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Dynamic Data Driven Methods for Self-aware Aerospace Vechicles

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Dynamic Data Driven Methods for Self-aware Aerospace Vehicles
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Final Report

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Abstract

This project has developed mathematical and computational foundations of Dynamic Data Driven Application Systems (DDDAS) methods that combine physics-based and data-driven perspectives. The research has been motivated by and demonstrated in the particular context of structural health management for a self-aware unmanned aerial vehicle (UAV); however, the developed methods and approaches are broadly applicable across DDDAS applications.

Significant outcomes of the project include a new methodology for creating a Predictive Digital Twin, using component-based reduced modeling and interpretable machine learning. The Digital Twin is built from a library of component-based reduced-order models that are derived from high-fidelity finite element simulations of the vehicle in a range of pristine and damaged states. In contrast with traditional monolithic techniques for model reduction, the component-based approach scales efficiently to large complex systems, and provides a flexible and expressive framework for rapid model adaptation—both critical features in the digital twin context. The project demonstrated a Digital Twin use case for rapid structural health assessment and dynamic mission re-planning. Another significant outcome is a new suite of approaches for managing sensors and sensing strategies, including detection and correction of sensor errors, multiple information source fusion, and optimization of sensor locations to support real-time operational decision. Finally, the project achieved design and construction of a flight test vehicle that serves as a DDDAS testbed.

The contributions are built on a range of mathematical and computational technologies, including reduced-order modeling, multifidelity modeling, uncertainty quantification, dynamic model adaptation, optimization, physics-based structural modeling, and machine learning. As well as the application-oriented project outcomes described above, the project has made contributions that serve to advance foundational theory and methods in these underlying areas.

The project has trained three PhD students, five Master's students, one undergraduate researcher, and three postdoctoral researchers. These students and researchers now hold positions at various academic and industrial institutions.

Contents

1 Project Objectives

The specific research objectives of this research were proposed as:

1. to systematically relate component-model fidelity to vehicle-level performance estimation, and to accordingly enrich our collection of multifidelity models through the development of physics-based models of composite damage;

2. to develop DDDAS methods that guide construction of an offline damage library given mission information, storage limits, data retrieval capability, and sensing capability;

3. to develop DDDAS methods to exploit online sensor information for decision-making and for model adaptation, explicitly considering the opportunities associated with multiple modalities of sensor data; and

4. to develop design methods for DDDAS-enabled self-aware aircraft.

The project has accomplished these objectives and has also gone beyond in laying the mathematical and computational foundations for creating a Predictive Digital Twin using DDDAS concepts. The remainder of this report summarizes the main project outcomes and accomplishments.

2 Main Accomplishments

The most significant accomplishments of the project are:

- Methodology for creating a Predictive Digital Twin, using component-based reduced modeling and interpretable machine learning.

- Demonstration of a Digital Twin use case for rapid structural health assessment and dynamic mission re-planning.

- Approaches for managing sensors and sensing strategies, including detection and correction of sensor errors, multiple information source fusion, and optimization of sensor locations to support real-time operational decisions.

- Design and construction of a flight test vehicle that serves as a DDDAS testbed.

3 Research Contributions

The major research contributions include

- Developed a scalable approach to building and rapidly updating a Digital Twin using a library of component-based reduced models [3].

- Created a data-to-decisions framework using a Predictive Digital Twin to assist real-time decisions associated with structural monitoring and informed by incomplete, noisy measurements. The methodology relies on an offline-online decomposition of tasks, and combines reduced-order modeling and machine learning [3].

- Developed a machine learning approach for detecting and correcting sensor errors via knowledge inferred from available, heterogeneous, sensing capabilities in flight [6].

- Developed a conjunctive filter for aircraft capability estimation that fuses information from multiple maneuvers to improve confidence in capability estimates [2].
- Developed an efficient and accurate filtering algorithm for online capability estimation that uses offline high fidelity modeling to enable online independence from forward model evaluations [1].
- Developed a mathematical foundation for Digital Thread in the context of iterative design [5].
- Developed a data-driven design methodology that uses Digital Thread and considers an iterative design process using data that are not available all at once, conducts uncertainty quantification through Bayesian filtering, and performs multistage decision making for iterative design setups [5].
- Developed a computational strategy to determine optimal sets of sensor locations to support real-time operational decisions [4]. We exploit unsupervised learning strategies (specifically self-organizing maps) to identify the most informative locations to place sensors.

We highlight some of these accomplishments in more detail in the following sections.

4 Research Highlights

4.1 Toward predictive digital twins via component-based reduced-order models and interpretable machine learning

We have developed a methodology for creating and updating data-driven physics-based digital twins, and demonstrated the approach through the development of a structural Predictive Digital Twin for a 12ft wingspan unmanned aerial vehicle. The Digital Twin is built from a library of component-based reduced-order models that are derived from high-fidelity finite element simulations of the vehicle in a range of pristine and damaged states. In contrast with traditional monolithic techniques for model reduction, the component-based approach scales efficiently to large complex systems, and provides a flexible and expressive framework for rapid model adaptation—both critical features in the digital twin context. The Digital Twin is deployed and updated using interpretable machine learning. Specifically, we use optimal classification trees (OCTs)—a recently developed scalable machine learning method—to train an interpretable data-driven classifier. In operation, the classifier takes as input vehicle sensor data, and then infers which physics-based reduced models in the model library are the best candidates to compose an updated Digital Twin. In our example use case, the data-driven Digital Twin enables the aircraft to dynamically replan a safe mission in response to structural damage or degradation. This work is described in the AIAA Scitech paper [3].

As an illustration of the methodology, we simulate a UAV path consisting of three obstacles and spanning 100 timesteps. To evaluate the UAV's decision-making ability, we simulate a linear reduction in stiffness in each of the damage regions from 0% to 80% over the 100 timesteps. At each timestep the UAV obtains noisy strain measurements from each of the 24 strain gauges. These measurements are used as inputs in the OCTs for estimating damage parameters. The resulting damage estimates are used to rapidly update the physics-based Digital Twin, which in turn provides dynamic capability updates and informs the UAV's decision about which flight path to take. The results of this simulation are summarized in Fig. 1, which shows snapshots at three different timesteps.[1]

[1] A video of the full simulation is available online at kiwi.oden.utexas.edu/research/digital-twin.

