Real-Time Predictions of Vehicle Capabilities for Reconfigurable Mission Planning

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ABSTRACT

Reliability and operational availability of unmanned vehicles can be augmented through a dynamic reshaping of their operational and mission profile in response to the evolution of their health state and contingencies. In hazardous settings, the dynamic reconfiguration of a mission profile requires real-time predictions of residual capabilities which determine the set of feasible manoeuvres to preserve the vehicle and complete the mission successfully. This work discusses two computational frameworks to predict system capabilities from on-board sensor measurements and actualize a form of self-awareness for unmanned air vehicles in support of reconfigurable mission planning. The first framework relies on a traditional approach to diagnostics and prognostics: model reduction and supervised learning are combined to accelerate both the identification of damage parameters and the prediction of system capabilities. The second framework introduces a priority shift that emphasizes the prediction of vehicle capabilities over the characterization of the damage: an original bypass scheme (named MultiStep-ROM) combines projection-based model reduction and unsupervised machine learning into a form of transfer learning that computes adaptive models directly mapping measurements into capabilities. The two approaches are presented through the example cases of unmanned air vehicles that undergo failures of on-board actuation devices and structural damages. The computational experiments indicate that the bypass approach allows to obtain sensitively faster predictions of vehicle capabilities and is better suited to meet real-time responsiveness requirements than the traditional scheme.

1. INTRODUCTION

Unmanned vehicles (UxVs) are autonomous systems whose adoption is sensitively growing across multidomain settings spanning air, ground and sea environments. UxVs are becoming key players in civilian and military operational scenarios, which both demand for advanced reliability and readiness of the interoperating systems. Reliability and operational availability of unmanned vehicles can be augmented through the possibility for those systems to dynamically reshape their operational and mission profile in response to the evolution of their health state and contingencies. As an example, we can consider the specific case of unmanned aerial vehicles (UAVs) that are tasked to complete a mission in hazardous settings. The source of hazard might be hard to characterize a priori, but the impact onto the mission could result in a catastrophic failure. The structural integrity or the nominal functioning of the systems could be dramatically jeopardized, eventually leading to the loss of the vehicle. The possibility to reconfigure the mission would allow the UAVs to continue operating safely under degraded and damaged conditions, without over-replacing parts, oversizing components, and multiplying systems redundancies.

To enable dynamic mission replanning, unmanned aerial vehicles can be equipped with advanced artificial reasoning that learns about the actual health of the systems from sensor measurements, and predicts in real-time the evolving/residual capabilities that constrain the decision space (feasible manoeuvres) of possible actions (mission profile) (Allaire et al. 2014; Mainini and Willcox 2015; Lecerf et al. 2015; Burrows and Alllaire, 2019). This Sense-Plan-Act (SPA) flow relies on a form of artificial awareness about what a system can still do under degraded conditions, as opposed to exactly knowing about the specific *injury* that a system is experiencing. The identification of the fault requires the systems to self-diagnose and characterize the damage conditions, possibly in real-time. Therefore, condition assessment tasks relate to diagnostics and prognostics problems, and rely on the detection and identification of damage type and extent —sometimes even fault modes and root-causes— which would then inform the prediction of system reliability and the decisions about maintenance interventions and planning.

Both dynamic mission reconfiguration and vehicle condition assessment are Sense-Plan-Act flows demanding for advanced forms of system/vehicle self-awareness: the former prioritizes the prediction of systems capabilities (what the vehicle can do), the latter emphasizes the identification of the damage parameters (what is affecting the vehicle). These shades of priorities become critical when seeking avenues to accelerate the computational flow from measurements to predictions to run onboard UAVs, since asking the measured data for the right questions is of key importance to actualize reasoning efficiency and cope with the limited computing resources (Mainini, 2017). This reasoning would enable a form of proactive maintenance which relies on the ability of the autonomous vehicle to promptly counteract to contingencies: by dynamically adapting the operational behaviour, the UAV would not only survive a particular event, but also complete the mission successfully.

