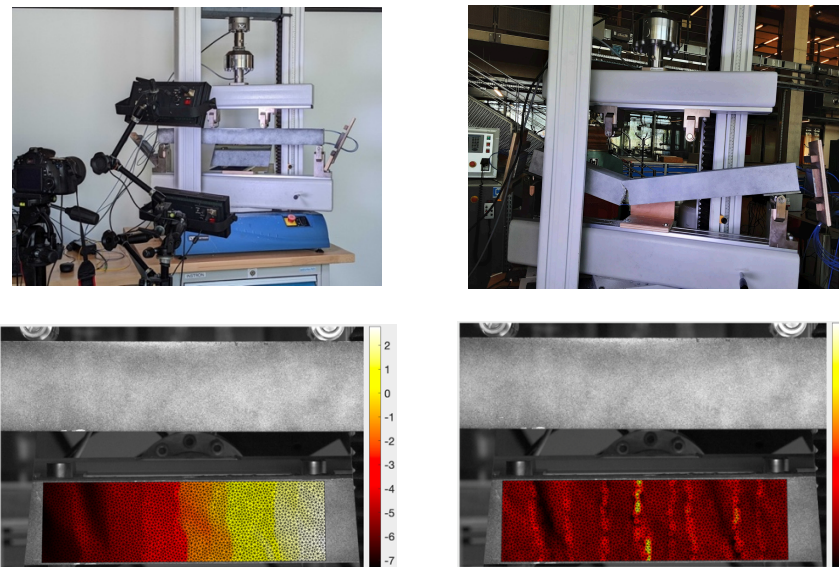
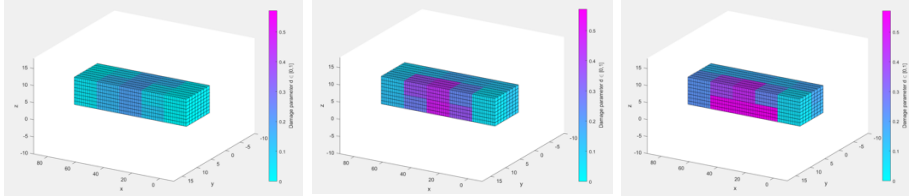


Fig. 13 Experimental setting (top) and additional local DIC measurements (bottom).

Results in terms of distribution of damage inside the beam, at various instants of the test, are shown in Figure 14.



**Fig. 14** Distribution of damage inside the beam at three instants of the bending test.

Currently, several research works on iterative (dynamic) data assimilation with DOFS are being investigated. The first one deals with *dynamical model selection*, as here again the CRE part of the mCRE functional can be analyzed to detect zones with large modeling error and adapt both the model and the parametric space accordingly (i.e., enriching the material behavior representation in local regions where damage occurs, that is multi-fidelity modeling). Second, an interesting aspect when dealing with DOFS is experimental design in terms of *constrained optimal fiber placement*. For this purpose, and following the strategy developed in [83] for the case of sparse sensors, a strategy mixing mCRE and information entropy has been designed for the constrained placement of fibers parametrized by means of B-splines [84]. Third, the interest of using *sparse regularization* [85, 86, 87] as a complementary term in the mCRE functional to tailor the approach to the context of localized damage is being analyzed. Eventually, including the dissipative part of the constitutive model (i.e., evolution laws) in the mCRE and MDKF strategies is for sure an important step forward.

### 3.2 Constitutive model enrichment with physics-augmented learning

As indicated before, the mCRE approach assesses the relevance of the employed mathematical model, and in particular the structure of the constitutive law. The constitutive law is usually chosen empirically, and supposed to fit within a given parametric representation, for direct physical interpretability. Yet, the interpretability comes at the price of model bias, while an accurate constitutive model is crucial for easier interpretation and more reliable prediction of the structural behavior in SHM. In order to build such an accurate constitutive model (which may be complex), and therefore correct model bias, machine learning (ML) and data science can be of high interest.

