Mechanics-Aware Rotorcraft Controls: Towards Damage-Adaptive Rotorcraft Manoeuvre Design

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ABSTRACT

Rotorcraft experience continuous cyclic loading during flight that can degrade critical components over repeated missions. While new structural and aerodynamic designs can be implemented to reduce vibratory loads or stress cycles, lifetime extension for currently operational aircraft can be obtained through intelligent design of the manoeuvres undertaken during flight. This research discusses a methodology for designing rotorcraft flight such that the stress (or damage growth or vibratory load) in a critical mechanical component is minimized while satisfying the operational constraints. To this end, a digital twin of a rotorcraft is proposed to be built and updated with data obtained during operation. The digital twin framework seeks to duplicate the real-world system in a virtual environment by not only representing the physics of the system accurately but also by tracking the degradation and usage of the system throughout its operational history and updating the virtual model accordingly. A comprehensive rotorcraft analysis program (RCAS), a stress analysis (finite element) software as well as rotorcraft sensor data are used to build and update the digital twin. The digital twin thus enables the computation of rotorcraft component stresses (or damage or vibratory loads) given the pilot control inputs. Finally, optimization of the mission flight plan is performed to minimize damage, stress, or vibratory loads. Mechanics-aware flight optimization will allow for extension of a rotorcraft's operation and the development of manoeuvres that minimize stress exerted on the component of interest. The proposed methodology is demonstrated by performing simulation experiments.

1.0 INTRODUCTION

The complexity of the battlefield environment imposes a high requirement on the reliability, robustness and resilience of the deployed engineering systems. Significant advancements have been made in recent decades in areas of computational science and probabilistic engineering design to address the uncertainty in the design and operation of vehicle structural components. However, the current design and operational risk management frameworks need to be substantially enhanced to tackle new opportunities introduced by structural health monitoring, machine learning, predictive analytics, optimization techniques, and computational technology.

Modern engineering systems often work in dynamic environments with variability in loads, operational requirements, and environmental conditions. Additionally, they need to cope with degradation and failures of the physical components due to aging, operational stress, and environmental conditions. Current methods for structural risk management focus primarily on crack initiation and propagation; however, cracking only accounts for about the last 20% of the service life. Instead of directly detecting the damage, it is possible to detect damage precursors (such as material states) through continuous monitoring of the system performance variables, anomaly detection, and Bayesian inference. During extended battlefield engagements, there is need for vehicles and equipment to operate for long periods of time without the opportunity for maintenance or repair. Strategies for extending the maintenance-free operation window become important, thus increasing the resilience of the vehicle system or components. These may include reconfiguration of the system, such as changing the manoeuvre of the vehicle to reduce or redistribute the stress and thus slowing down the damage progression. The optimum choice of strategy depends both on the health state and its diagnosis, such as before damage initiation, after damage initiation but below the detection threshold, or after detection.

Ongoing research by the authors is investigating a new risk management paradigm for achieving robust and resilient systems, through the integration of three ideas: information fusion, probabilistic diagnosis and prognosis, and system control and reconfiguration. The digital twin paradigm is well-suited for performing information fusion from heterogeneous sources such as sensor data, physical equations, and inspection information. A digital twin is regularly updated using diagnostic information to accurately represent the behaviour of its real-world counterpart. The system control can be applied to the digital twin to promote optimal flight to reduce the probability of failure. Therefore, this work builds a digital twin of the system of interest (a rotorcraft) to design mechanics-aware rotorcraft controls.

The digital twin for the rotorcraft needs to handle three important tasks: probabilistic diagnosis, probabilistic prognosis, and optimization under uncertainty. Probabilistic diagnosis is concerned with evaluating the current state (stress state, state of degradation etc.) of the system or the component of interest. Diagnostic (physics-based or data-driven) models and sensor data are used for performing diagnosis and quantifying the diagnosis uncertainty. Probabilistic prognosis is concerned with estimating future states of the system given the current state and candidate operational regimes. A composition of system models and diagnosis estimates (along with the diagnosis uncertainty) are used to perform probabilistic prognosis. In the case of a rotorcraft, these may include a comprehensive rotorcraft analysis model (to estimate component loads given pilot control inputs), a stress analysis model (to estimate component stresses, or damage, given component loads), etc. Finally, an optimization algorithm is employed to arrive at the operational regime that maximizes the chosen system performance metric, while considering the uncertainty in diagnosis and prognosis. The digital twin methodology for designing mechanics-aware rotorcraft controls is discussed in the following sections.