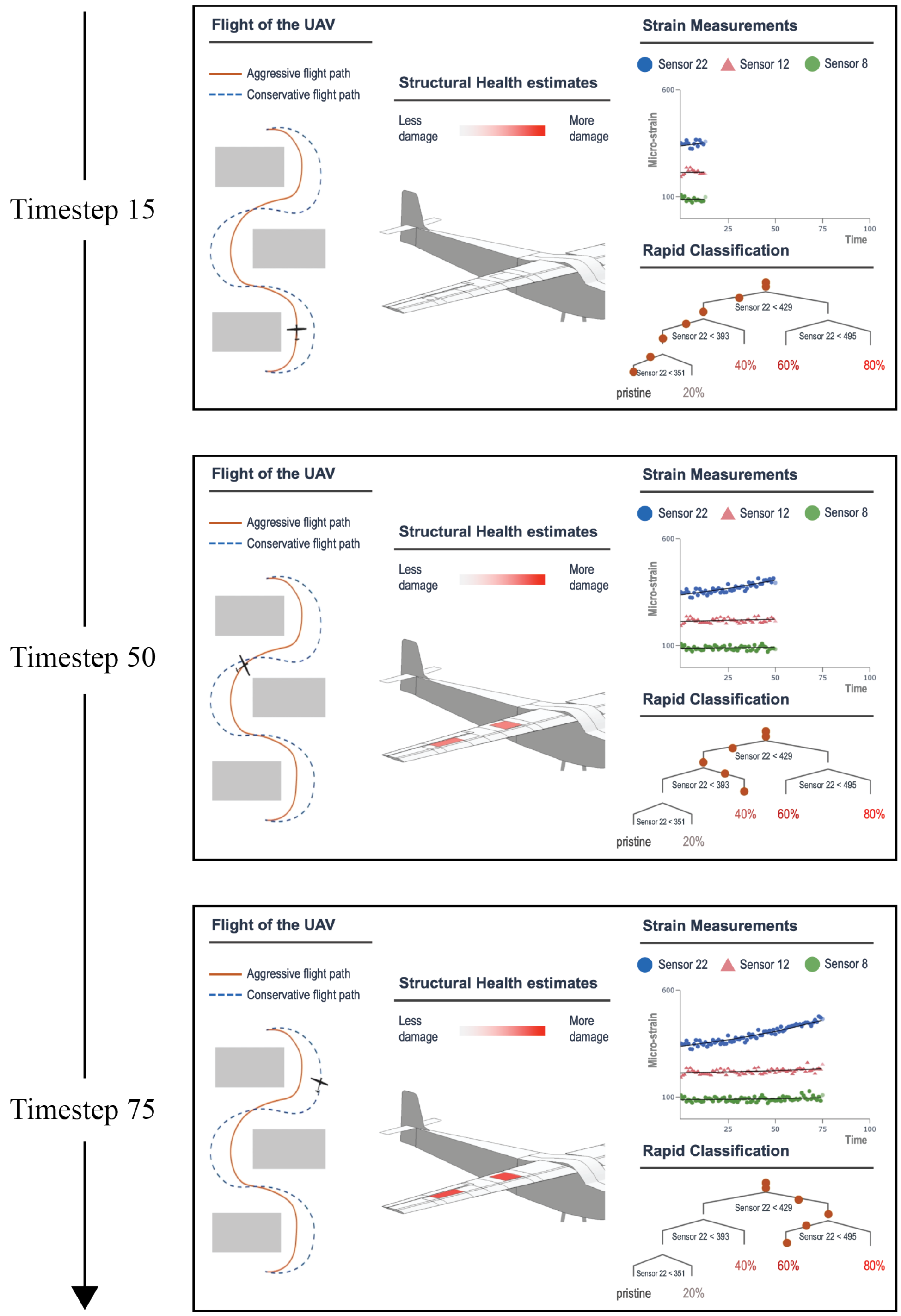

Figure 1: Snapshots of the simulated UAV mission. Left: the UAV, obstacles, and possible flight paths. Center: UAV structural health estimates as provided by the Digital Twin. Right: Noisy load-normalized strain measurements (showing three of the 24 strain gauges) and the classification tree being used to classify the damage state of the UAV (showing here the OCT for damage parameter μ_1). The first snapshot shows the UAV beginning in pristine condition and flying the aggressive flight path. In the second snapshot the digital twin estimates that the damage has progressed to 40% in each damage region. At this point the UAV dynamically replans the mission, deciding to take the more conservative flight path in order to avoid structural failure. The final snapshot shows the UAV taking this conservative flight path around the third obstacle.

4.2 Engineering Design with Digital Thread

Digital Thread is a data-driven architecture that links together information generated from across the product lifecycle. Though Digital Thread is gaining traction as a digital communication framework to streamline design, manufacturing, and operational processes in order to more efficiently design, build and maintain engineering products, a principled mathematical formulation describing the manner in which Digital Thread can be used for critical design decisions remains absent. The contribution of this work is to establish such a formulation from the context of a data-driven design and decision problem under uncertainty. This formulation accounts for the fact that the design process is highly iterative and not all information is available at once. Output design decisions are made not only on what data to collect but also on the costs and benefits involved in experimentation and sensor instrumentation to collect that data. The mathematical formulation is illustrated through an example design of a structural fiber-steered composite component. In this example, the methodology highlights how different sequencing of small-scale experimentation with manufacturing and deployment lead to different designs and different associated costs. This work is described in the *AIAA Journal* paper [5].

4.3 Nonlinear Kalman Filtering without Forward Model Cost

Monitoring the evolution of damage on composite wing panels is essential is to online capability awareness for unmanned aerial vehicles. This problem is challenging for two major reasons: accurate forward models of aero-structures can take the form of expensive finite element based fluid structure interaction codes and damage evolution modeling is challenging and uncertain for complicated composite layups and structures. To handle these challenges, we have developed a novel Kalman filtering algorithm for nonlinear systems that is independent of forward model cost. This is achieved by adapting a recent Monte Carlo integration technique based on optimal importance weights to solve the Kalman filtering equations. Our approach outperforms both the extended Kalman filter and the unscented Kalman filter in both efficiency and accuracy on a 4D structural health monitoring problem. This work is described in the *ASME Journal of Dynamic Systems, Measurement and Control* paper [1].

4.4 Online Sensor Error Detection and Correction

Sensors are crucial to self aware systems. However, the location of these sensors can often make them vulnerable to outside interferences and failures, and the use of sensors over a lifetime can cause degradation and lead to failure. If a system has access to redundant sensor output, it can be trained to autonomously recognize errors in faulty sensors and learn to correct them. We have developed a novel data-driven approach to detect sensor failures and predict the corrected sensor data using machine learning methods in an offline/online paradigm. Autocorrelation is shown to provide a global feature of failure data capable of accurately classifying the state of a sensor to determine if a failure is occurring. Feature selection of the redundant sensor data in combination with k-nearest neighbors regression is used to predict the corrected sensor data rapidly, while the system is operational. We demonstrate our methodology on flight data that contains failures in the pitot static system resulting in inaccurate airspeed measurements. Our approach is able to significantly improve airspeed estimates throughout the flight envelope. This work is described in the *ASME Journal of Computing and Information Science in Engineering* paper [6].