This work discusses this priority shift, which might be sensitively beneficial to the efficient actualization of dynamic reconfigurable mission planning for improved UAV readiness and reliability. The change of perspective is illustrated through two approaches that differently combine model reduction and learning schemes to speed up the SPA computational flow. The first framework is developed to accelerate diagnostics and prognostics, which are the traditional phases that enable vehicle readiness and reliability through condition-based maintenance planning. The second framework prioritizes the prediction of vehicle capabilities over the characterization of the damage, which is better suited to augment vehicle readiness and reliability through reconfigurable mission planning. Our approaches are presented through the example cases of unmanned air vehicles that undergo failures of on-board actuation devices and structural damages.

The remaining of the paper is organized as follows: Section 2 discusses the two approaches. In particular, Section 2.1 presents the SPA paradigm adopted to cast the information flow that characterizes the artificial reasoning for reconfigurable mission planning; Section 2.2 proposes an overview of the two approaches we developed for real-time capability prediction to enable condition-based maintenance planning (Section 2.2.1) and reconfigurable mission planning (Section 2.2.2), respectively. Finally, Section 3 summarizes the concluding remarks.

2. APPROACH AND DISCUSSION

2.1 From the Sense-Plan-Act to the Sense-Infer-Plan-Act information flow

Reconfigurable mission planning is a decision problem that can be casted according to the Sense-Plan-Act paradigm broadly adopted in robotics (Allaire et al. 2014). The SPA paradigm models the information flow that artificial systems follow to autonomously complete a task by computing the most appropriate sequence of actions and procedures from sensed data. We focus on the Sense-to-Plan portion of the SPA flow: in particular, we seek computational strategies to extract highly informative content from sensed data and synthetize it into useful reliable knowledge about the health of the autonomous aerial system/vehicle. This knowledge can then be leveraged to enable the responsive amendment of system behaviour, and the update of the manoeuvre sequence to (i) preserve the vehicle and (ii) complete the mission successfully.

The Sense step is inevitably associated with measured data and acquired signals (measurements) which are physical quantities that depend on the state of the vehicle and can be measured directly during the operational activity. For the case of unmanned air vehicles, those might include the acquisition of structural deformation measures (Mainini and Willcox 2015, Lecerf et al. 2015), envelope current signals (Berri et al. 2018, 2019) or counter-electromotive force of on-board electric motors, aerodynamic load peaks or distributions. On the other hand, the space of possible planning decisions is constrained by the residual capabilities of the vehicle undergoing degradations. Those capabilities are also physical quantities that evolve with the health condition of the vehicle, but —differently from the measurements— cannot be directly measured. Examples of capability quantities for UAVs include structural failure indices (Mainini and Willcox 2015, 2017), and measures of system reliability such as the allowable load factors (Lecerf et al. 2015, Singh and Willcox 2017) and the remaining useful life (Berri et al. 2018, 2019).

Within this context, it is possible to notice that the Sense-to-Plan flow intrinsically consists of two computational tasks (Figure 1): an identification step to infer the details of the health condition (damage parameters) from measurements; and a prediction step to estimate the actual capabilities of the system and their evolution, which in turn inform the decisions about operations (mission and maintenance) replanning. Hence, it is possible to expand the Sense-Plan-Act flow into the Sense-Infer-Plan-Act flow, which acknowledges the intermediate step of inference about the parameters that describe the actual damage/fault condition (Mainini and Willcox, 2015). The identification step is an inverse problem whose solution might require interrogating costly models many times. The prediction step implies to solution of forward problems through the evaluation of physics-based models of systems and structural behaviour. Both the computational steps of identification and prediction are frequently too expensive and unsuited to meet the responsiveness requirements imposed by real-time operations.