The idea to represent the constitutive relation by a neural network (NN) was proposed in the past (e.g., [88]), with a purely data-driven approach. More recently, techniques coupling deep learning (DL) and physics knowledge helped alleviate frequent concerns in the NN, such as the lack of physical consistency, the lack of generalization, and the difficulty to train (quantity of data, hyperparameters tuning) [89, 90]. A first approach referred to as “physics-informed” or “physics-enhanced” is to include physical knowledge

in the loss function used to train the NN, usually by means of a penalization term [89, 91, 92]. A second approach, referred to as “physics-augmented”, is to enforce the physical knowledge (e.g., thermodynamics laws) in the NN architecture [93, 94, 95, 96]. These latter techniques are based on imposing convexity by means of an input-convex neural network (ICNN) introduced in [97]. A third approach, often referred to as transfer learning (TL) through domain adaptation, consists of informing prior knowledge in the network initialization; out of decreasing the quantity of data used for training, this reduces the sensitivity of a random initialization on the training result.

In addition, when dealing with learning constitutive laws, NNs may be trained using a supervised procedure with a strain-stress database (or strain-free energy) generated from a known constitutive model [94, 98, 96, 99, 100, 101, 93]. In [102, 95], unsupervised training was considered by using full-field observations as input of the NN (with a loss function that penalizes the non-satisfaction of balance equations).

In this context, and still relying on the mCRE framework, we recently developed the *NN-mCRE* approach for unsupervised learning of (nonlinear) state laws with a NN [103, 104]. This approach naturally focuses the strategy on what needs to be learnt, that is the constitutive relation, and permits a data-based enrichment of an *a priori* constitutive model. NN-mCRE integrates all the recent trends described above on learning (physics-informed, physics-augmented, transfer learning), by the specific definition of the loss function, the chosen architecture of the NN, and the physics-guided initialization. It also requires only partial observations on displacement or strain, such as the case with optic fiber measurement.

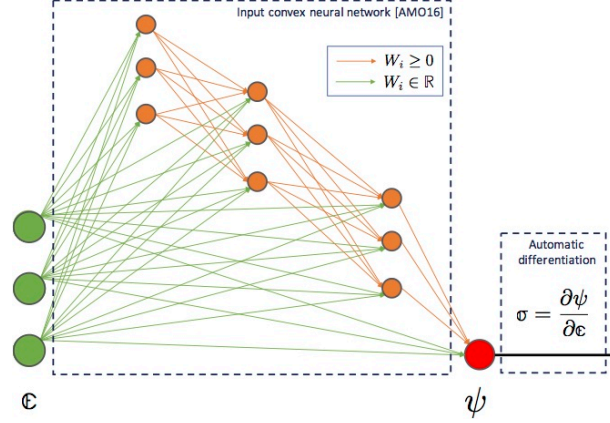
The NN is trained thanks to a procedure in which the mCRE functional (defined in Section 2.1) is used as loss function and minimized. This NN aims at defining the potential  $\psi$  (free energy) involved in this functional, taking the strain tensor  $\epsilon$  as input and recovering the stress tensor  $\sigma$  with automatic differentiation. The iterative minimization procedure is then similar to the one described in Section 2.1; each iteration consists of two steps that read:

$$\begin{aligned} (\hat{\epsilon}^{(n+1)}, \hat{\sigma}^{(n+1)}) &= \underset{(\hat{\epsilon}, \hat{\sigma}) \in A_d}{\operatorname{argmin}} \mathcal{E}_{mCRE}^2(\hat{\epsilon}, \hat{\sigma}; p^{(n)}) \\ p^{(n+1)} &= p^{(n)} - l_r \nabla_p \mathcal{E}_{mCRE}^2(\hat{\epsilon}^{(n+1)}, \hat{\sigma}^{(n+1)}; p^{(n)}) \end{aligned}$$

where the parameter set  $p$  now denotes weights of the NN describing  $\psi$ . With its rich physical sense, the mCRE informs on modeling error continuously defined over the structure (through its CRE term), and it can be used as a quality indicator and a relevant stopping criterion in the inference phase.