4.5 Information Gathering Maneuvering and the Conjunctive Filter

Self-aware vehicles have the potential to perform certain maneuvers for the purposes of information gathering. Information learned can then be used to update capability estimates. This concept can be extended to that of optimal information gathering, where a vehicle identifies most informative maneuvers with regards to specific quantities of interest. We have developed a data-driven approach to producing rapid, online estimates of aircraft capability using multiple maneuvers for information gathering. The process involves using physics-based models to produce an offline library of various damage states and associated capabilities. This association can be performed in-flight by an online Bayesian classification process, using single maneuver sensor readings to predict capability. Because of sensor noise, misclassifications can occur. The ability to estimate capability for multiple maneuver types enables the performance of sequential information-gathering maneuvers, often resulting in more accurate, less uncertain estimates through information fusion. Information gained by performing sequential information-gathering maneuvers can be fused using standard Bayesian fusion techniques, as well as a novel conjunctive fusion method that was also developed in this work. Our conjunctive filter is shown to perform with a lower mean squared error than the Bayesian fusion technique and the single-maneuver classification with no fusion step. Our methodology and demonstrations have been developed in the context of a medium altitude, long-endurance unmanned aerial vehicle. This work is described in the *AIAA Journal of Aerospace Information Systems* paper [2].

5 Design, Construction and Testing of a DDDAS Testbed Vehicle

Aurora Flight Sciences successfully designed, manufactured, integrated, and tested a testbed aircraft system meant to serve as a surrogate for the low-cost attritable aircraft (LCAA) class of configurations currently being developed within the government. This testbed aircraft system is capable of conducting flight tests and collecting data—both flight performance data and distributed strain data—on multiple wings in a single flight test due to a simplified wing-fuselage joint and generalized flight avionics hardware. Over the course of the program, Aurora demonstrated the testbed aircraft's capabilities by designing and manufacturing a set of custom carbon wings, outfitted with I/O expanders and distributed strain gauges on the top skin of the right wing and logged in flight via a custom developed sensor board. These wings were integrated with the overall vehicle system and flight tested to validate full system functionality and collect an initial set of in-flight strain gauge data. The onboard avionics systems—flight control and wing-sensor—were synchronized and overlaid, which allowed a mapping of distributed strain readings to vehicle flight state (and thus maneuvers). While the full capability of the testbed platform was not realized over the course of this program, the development of a fully functional aircraft system serves as a key enabler towards validating and verifying the DDDAS approach for a self-aware aircraft system. Now that the platform exists and has been verified as fully functional in flight and appropriate for the needs of data collection and flight test verification, future work will be able to leverage the system for further advancing the DDDAS paradigm in self-awareness of aircraft structures. In particular, the manufacture of multiple sets of intentionally damaged wings would enable the collection of data for a progressively damaged wing in-flight, from which the flight data could be used to further enhance the offline damage library for use in the online DDDAS algorithms. Ultimately, it is envisioned that the DDDAS algorithms would be implemented on the flight hardware, to begin testing the objectives of the structurally self-aware vehicle in a real-time flight environment.

The remainder of this section provides detail on the testbed system, the testbed aircraft design and methodology, and the testing procedures and results.

5.1 Attritable UAV Problem Motivation

Aurora envisions a number of crucial and relevant technologies stemming from the DDDAS algorithms being developed under this program – both the offline/online reduced modeling approach for real-time decision making and the overall concept of a self-aware vehicle, in general – as they specifically relate to UAVs, especially given the potential tie-ins with a number of Air Force efforts that are building considerable momentum at AFRL and within the Air Force community at large. Namely, Aurora has been involved in several early stage programs for the Low-Cost Attritable Aircraft Technology (LCAAT) where a design space exploration and development planning with AFRL were performed; this work highlighted the importance of dynamic, real-time decision making – specifically as it relates to the health of aircraft subsystems – for these UAVs given the likelihood of reduced reliability requirements. AFRL has stated that two key metrics for the LCAAT vehicles are flexibility and increased risk tolerance, both of which are more fully enabled with the self-aware vehicle technology being developed under this DDDAS program. Furthermore, these LCAAT systems will likely be operating in contested environments, so the idea of dynamic mission re-planning to maximize vehicle survivability will necessarily reduce total system cost per system capability, the primary metric being used to develop these systems.

Figure 1: The Aurora LCAAT/Loyal Wingman concept. LCAAT vehicles must operate autonomously in complex environments and are designed for a cost per capability metric, thereby requiring the reduction of subsystem reliabilities. Vehicle self-awareness therefore will play a key role in the mission performance of these systems.

Similarly, the self-aware vehicle concept – specifically the dynamic mission re-planning aspects of our program – aligns very well with AFRL's Loyal Wingman program, wherein a UAV will be demonstrated to operate autonomously as it accompanies an exquisite manned aircraft and therefore must respond to changing operational or environmental conditions in a manner consistent with mission-planned contracts. Clearly, a self-aware vehicle is a critical component to the human-machine teaming framework to meet these program objectives for both dynamic re-planning in a wingman configuration and to aid in reasoning for unplanned events.

5.2 Testbed System

While the design and manufacture of a full-scale LCAAT system was beyond the scope of this program, a surrogate testbed aircraft system was designed and manufactured to begin working through the integration challenges presented by the self-aware vehicle technology. Furthermore, the hardware designed, manufactured, and integrated during the course of the program would enable full systems level testing – both in the laboratory and in flight – in order to verify the integration approach, collect real data to supplement simulated results for algorithm development and calibration, and encode the DDDAS algorithms into the flight hardware for verification and validation of the overall approach. Thus, even at a reduced scale and with a diminished flight envelope, a testbed aircraft system provided a necessary step in truly developing and testing the DDDAS algorithms to enable a structurally self-aware aircraft.

The testbed aircraft system designed, integrated, and tested during the course of the program consisted of a giant Telemaster aircraft kit (fuselage, landing gear, empennage), but outfitted with custom-designed and manufactured carbon fiber wings containing distributed strain gauges and custom avionics (Pixhawk autopilot, custom-built sensor boards, off-the-shelf power hardware). Moreover, the fuselage-wing joint consisted of a metal tube fitting so that different wings could be swapped onto the aircraft with minimal effort and in a rapid succession, such that multiple wings could be tested within a single flight test session.