2.0 METHODOLOGY

The overall goal of the methodology is to create a method for operating the mechanical system of interest (a rotorcraft) while satisfying a predefined performance metric (minimization of maintenance cost, or system degradation, etc.). In rotorcraft operation, safe usage is always a primary goal but in the presence of damage, the health (state) of the system deteriorates over time. Any method that seeks to operate a system in the presence of damage or degradation will need to be aware of the damage or degradation mechanics for the system and its critical components. This mechanics-aware approach provides a path to decision making that is cognizant of the current or recent state of the system and the potential future states of the system. The diagnostic information as well as prognostic models contain aleatory and epistemic uncertainty that needs to be adequately handled in the optimization. The fusion of heterogeneous information from sensors, models, and other sources as well as rigorous treatment of the uncertainty are thus key requirements from an intelligent operation design framework.

Information fusion can be leveraged for effective system health management, which extends classical damage tolerance techniques by applying sensing, diagnosis, and prognosis. The health monitoring model is constructed from heterogeneous sources of data and models of components and component assemblies that explicitly and implicitly define the interfaces and interactions. The model can be used to infer the evolution of structure and material states based on monitored quantities. Then, the model can be used to predict the damage propagation across the assembly of components, which can be used for prognosis of the overall system health and capability. The model can be further extended to health management actions, by including mitigation of damage effect during operation and offline maintenance.

A promising approach to realize a health monitoring and management model while accounting for aleatory and epistemic uncertainty is to use a Bayesian network (BN). A Bayesian network is a directed acyclic graph representation of conditional dependencies between the stochastic system variables. Engineering systems are often hierarchical (multi-level) and dynamic (time-dependent processes), so a Dynamic Hierarchical Bayesian Network (DHBN) approach is best to aggregate the uncertainty across multiple levels of the system hierarchy and over time.

The required information fusion as well as uncertainty analysis can be performed effectively by building a digital twin of the system as discussed in the next section.

2.1 The Digital Twin Paradigm

A digital twin is an integrated multi-physics, multi-scale, probabilistic simulation of an as-built vehicle or system that uses the best available physical models, sensor updates, fleet history, etc., to mirror the life of its corresponding flying twin (Glaessgen and Stargel, 2012). Digital twin enables decision making with up-to-date information learned from sensor data obtained from the physical. The digital twins have previously been investigated for manufacturing, intelligent system maintenance, and asset sustainment (Lee, Bagheri and Kao, 2015; Li, et al, 2017; Söderberg, et al, 2017). Here, we utilize the digital twin of a rotorcraft to perform intelligent rotorcraft control design that ensures satisfaction of a component stress or degradation metric. The digital twin approach inherently requires the fusion of probabilistic information which allows for the treatment of aleatory and epistemic uncertainty in the system and data in the diagnosis and prognosis.

System diagnosis is an inverse problem, which is typically resolved using data-driven, physics-based, or hybrid system models. The forward prediction model (either mechanistic or empirical) predicts a response quantity sensitive to the change of system state (e.g., damage growth) to a known excitation. The inverse problem aims to detect/localize/quantify the system change, using the model of choice, and the measured, system response (data). The key sources of uncertainty in diagnosis thus include variability of inputs and parameters used in the model, noisy and erroneous data from faulty or damaged sensors, as well as the epistemic uncertainty in the forward prediction model.

System prognosis is a forward problem. Models of different level of fidelity could be built to estimate system behaviour in different operating regimes. These models involve inputs and parameters that are uncertain due to natural variability; experimentally obtained parameters that suffer from data uncertainty; and model errors. Thus, the sources of uncertainty that need to be considered for probabilistic system prognosis are: a) diagnosis uncertainty, b) natural variability in prognosis model inputs (loads, etc.) and parameters, c) epistemic uncertainty in prognosis model parameters calibrated using experimental data, and d) epistemic uncertainty due to model errors (model form error, numerical discretization error, surrogate model error, etc.). The workflow of constructing the digital twin can be seen in Figure 1 (Karve, et al, 2020).