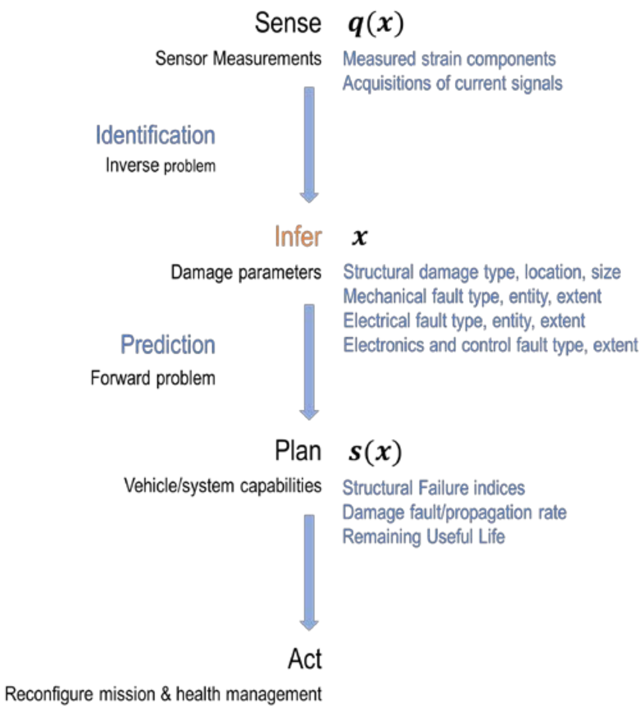

Figure 1: The Sense-Infer-Plan-Act flow which expands the Sense-Plan-Act paradigm to acknowledge the intermediate step of damage inference; the inferred damage parameters are then used to predict the residual capabilities of the unmanned vehicle/system.

Our work aims to accelerate the Sense-to-Plan information flow (data processing and knowledge synthesis) from sensed data (measurements and signal acquisitions) to predict evolving systems' capabilities. These predictions are of critical importance to assist the dynamic reconfiguration of the mission profile in real-time, which in turn will enable the vehicle to proactively preserve its integrity and respond to the contingencies.

2.2 Real time predictions of vehicle capabilities from measurements

We discuss the computational frameworks to realize the Sense-to-Plan information flow for the real-time prediction of system/vehicle capabilities to enable either condition-based maintenance planning or reconfigurable mission planning. The two approaches are described through the example cases of the prediction of the remaining useful life of electro-mechanical actuators (EMAs) and the prediction of failure indices of composite panels. The former is a multidomain application that considers multiple fault modes affecting mechanical (gearbox), electrical (motor) and electronics (control) elements of the EMA device for the secondary flight controls of an unmanned air vehicle (Figure 2). The latter is a single domain application that considers structural damages affecting composite wing panels of an unmanned air vehicle (Figure 3).

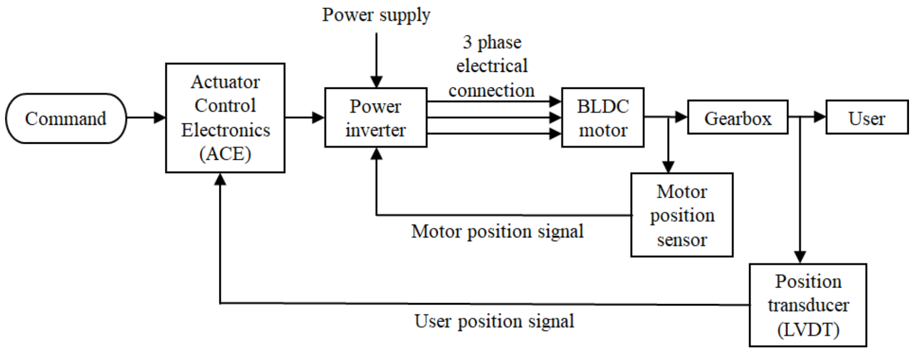

Figure 2: Architecture of the electro-mechanical actuator for a UAV secondary flight controls (Berri et al., 2019).