It was envisioned that this capability would enable several wings – from a pristine 'baseline' wing configuration through progressively more damaged wings – to be tested over the course of a single flight test, so that the same flight conditions and the same platform could be used to both collect sensor data and to test the DDDAS algorithms in real flight conditions.

Figure 2. A giant Telemaster RC aircraft system was chosen as the basis around which the testbed aircraft was developed. This aircraft system provided a large enough wing planform to house the required sensors and avionics and enabled custom wings to be easily swapped out within the same flight test.

5.2.1 Testbed Aircraft Design and Methodology

Wing Structure Design

The driving requirement on the design of the testbed aircraft system was that the wing provide a structurally-similar response to a larger, more advanced LCAAT wing structure. Thus, even at the smaller scale, the preferred structural design of the wing used techniques similar to that of the larger, production-worthy LCAAT wing (albeit with reduced flight performance).

In particular, the following criteria were established

- Hollow carbon construction. Male and female plug required.
- Each "complete" wing will be 12ft in span divided in two halves (each half will be 6ft in length)
- Each wing half will consist of an aileron and flap (aileron will be top hinged, flap will be bottom hinged). Hinging material will be Kevlar and each control surface should be able to deflect +/-45-degrees for the aileron and ~60-degrees for the flap.

- Carbon fiber, C-channel spar
- Carbon skin ply count determined from finite element sizing analysis. The total weight of the aircraft should be around 35 lbs (to comply with Part 107 regulations) and should be able to handle 4Gs.
- Control horns will be fabricated internally. However, the wing structure will need two slots per servo (we are going to sandwich a ball-link between each control horn). With that said, we will need the slots to be made into the control surface (slots on bottom of the wing up to the underside of the top surface after the layup). Hard points will be required for each control horn.
- The wing will consist of a single aileron servo per aileron and a single flap servo per flap surface. Servo bays and the appropriate channels to route the extensions should be made. Servo wire left in each channel to solder the servo directly.
- Wing tip/root rib made of plywood. The root rib will consist of two (2) 1/4x20 T-Nuts within the root rib so we can secure the wing to the fuselage internally.
- The inner and outer wing portion will have a hardpoint along the wing tube that should be threaded and will use a 6-32 bolt, or similar, to attach the wing halves together (to the wing tube).
- For the main phenolic, we will have a rib made of 1/8" basswood. This rib acts as a stopper for the carbon tube once it is inserted into the wing.

Figure 5 and Figure 4 show the dimensioned drawings – both a top view and a cross section view – of the testbed wing. The six-foot half-span wing was designed to have a zero-sweep line at the rear spar with a moderate taper ratio, to mimic a long-endurance type LCAAT configuration's wing (though the LCAAT wing would likely have increased sweep to account for sprint requirements). The wing uses a constant 9% thick airfoil section representative of typical profiles at the mid-subsonic speed range (NACA 2309). The wing structure is split into 4 bays, as shown in the drawings, where the boundaries of each bay are designated by plywood ribs. A split flaperon (carbon laid up over a foam core) is located in the outer two bays.

The wing spar was sized for a maximum tip deflection in a 4G pull-up maneuver. The spar structure is a C-channel with a constant 1" wide cap consisting of 8 plies of 5.8 oz carbon weave and a 3-ply web of the same material. The wing skins were sized for buckling in a 4G pull-up maneuver. The first rib bay top skin was sized to 4 plies of 5.8 oz carbon weave, while all other skins were sized to 3 plies of the same material, all placed in the 0 orientation. Finally, the wing was designed to have access panels on the bottom skin so that any sensors, wiring, or other flight hardware could be placed or modified after the wing constructed and assembled. Figure 3 shows the internal wing structure during assembly.

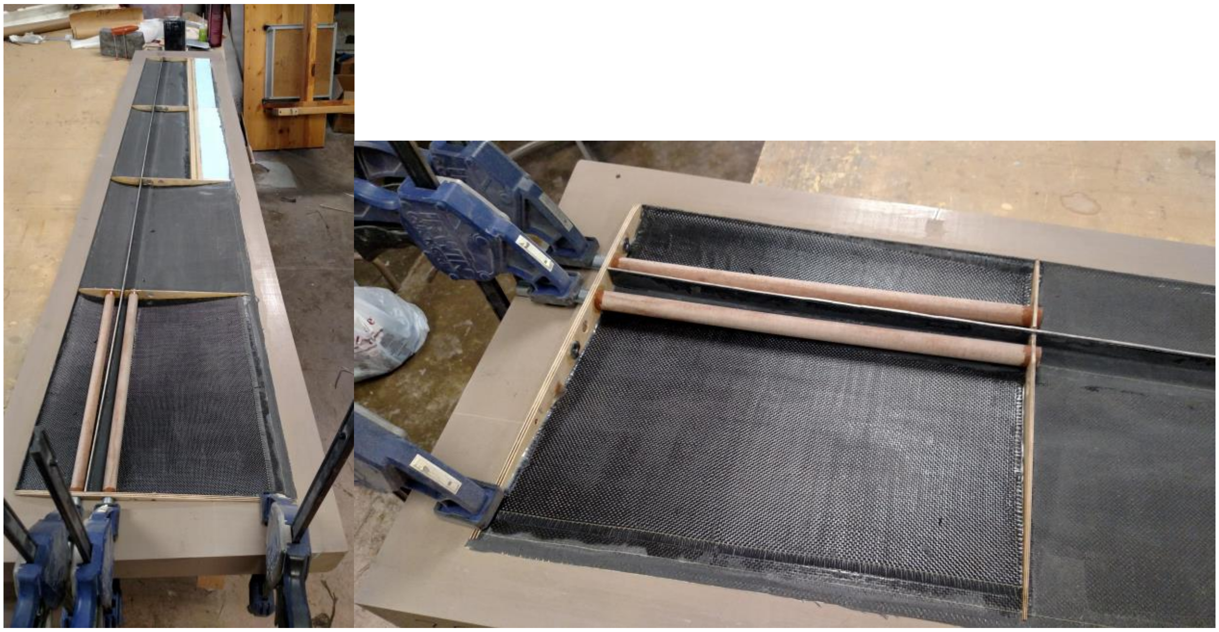

Figure 3. Internal structure of the DDDAS wing during assembly.