In the process, thermodynamics consistency is enforced through the specific NN architecture. The free energy  $\psi$  is indeed made convex by using a ICNN architecture (Figure 15), and enforcing zero stress when there is zero strain. In such a ICNN architecture, weights between intermediate layers are positive and activation functions are convex and non-decreasing. Additional classes of symmetry may also be added in the network architecture.





**Fig. 15** ICNN architecture of the neural network used.

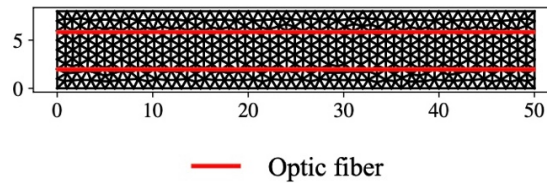
As typical DDDAS-based SHM applications require that the NN be trained online, an important focus was given on automatic and adaptive tuning of sensitive hyperparameters of the NN-mCRE approach that are the learning rate  $l_r$ , the weighting between losses (which is here natural compared to alternatives of the literature [105]), the number of epochs, the batch size, and the network initialization (see [104]). In particular, the network is initialized by means of a first training with an *a priori* constitutive model; it is performed in a classical supervised way with the Adam (Adaptive Moment estimation) optimizer and a mean square error loss.

We showed that when the training database is rich enough with respect to the loading case, the proposed method achieves remarkable performance regarding quality of the learned constitutive model, noise robustness (up to 40% noise!!), and low sensitivity to user-defined hyperparameters.

We illustrate here the method with a reference non-quadratic potential in the small strain regime and with synthetic optic fiber measurements inside a beam structure (see Figure 16). The chosen non-quadratic potential to be learnt distinguishes behaviors in traction and compression along the longitudinal axis of the beam; it reads:

$$\psi(\epsilon) = \frac{1}{2}E_+ \langle \epsilon_{11} \rangle_+^2 + \frac{1}{2}E_- \langle \epsilon_{11} \rangle_-^2 + \frac{1}{2}E \epsilon_{22}^2 + G \epsilon_{12}^2$$

where  $\langle \cdot \rangle_+$  and  $\langle \cdot \rangle_-$  denote positive and negative parts, respectively. The network is initialized with a linear elasticity model (quadratic potential). The database includes ten different loading cases with a combination of pure bending, traction and compression, and additional Gaussian noise.



**Fig. 16** Configuration of the studied beam with embedded optic fiber sensor.

Some results are shown in Figures 17 and 18. We observe in Figure 18 that with the proposed strategy, the convergence rate of the training is no longer sensitive to user-defined hyperparameters.

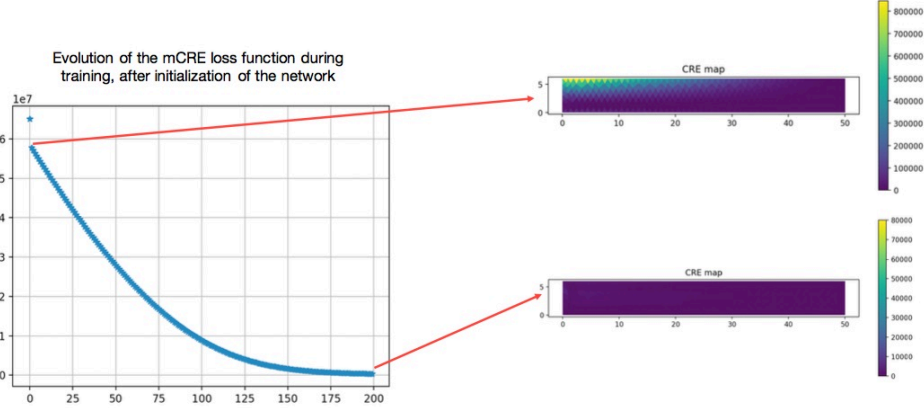


Fig. 17 Convergence of the mCRE-based loss function along the learning process.