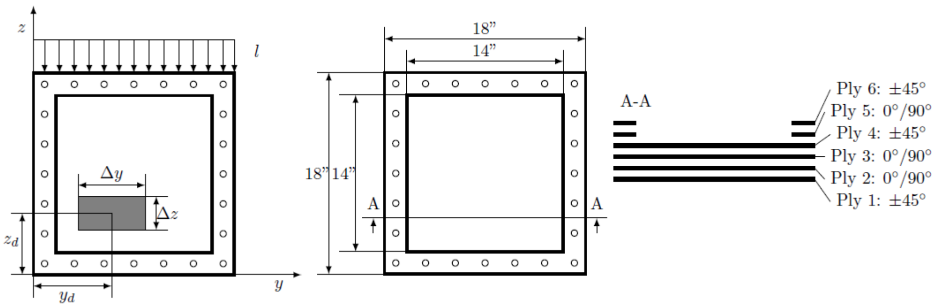

Figure 3: UAV wing panel layout and layer sequence (plain-weave carbon-fiber plies); damage parameters (location and size) and compressive loading (Mainini and Willcox, 2015).

Both the approaches are based on an offline-online structure: offline we combine model reduction techniques and learning schemes to obtain cheap-to-evaluate representations of system behaviours that synthesize and embed the specific knowledge required for our prediction tasks; online those representations are used to obtain fast predictions of vehicle capabilities from measured data and actualize the Sense-to-Plan flow.

2.2.1 Diagnostics and prognostics to enable condition-based maintenance planning.

Figure 4 illustrates the framework developed for the nearly real-time assessment of the health condition and reliability of an autonomous system to support a responsive re-planning of maintenance and operations. In particular, we observe the strategy developed for the prediction of the remaining useful life $\boldsymbol{s}(\boldsymbol{x}) = t_{RUL}(\boldsymbol{x}) \in \mathbb{R}^{n_s}$ of the onboard EMA system (capability) from acquisitions of the stator envelope current $\boldsymbol{q}(\boldsymbol{x}) \in \mathbb{R}^{n_q}$ (measurements). Both measurements and capabilities are sensitive to the multi-physics fault parameters $\boldsymbol{x} \in \mathbb{R}^{n_x}$, affecting the mechanical transmission (friction and backlash), the electrical motor (partial short circuit and static eccentricity), and the control electronics (drift of the position control loop gain). The condition assessment problem consists of diagnostics and prognostics steps, that is the full completion of both the identification of damage parameters from sensor acquisition and the prediction of capabilities from the damage parameters.

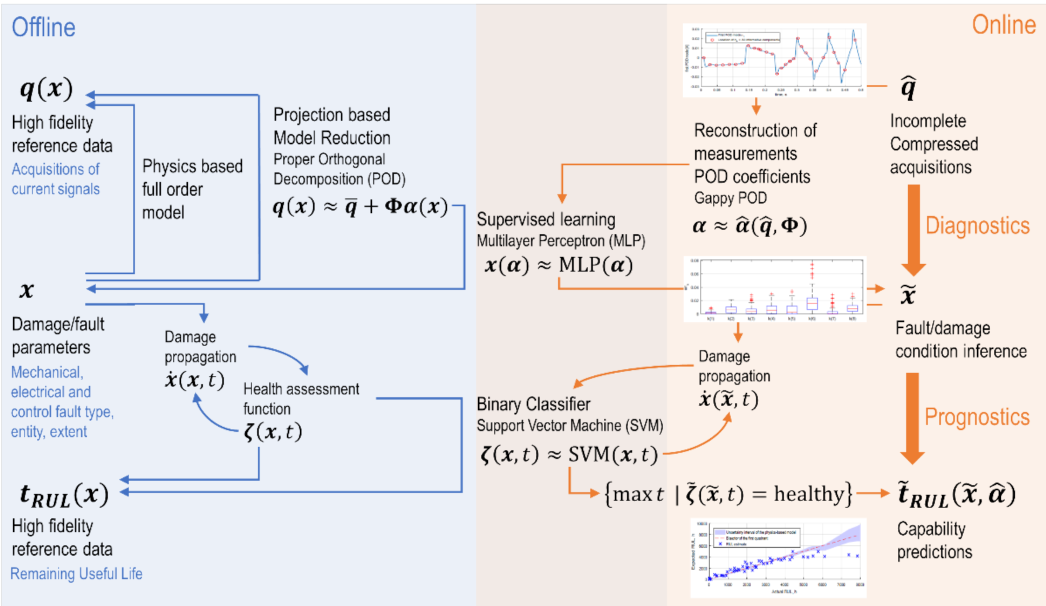

Figure 4: Computational framework for diagnostics and prognostics to enable responsive re-planning of maintenance and operations: the inference step is fully addressed. The left-hand side (blue) illustrates the offline flow, the right-hand side (red) indicates the online flow: the models computed offline and used online are at the intersection.