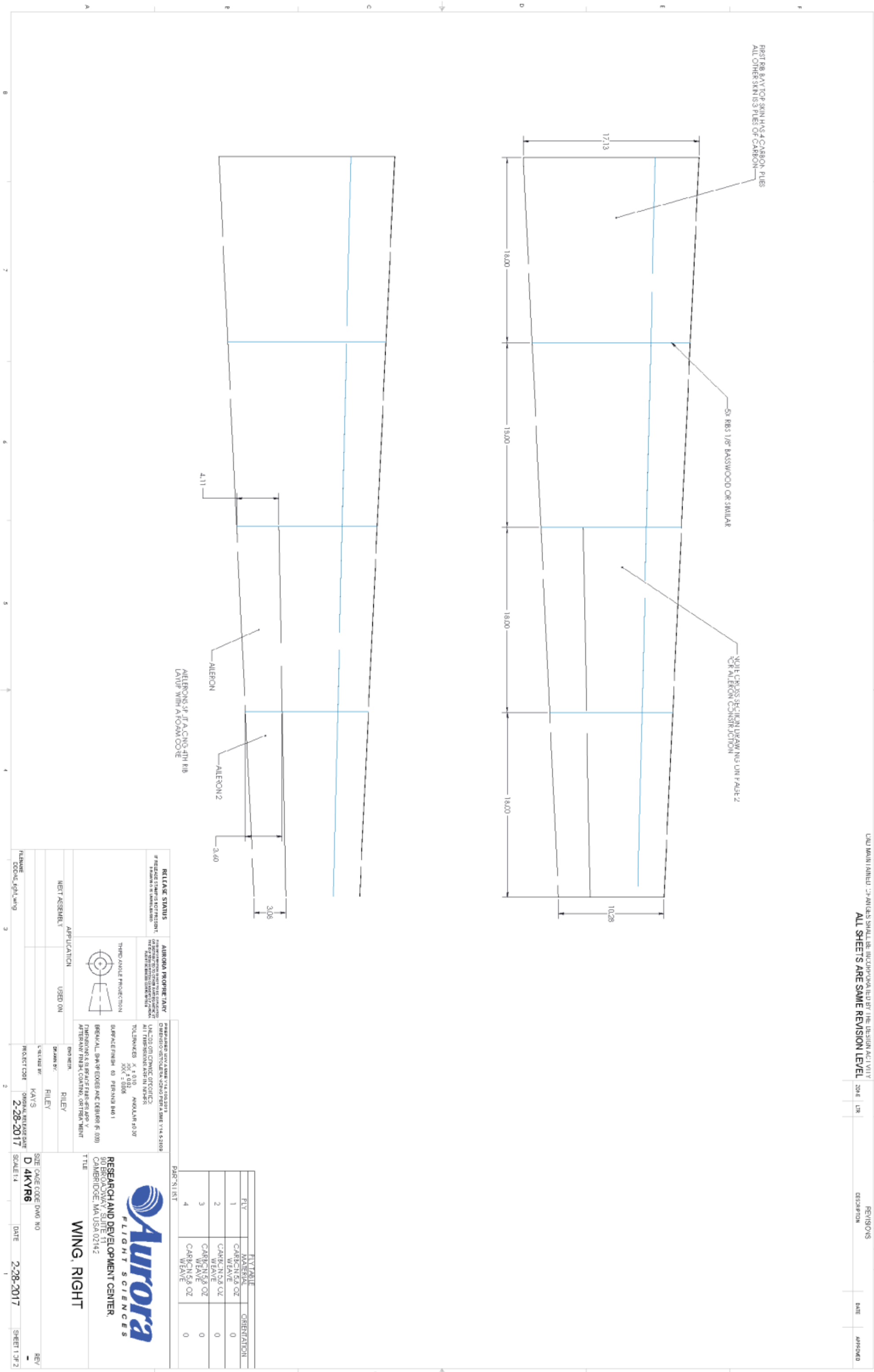

Figure 4. Manufacturing drawing of the 6 ft half-span top view of the DDDAS wing planform.

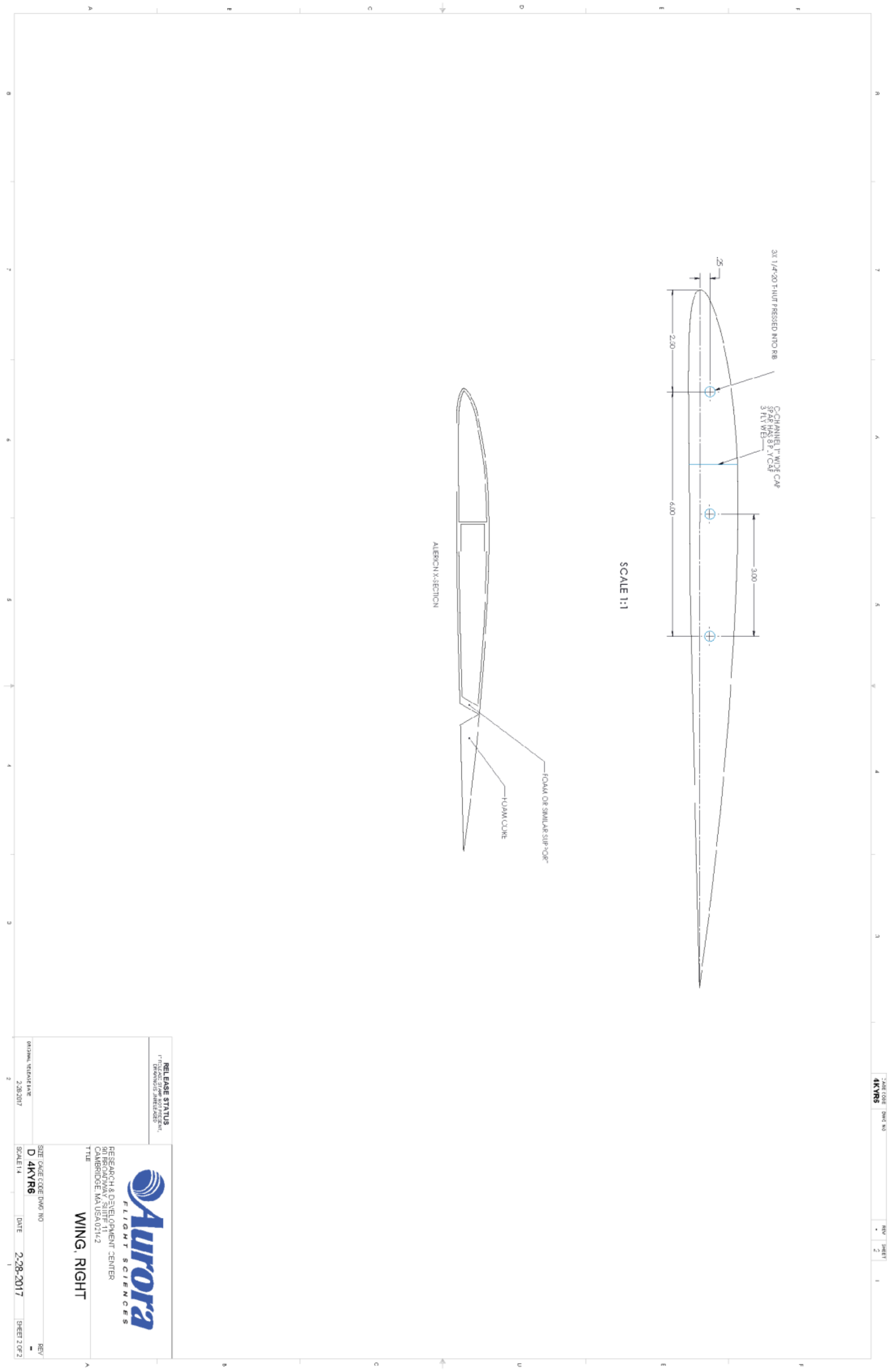

Figure 5. Manufacturing drawing of the side profile view of the DDDAS wing structure cross-section.