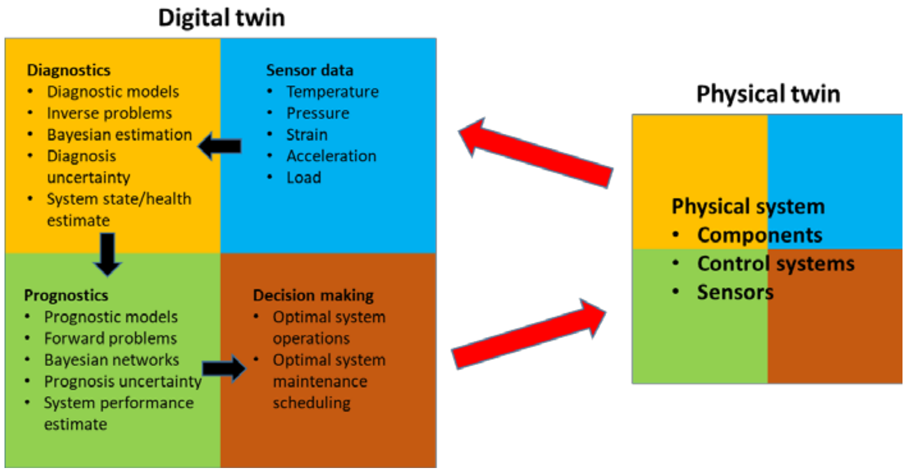

Figure 1: Digital twin workflow

If an estimate of the current system state (probabilistic system diagnosis) and possible system states for candidate system operational regimes (probabilistic system prognosis) are available, then intelligent system operations that satisfy a given system performance metric could be designed by solving a stochastic optimization problem. Various algorithms, such as robustness-based optimization or reliability-based design optimization, are available to perform system optimization under uncertainty. A judicious decision regarding the choice of optimization algorithm could be made by considering the computational complexity, computational resource, and time available for the specific problem of interest.

2.2 Digital Twin for Mechanics-Aware Rotorcraft Control

The digital twin approach is applied to a five-blade rotorcraft flying multiple missions (Figure 2). The rotorcraft mast is assumed to be damaged from corrosion induced reduction in cross-sectional area. A degradation growth rate is assumed, and used in synthetic experiments. Probabilistic diagnosis is performed using strain sensor installed on the outer surface of the mast, and a Gaussian process surrogate model built using stress analysis data for the mast with variable cross-sectional area. The reduction in the cross-sectional area due to degradation is tracked through Bayesian calibration using data from a sensor present on the mast. Probabilistic prognosis is performed using multiple system models. The flight dynamics and loading of the helicopter are modelled using a program called Rotorcraft Comprehensive Analysis System (RCAS). A finite element structural and aerodynamic model is created in RCAS and the appropriate equations of motion are considered to model the rotorcraft state given a control input history. The corresponding loading and kinematic (position, orientation, velocity, etc.) histories are recorded. The loads are applied to a finite element model of the mast (Figure 2). The digital twin is thus composed by fusion of data from the RCAS rotorcraft dynamics model, the mast's finite element stress analysis model, the diagnostic stress-strain finite element model, and strain data from the strain gage.

Once the digital twin is built, the system control and reconfiguration process can be undertaken. A simplified problem is considered, where system controls are replaced by horizontal and vertical speed of the rotorcraft. That is, instead of searching in the space of rotorcraft controls, a search is made in the space of rotorcraft velocities. Note that this setting may be more suitable from a practical standpoint, where specifying rotorcraft velocities may be easier to implement. The system control optimization problem thus involves finding rotorcraft velocities that minimize the stress experienced by the mast (Sisson, Karve and Mahadevan, 2021). The optimization problem can be suitably modified accomplish other objectives of interest. The mission profile can seek to minimize vibratory load to increase pilot stability or to minimize the damage growth in a critical component. This framework could also include a multi-objective case where both damage growth as well as vibration minimization are included in the objective function.