Offline, full order physics-based models are used to obtain reference datasets collecting high dimensional acquisitions ($n_q \sim 10^6$) of the envelope current signals $\boldsymbol{q}(\boldsymbol{x})$, damage propagation rates $\dot{\boldsymbol{x}}(\boldsymbol{x}, t)$ and associated failure (assessment) labels $\boldsymbol{\zeta}(\boldsymbol{x}, t)$ for a variety of combinations of fault conditions $\boldsymbol{x}$. The reference datasets are used to learn reduced representations of $\boldsymbol{q}(\boldsymbol{x})$ through Proper Orthogonal Decomposition (POD), which allows to approximate the high-dimensional acquisition of the envelope current signal as a liner combination of dominant modes (POD basis vectors $\boldsymbol{\Phi} = \{\varphi_i\}_{i=1}^{n_\varphi}$, with $n_\varphi \sim 10^1$). The POD coefficients $\boldsymbol{\alpha}(\boldsymbol{x})$ express the relationship between the fault parameters $\boldsymbol{x}$ and the envelope current in the n_φ-dimensional reduced space of the POD, rather than in the n_q-dimensional space of the acquired signal, with major computational savings since $n_\varphi \ll n_q$. Then, we use supervised learning, specifically a Multi-Layer Perceptron, to compute a model of the fault conditions $\boldsymbol{x}$ as a function of the POD coefficients $\boldsymbol{\alpha}$: having reduced the dimensionality of the problem via POD, we wish the MLP to better capture the information content of the limited set of available training data $\boldsymbol{q}(\boldsymbol{x})$. Eventually we seek a model to approximate the expensive-to-evaluate assessment function $\boldsymbol{\zeta}(\boldsymbol{x}, t)$ that provides the healthy/faulty response by integrating the damage propagation model over time. We chose a Support Vector Machine (SVM) to learn a binary classifier that associates either a healthy or faulty label to a given $\boldsymbol{x}$.

Online, the acquisitions of the electric current signals $\hat{\boldsymbol{q}}$ are compressed and processed to compute the associated POD coefficients via gappy POD $\hat{\boldsymbol{\alpha}}(\hat{\boldsymbol{q}}, \boldsymbol{\Phi})$. Given the reconstructed coefficients $\hat{\boldsymbol{\alpha}}$, the identification step in completed with the estimate of the fault combination $\tilde{\boldsymbol{x}}(\hat{\boldsymbol{\alpha}})$ through the MLP model. Then, the fault propagation is simulated, and the associated health states are evaluated through the SVM until the faulty response is achieved: the estimate of the $\tilde{\boldsymbol{s}}(x) = \tilde{t}_{RUL}(\tilde{\boldsymbol{x}}, \hat{\boldsymbol{\alpha}})$ completes the prediction step. This kind of application targets the identification of the particular combination of faults $\boldsymbol{x}$ affecting the onboard electromechanical actuation device of the secondary flight controls, and enable condition-based maintenance planning. Therefore, the goal is to actualize system self-awareness for the characterization of the specific damage that is causing a degradation of the overall vehicle capabilities. In this case, both the identification and the prediction steps have the same priority within the Sense-to-Plan flow, and the inference step cannot be skipped or bypassed. This type of frameworks is more traditional and allows to obtain predictions of the remaining useful life of the multi-physics EMA device in about $0.2 - 0.3s$ on a common laptop, as opposed to the hours that are required to solve the full order identification and prediction steps. More details about case-specific implementations and computational setups are discussed by Berri et al. (2018, 2019)