Structural Analysis of Testbed Wing

Extensive analysis was performed on the wing structure using finite element analysis (FEA) to both size the nominal wing structure and to determine sensitivities of strains on the wing due to various damage conditions. As discussed above, the baseline wing structure – wing spar cap and web, and wing skin thickness within each bay – was sized to a desired tip deflection for a 4G pull-up maneuver. The primary purpose of the parameterized damage study was twofold: first, to determine what type of damage scenarios might realistically be induced on the real wing structure that might also be modeled within the wing's finite element model (FEM) and, second, to perform a parameterized analysis across each selected damage type to determine which damage scenario provides sufficient sensitivity for sensing on the real wing structure. Additionally, all of the analysis can be used to supplement the offline damage library, regardless of whether it might not be appropriate for the actual flight hardware testing.

Before the full damage test matrix was analyzed and strain magnitudes were computed, it was necessary to characterize the wing's response to a high-load maneuver for different FEA solution types. Figure 6 shows the results of the initial study on the wing FEM to determine which solution type provided sufficient fidelity to determine strain sensitivities for a damaged (i.e., nominal delamination case) vs. undamaged wing structure. As the figure suggests, to truly capture the sensitivity of the wing's deflection – and thus principal stress/strain – to damage cases, a nonlinear structural analysis is required, since the linear solution severely underpredicts the wing's tip deflection and provides no sensitivity between the damaged and undamaged case, respectively. This is primarily due to buckling of the skin in high-load scenarios.

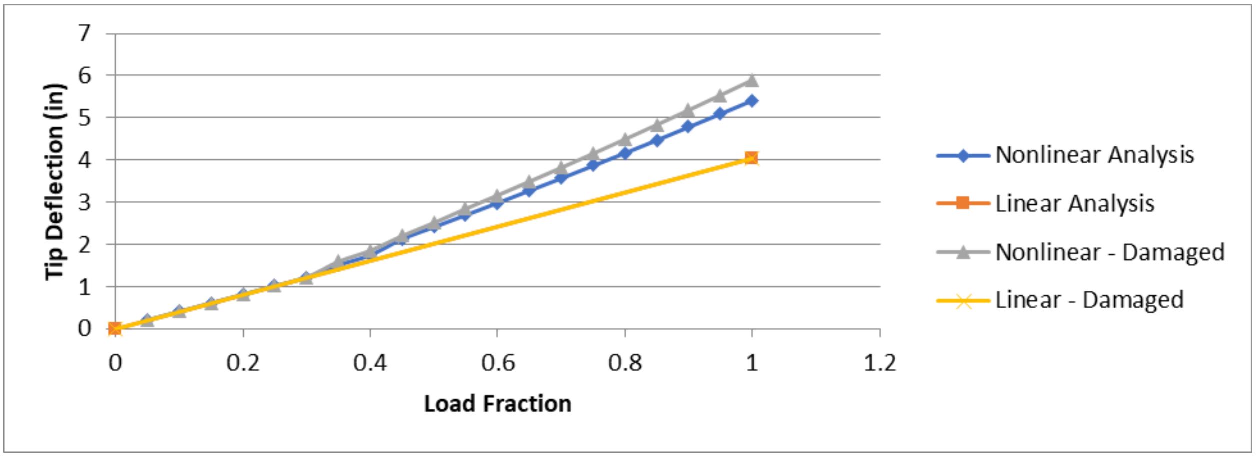

Figure 6. A study of the wing FEM to determine sensitivity of the wing's response based on solution type.

Once the required solution type was determined, an analysis of different structural damage scenarios was conducted. It was determined that there were two damage types that could be both introduced to the real wing structure in a controlled manner and modeled in the FEM in a parameterized way. In particular, the realizable damage types chosen for the study were a delamination between spar cap and top or bottom skin and a hole developing in various parts of the structure (spar cap and web, top and bottom skin).

To model the delamination damage case (and to parameterize the damage within the wing FEM), all elements of the outer ply of the spar cap were connected to their adjacent element on the inner skin ply (both top and bottom) via a rigid-body element. Thus, to introduce a specific delamination into the model, the rigid-body elements in the region of the delamination were simply deleted, thereby releasing the constraint between wing spar and wing skin. Further, this damage type can be finely controlled during the layup of the wing structure by placing a thin Teflon strip between plies in whichever area the delamination is desired. This damage type offers both the most realistic damage scenario for an LCAAT wing structure, as well as the most easily modeled in the FEA and the most controllable in the flight hardware.

Figure 7 shows a selection of results from the study, while Table 1 shows the test matrix and maximum principal stress estimated for the top skin for the spar delamination damage case. In particular, the location and size of the spar delamination were varied in order to determine the maximum principal stress in the top skin surface and its location on the wing.