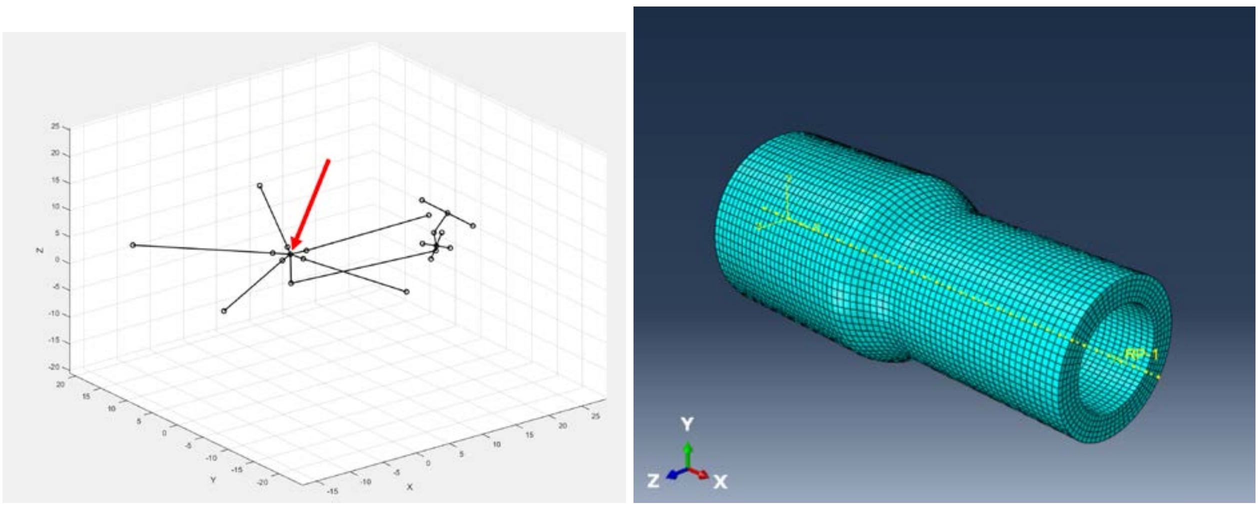

Figure 2: (Left) Structural model for rotorcraft system with arrow pointing to mast node, (Right) Finite Element Analysis model of the rotorcraft mast

3.0 CONCLUSION

The current work outlines the development of a digital twin for mechanics-aware rotorcraft control. The proposed framework includes probabilistic system diagnosis and prognosis using the digital twin, and the optimal stochastic system control. Past work has demonstrated the optimal flight of a five-blade helicopter, however the possible manoeuvres undertaken by the helicopter were restricted to constant velocity flight. The inclusion of more complicated manoeuvres is being undertaken, and can theoretically be merged into the existing framework without significant modification to the overall methodology.

4.0 FUTURE AND ONGOING WORK

Research aimed at building a virtual pilot to obtain control histories given a desired rotorcraft trajectory using reinforcement learning techniques is currently being undertaken. This will enable consideration of complex and realistic rotorcraft flight paths, as opposed to simplified rotorcraft flights considered in previous work (Sisson, Karve and Mahadevan, 2021). If a path between a beginning and end point are specified, the digital twin will need to follow that path so that the corresponding loading can be calculated. By using reinforcement learning, adherence to the path is rewarded and the component loads can be obtained. The reinforcement learning algorithm needs to be aware of the physics (flight dynamics) of the problem, hence a surrogate model of RCAS is built using a Deep Neural Network (DNN) where the pilot controls and the current states are inputs and the future states are outputs.

This model is trained using simulation data obtained from a sweep of inputs in RCAS that elicit the non-linear state response. The resulting flight dynamics model is used by the agent in the reinforcement learning loop to predict the next state and fly the helicopter along a specified path. Then the previously mentioned optimization framework will be modified to choose an optimal path, where optimality is defined in terms of minimization of the damage or stress on the critical rotorcraft component.

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