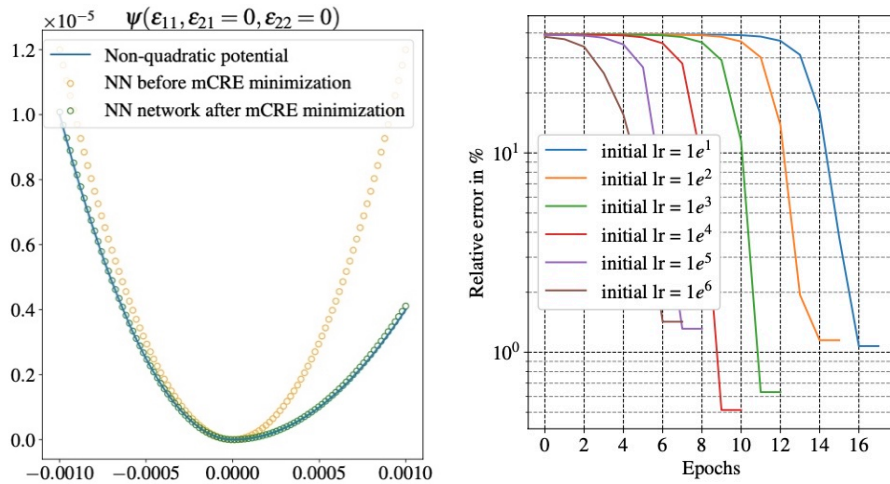


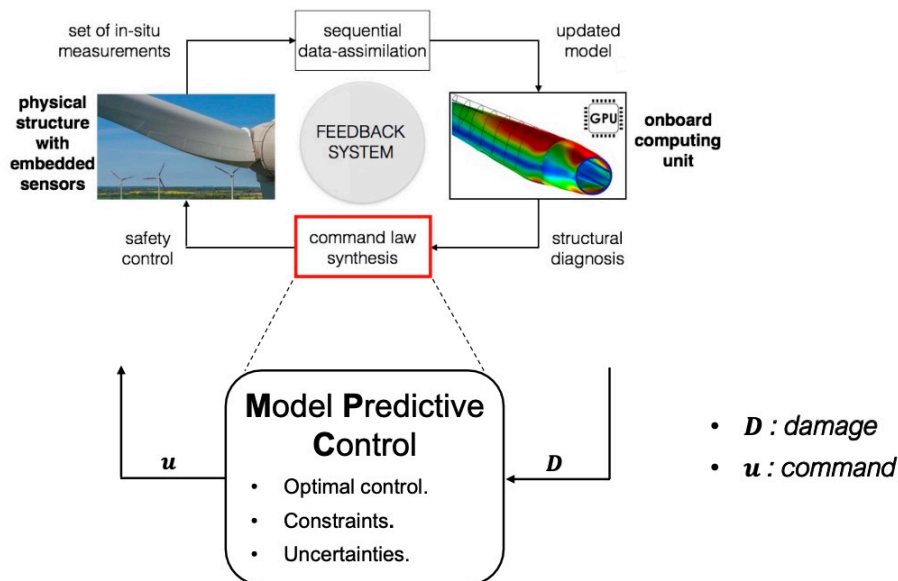
Fig. 18 Initial and final potentials defined by the neural network (left), and convergence of the error for various learning rates (right).

Works in progress on this topic deal with the learning of evolution laws by including dissipation potentials in the mCRE loss function, and the optimized constitutive model learning using sparsity of the NN architecture and the sensitivity of the CRE modeling error term.