2.2.1 Bypassing damage inference to enable reconfigurable mission planning.

Figure 5 illustrates the computational framework we proposed for the real-time prediction of systems and vehicle (residual) capabilities to support the dynamic autonomous reconfiguration of the mission profile. We present the framework through the specific example of predicting the structural failure index $\boldsymbol{s}(\boldsymbol{x}) \in \mathbb{R}^{n_s}$ of a composite wing panels (capability) from acquired values $\boldsymbol{q}(\boldsymbol{x}) \in \mathbb{R}^{n_q}$ of strain components (measurements). Both measurements and capabilities are sensitive to the presence, location and extent of the damage $\boldsymbol{x} \in \mathbb{R}^{n_x}$ that degrades the structural properties of the panel. The replanning of the mission profile prioritizes the prediction of capabilities from sensor acquisition, while the full identification of the damage parameters is not essential. Therefore, we aim to compute an efficient and informative mapping from measurements to capabilities that exploits the opportunity to bypass the inference step.

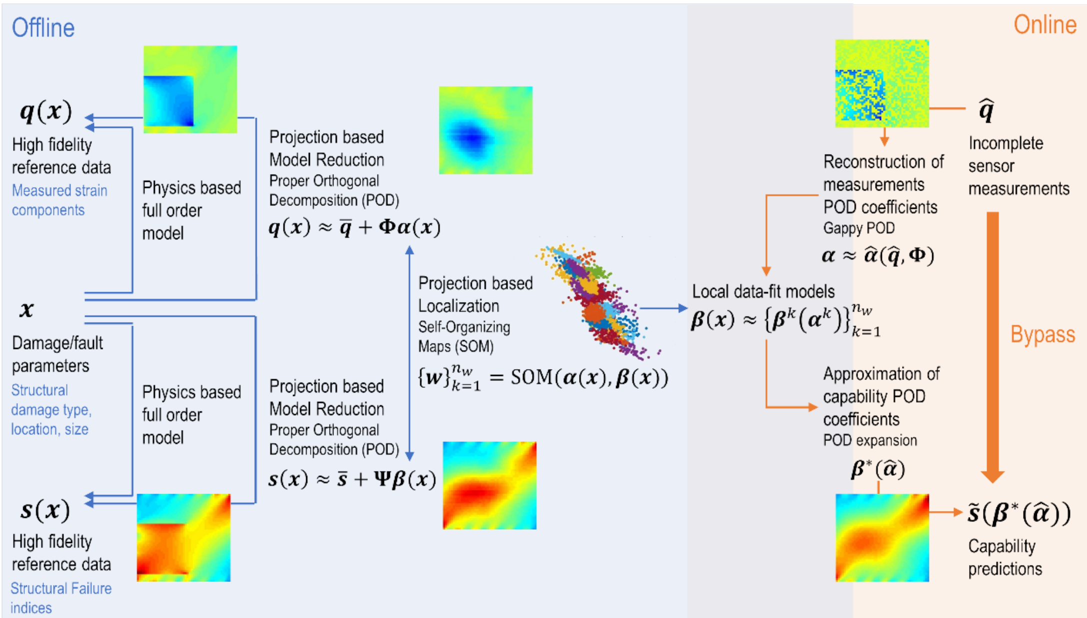

Figure 5: Computational framework for vehicle capability predictions from measured data to enable real-time mission reconfiguration as a form of proactive maintenance: the inference step is bypassed. The left-hand side (blue) illustrates the offline flow, the right-hand side (red) indicates the online flow: the models computed offline and used online are at the intersection.