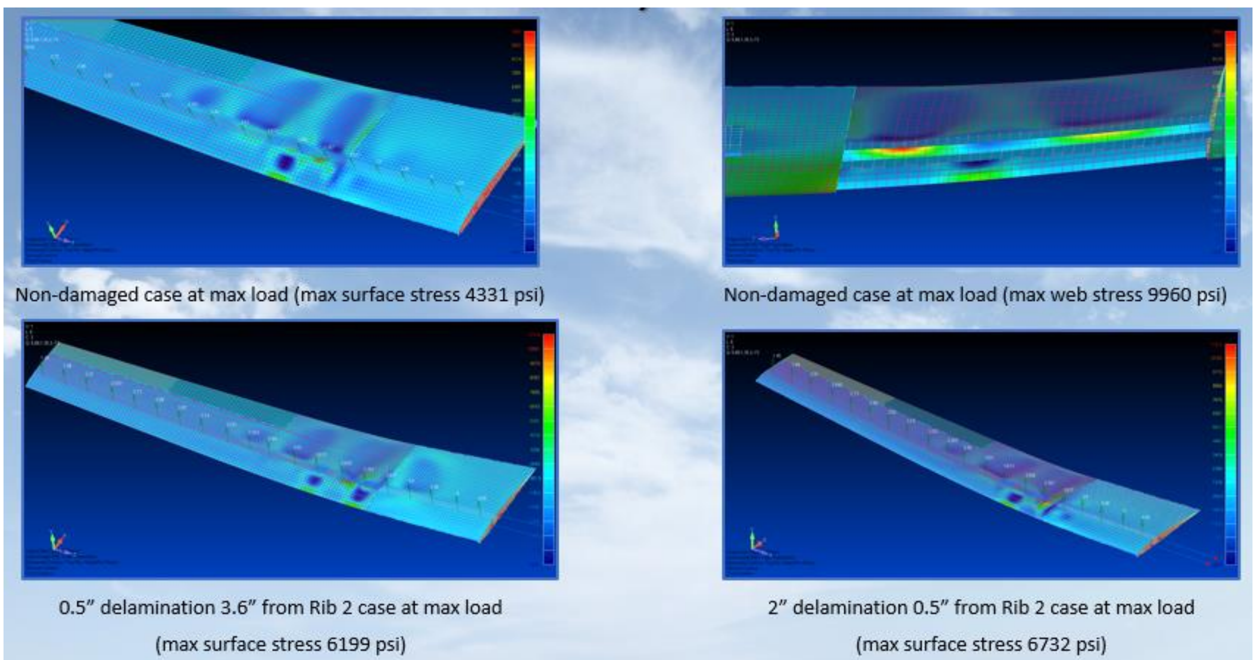

Figure 7. Example finite element analysis performed on wing structure. A parameterized damage model was developed to trade both delamination size and location to find stress sensitivities for sensor placement and damage case selection.

Table 1. Wing damage test matrix and maximum principal stress.

Delamination size (in)	Delamination distance from rib 2 (in)	Maximum principal stress (psi)
None	None	4,331
0.5	0.5	5,646

0.5	1.5	8,633
0.5	2.6	7,582
0.5	3.6	6,199
0.5	5.7	5,854
2.0	0.5	6,732
2.0	2.6	5,109 (70% load)
2.0	4.7	4,892 (60% load)

The primary takeaways from this parameterized damage analysis of the wing structure can be summarized as follows:

- The stress concentration location translates along spar as the load increases
- With delamination size of 2" located at distance of 5.5" and greater away from rib 2, structural failure occurs at 60% of load
- Maximum stress concentration points are located from 0.95" to 1.4" from spar towards LE and 0.0" to 1.0" towards TE

As a result of both the FEA results and the limitations imposed on the sensor architecture due to access limitations of the assembled wing, the strain gauges were placed on the outer top skin of the wing, spanning bays 2 and 3 of the wing planform. Table 2 provides the rationale for the strain gauge placement based on the results of the parameterized FEA study. In particular, the distributed sensors were chosen to maximize coverage area across the wing's surface, both spanwise and chordwise (hence the choice of single-axis gauges in a staggered pattern), while minimizing strain noise due to normal deflection of the wing. This coverage area also maximizes the probability that the location of max strain can be sensed across all delamination cases studied.

Figure 8 shows the strain gauge integration and layout on the fully assembled wing. While this outer-mount scheme is non-ideal from a flight performance perspective, care was taken to run the sensor wiring so as to minimize the drag increase of the exposed wires. Furthermore, the objectives of the testbed aircraft were not to maximize flight performance but rather to collect distributed strain data across the wing and validate the DDDAS approach in-flight, both of which the strain gauge architecture could meet.

Table 2. Strain gauge placement rationale.

Method	Advantage
Install 23 single-axis strain gauges on top skin of Bay 2 (12 at LE, 11 at TE)	Maximizes coverage area vs. use of 3-axis rosette (maximum of 24 gauges are possible)

Arrange gauges in staggered pattern at distance of 1.38” from each other orthogonally to spar	Enhances ability to sense deformation along entire Bay 2. Minimizes noise from normal deflection of the wing
Position LE row of gauges at 1.0” and TE row at 0.5” away from spar	Enables sensing of maximum stress translation paths
Lead gauges’ wiring around LE parallel to freestream into access openings	Minimizes adverse effect of drag increase due to exposed wiring running normal to freestream

Figure 8. Fully assembled wing with strain gauge layout.

Testbed Aircraft System Layout

In addition to the custom wing designed and manufactured for the DDDAS testbed aircraft system developed during the program, a full set of flight hardware – including aircraft flight control avionics, power system, and structural sensing avionics – was developed, integrated, and tested to bring the aircraft system to fully operational in flight.

Figure 9 shows a high-level layout of the full DDDAS aircraft system. The aircraft system consists of a Telemaster 12 ft laser-cut kit, which contains a two-piece fuselage for the respective cabin and tail sections, where the tail section contains the full empennage with control surfaces (two elevators and 1 rudder). The main internal volume of the fuselage houses all flight batteries and system avionics, as well as the nose-mounted electric motor used to drive the propeller in flight. The custom carbon wings, described above, are mounted to the fuselage cabin via a sliding carbon rod mechanism. The right wing contains the embedded I/O expanders and strain gauges, while the left wing contains a tip-mounted pitot-static system for airspeed indication. Each wing contains two ailerons, located in each of its outer two bays, where the inner control surface on each wing can also function as a simple-hinged flap.