### 3.3 Online synthesis of control laws

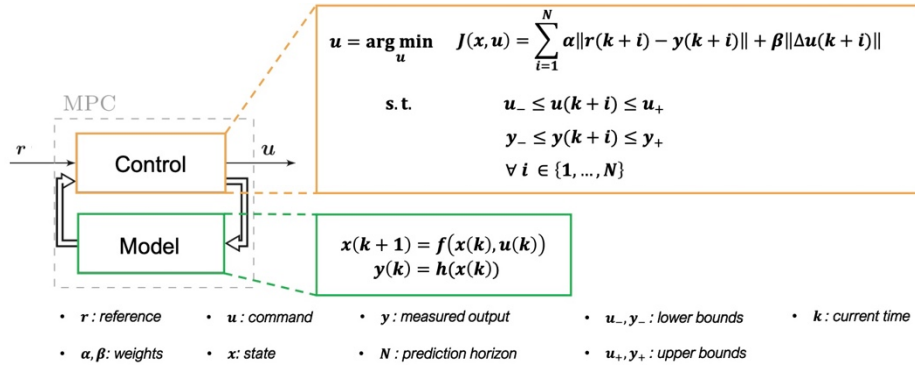
Implementing an effective DDDAS feedback loop for SHM requires to address the definition of a suitable computational framework for online guaranteed command

synthesis on evolving systems. Such a command aims at driving the structural loading to limit damage evolution and make the structure avoid critical zones at any time (operation at performance limits). To achieve this goal, Model Predictive Control (MPC) appears as an advanced and convenient strategy of optimal control theory [32, 106, 107, 108, 89, 109]; it will be used in the targeted DDDAS feedback loop (see Figure 19).



**Fig. 19** Use of the MPC strategy in the DDDAS feedback loop for SHM.

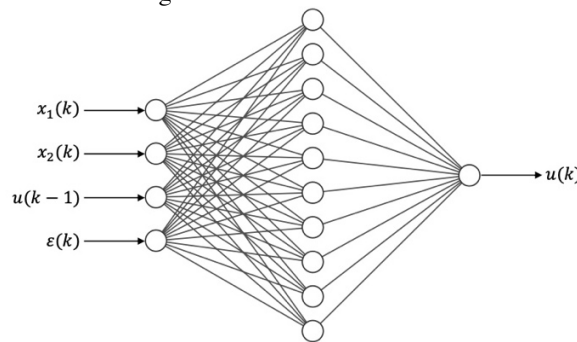
MPC has two special features: 1) the use of a computational dynamical model of the controlled process for online prediction of future states; and 2) the use of an optimization procedure to find online the best control depending on state measurements which incorporate feedback. An advantage of MPC over other predictive strategies is that it replans a new control trajectory from the measured data and updated model at each time step; the controller is thus robust by design, being able to account for unexpected disturbances by dynamically calculating paths to return to the desired states. MPC may also account for state and control constraints, such as those associated with controller capabilities and confinement in a safety region, leading to the solution of constrained optimization problem. MPC methods are increasingly popular in fast on-board systems such as autonomous driving systems. Typically, the system behavior is predicted over a shifted time zone (so-called prediction horizon) made of several time steps in time-discretized MPC, with recurrent online use of the underlying dynamical model. Of course, due to modeling error propagation, inaccuracy is likely to be larger for longer horizons, so that a high-fidelity computational model is requested. The overall architecture of MPC is given in Figure 20.



**Fig. 20** General scheme of MPC.

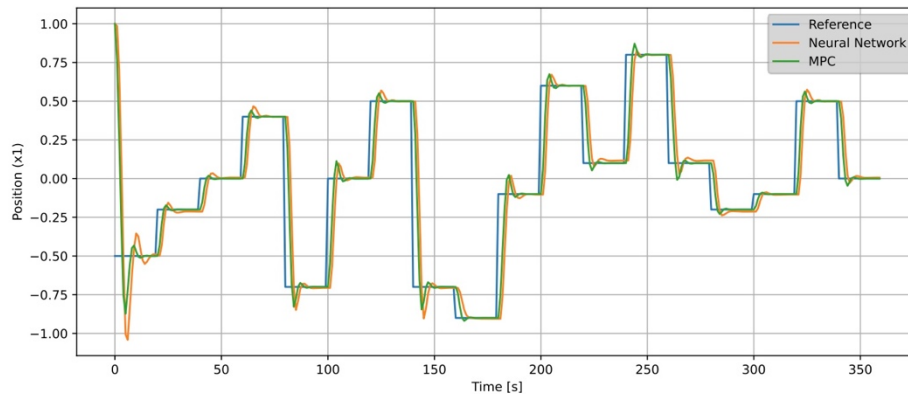
However, when a complex nonlinear dynamical model in large state dimension is used for prediction in MPC, a nonlinear optimization problem must be solved online at each sampling time (unless a linearized model is used). Iterative sampling results in two main difficulties which are the intensive use of computing resources (usually leading to large computation times that are not compatible with implementation on-board fast micro-controllers), and the multi-modal and non-convex features of the cost function to be minimized (so that shallow local minima may be found rather than a global solution).