Offline, full order physics-based models are used to obtain reference datasets of high dimensional snapshots ($n_q \sim 10^4, n_s \sim 10^4$) of the strain field $\boldsymbol{q}(\boldsymbol{x})$ and failure index field $\boldsymbol{s}(\boldsymbol{x})$ for a variety of combinations of damage conditions $\boldsymbol{x}$ by solving the forward problems through finite elements-based simulation. First, the reference datasets are used to learn reduced representations of the strain components and of the failure index in the form of POD expansions. The POD computes the set of basis vectors —$\boldsymbol{\Phi} = \{\varphi_i\}_{i=1}^{n_\varphi}$ for the measurements and $\boldsymbol{\Psi} = \{\psi_i\}_{i=1}^{n_\psi}$ for the capabilities— that constitutes physics-based parameterization of the fields $\boldsymbol{q}(\boldsymbol{x})$ and $\boldsymbol{s}(\boldsymbol{x})$, respectively (Swischuk et al., 2019). The POD coefficients $\boldsymbol{\alpha}(\boldsymbol{x})$ and $\boldsymbol{\beta}(\boldsymbol{x})$ express the relationship between the damage $\boldsymbol{x}$ and measurements and capabilities in the reduced space of the respective PODs, with major computational savings since $n_\varphi \ll n_q$ and $n_\psi \ll n_s$. Second, we seek an adaptive mapping from the reduced space of measurements $\boldsymbol{\alpha}$ to the reduced space of capabilities $\boldsymbol{\beta}$ through localization: we use unsupervised competitive learning (specifically Self Organizing Maps, SOMs) to identify $n_w \sim 10^1$ latent features $\{\boldsymbol{w}_k\}_{k=1}^{n_w}$ common to the two reduced spaces; then we compute n_w sets of local models $\boldsymbol{\beta}^k(\boldsymbol{\alpha}^k) = \{\beta_i^k(\boldsymbol{\alpha}^k)\}_{i=1}^{n_\psi}$ to characterize the subspace represented by each dominant feature $\boldsymbol{w}_k$.

Online, we compute reduced representations of measurements $\widehat{\boldsymbol{\alpha}}$ from compressed or sparse sensors acquisitions $\widehat{\boldsymbol{q}}$ via gappy POD. The reconstructed coefficients $\widehat{\boldsymbol{\alpha}}$ permit to associate the measured state with the most representative dominant feature $\boldsymbol{w}_*$, which elicits only the corresponding set of local models $\boldsymbol{\beta}^*(\widehat{\boldsymbol{\alpha}})$. De facto, the different sets of local models are dynamically activated to transfer/convey the information from the measurements space to the capability space through the common features exposed by the SOM. The POD expansion of the capabilities $\tilde{\boldsymbol{s}}(\boldsymbol{\beta}^*(\widehat{\boldsymbol{\alpha}}))$ completes the efficient prediction of what the system/vehicle can do, bypassing damage identification and characterization. This computational framework has been named *multistep reduced order modelling* (MultiStep-ROM) for the multiple projection steps introduced with the PODs and the SOMs (Mainini and Willcox, 2017); more recently, the formulation has been referred to as the *bypass approach* (Burrows and Allaire, 2019). This type of frameworks introduces a priority shift: from the characterization of the damage to the prediction of the capabilities. For our application, it allows to obtain predictions of the failure index of the wing panel in about $0.001s$ on a common laptop, as opposed to the hours required to solve the full order identification and prediction steps. More details about case-specific implementations and computational setups are discussed by Mainini and Willcox (2015, 2017)

3. CONCLUDING REMARKS

This document discusses the need for efficient artificial reasoning to support dynamic reconfigurable mission planning for the improvement of UAV readiness and reliability. Two frameworks are presented to actualize the form of system and vehicle self-awareness needed to support the planning task. The first framework relies on a more traditional approach: model reduction and supervised learning techniques are combined to both identify damage parameters and predict system capabilities. The second framework implements an original approach that combines projection-based model reduction and unsupervised machine learning into the MultiStep ROM bypass scheme, a form of domain aware transfer learning that computes adaptive models to map directly from measurements to capabilities.

Both the computational approaches target the sensitive acceleration of the Sense-to-Plan information flow by combining physics-based model reduction and data-driven learning schemes. However, a major speed up can be obtained through a priority shift that emphasizes the prediction of vehicle capabilities over the identification of damage/fault parameters. Indeed the first framework permits a reduction in computational time of about 3 orders of magnitude with respect to predictions based on full-order model evaluations, while the second framework allows savings of the order of 10^6 and more. Therefore, the bypass approach permits faster predictions which are better suited to the responsiveness requirements of dynamic reconfigurable mission planning tasks.

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