In order to circumvent the sampling challenges, fully or partially input convex neural networks (ICNN) may again be used with MPC [110, 111, 112, 113, 114]. Such ICNN networks are convex in one-step-ahead prediction, and a procedure can be employed to make a multiple-step-ahead prediction. An application of such a strategy on a representative problem is shown below; it involves a nonlinear Van der Pol oscillator, with constraints on command and state [115]. The considered control architecture is a one-step ahead predictive controller, and the used ICNN has 4 inputs and 10 neurons as shown in Figure 21.



**Fig. 21** Architecture used for the neural network performing MPC ( $x_1$  is the position,  $x_2$  the speed,  $\epsilon$  the error, and  $u$  the command).

For the training, synthetic data are obtained from a simple MPC simulation using various references, and constraints on the output are satisfied using an activation function. A set of 2160 training data are then used, with 5000 epochs. For comparison, classical MPC is designed with a time step of 0.5 s and a prediction horizon of  $N = 5$ . Results are shown in Figure 22; the mean squared error is 0.27 for the NN and 0.22 for MPC, while the CPU time is 0.008 ms for the NN and 2.178 ms for MPC. This shows the potential of ICNN to reach a good rapidity/accuracy compromise in MPC-based control.



**Fig. 22** Comparison between classical MPC and neural network for control.

The next step will be to deal with damage problems (using MPC-based neural networks to find an optimal loading path given various initial damage conditions to reach a desired structure configuration), and to integrate the mCRE/MDKF framework into MPC, i.e. using both the updated model and the optimal admissible fields that are outputs of the mCRE minimization in order to define the current structural state and next command to apply. An online adaptive control synthesis will thus be derived [116], for damageable systems here. Another task will be to implement the proposed MPC strategy on the Stewart platform actuator which is an element of the DDDAS proof-of-concept of Figure 2. Such a multi-axial actuator has already been used in several research works to drive mechanical tests [117, 118, 119, 120], but the various difficulties of the DDDAS application (complex nonlinear structural behavior, real-time command synthesis, etc.) entail new challenges to tackle in terms of stability and certification of the command with regards to uncertainty sources [121]. As an alternative to usual symbolic methods [122] which do not scale high dimensions, one option would be to resort to *correct-by-design* and set-based methods [123, 124] which are compatible with safety constraints even though the optimality of the command is not ensured.

## 4. Summary

We presented innovative and effective numerical approaches to implement a DDDAS framework in practical SHM applications. The proposed multidisciplinary

methodology has the potential to make the DDDAS framework applicable to real-life damageable structures, in order to go from smart materials to smart structures. It represents a key enabler for the next generation of integrated SHM technologies, envisioning the design of smart autonomous engineering structures with integrated monitoring capabilities, enhanced damage tolerance, timely optimized (reduced and condition-based) maintenance with extended operational efficiency and better coherence with sustainable protecting policies, and thus increased reliability and performance and competitiveness. It is thus expected to lead to significant scientific, technological, and societal outcomes in all industrial activities where large critical engineering structures are employed and where damage fault-tolerance is of paramount importance. We note that eventually the approach is of interest for other applications (including those where DDDAS has been applied), such as the design of numerically-assisted experimental tests on materials [125], the optimization of manufacturing processes [126, 127, 128, 129], or the development of computer-assisted medical surgery with potentially damaging tissues [130, 131].

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