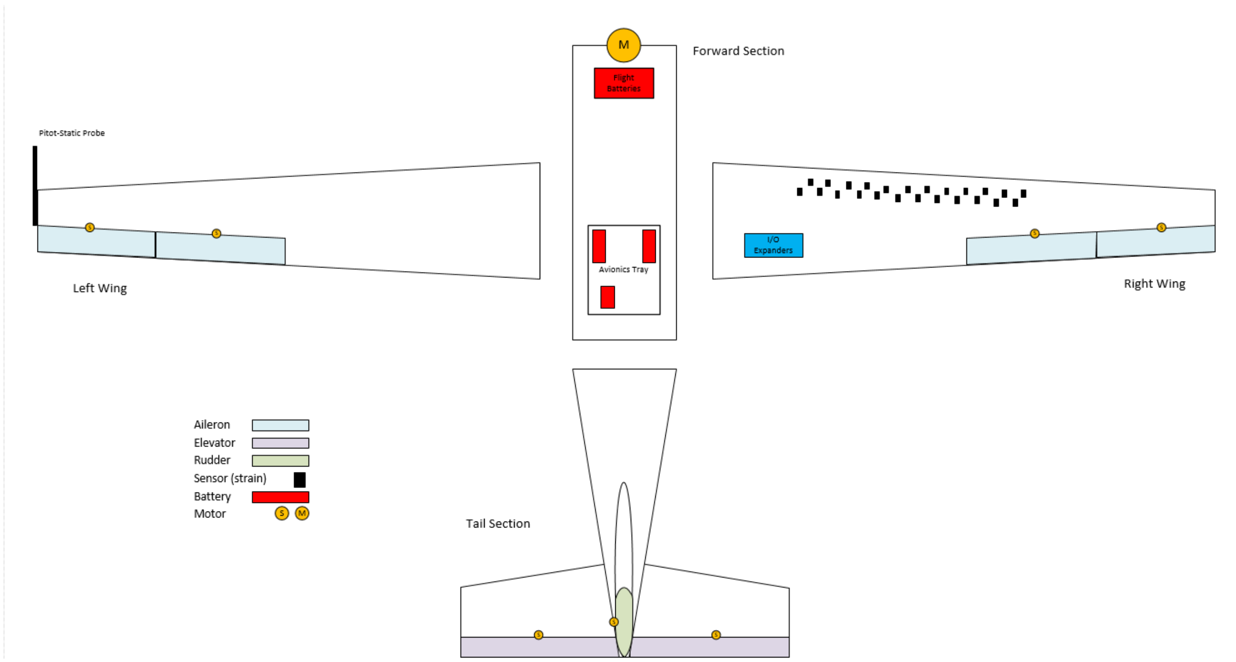

Figure 9. Testbed Aircraft System Layout

The avionics of the DDDAS aircraft is separated into two systems: the wing sensor board and the flight controller/main power system.

Figure 10 shows the flight control system architecture. The flight controller is a Pixhawk2 configured to control a standard fixed-wing aircraft. Sensors and coms included an external Here2 GPS, and compass module, and an RFD900 radio for ground station link. Sensor and relevant flight data are logged locally to the FCS and saved on a micro-SD card. All 7 control surface actuators are high-torque servos which operate at 7.4 V, 440 mA. Power to the actuators is supplied using a PowerBox Systems Powerbox and 2 2S avionics batteries (one primary and one reserve). Both the Powerbox and Pixhawk2 contain isolating diodes to prevent reverse current scenarios between batteries. The aircraft's main propeller was powered by its own 12S battery with a battery-eliminator circuit which isolated it from the avionics power system. In order to transmit the main flight battery voltage to the pilot, the main rotor's speed controller power inputs are wired to a voltage sensor on the RC receiver. This allows battery voltage to be inserted into the telemetry stream sent to the pilot. Main flight battery voltage is viewed on the pilot's transmitter while avionics battery voltage is viewed on the groundstation UI.

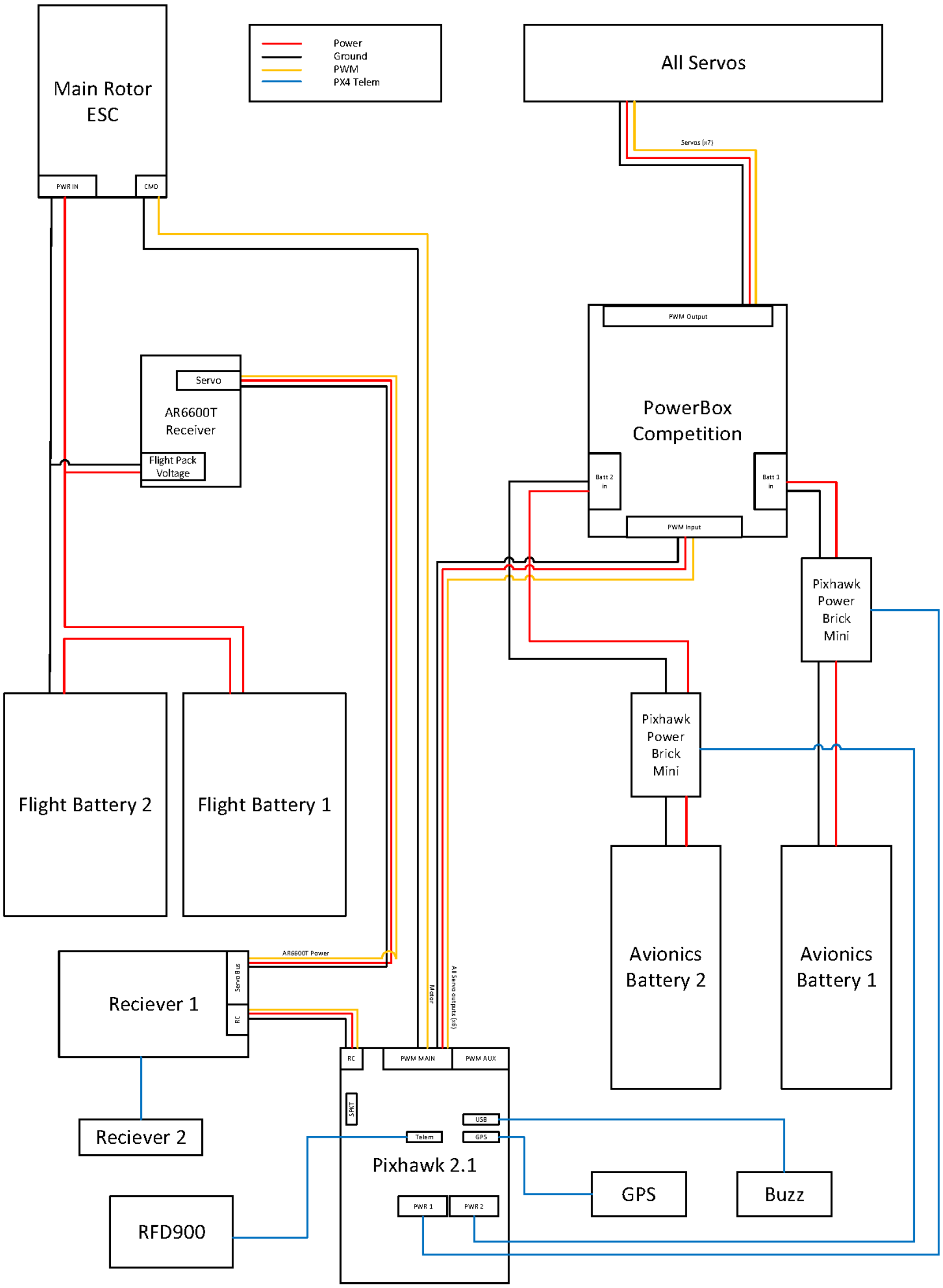

Figure 10. Diagram of flight control system avionics.

Figure 11 shows the layout for the wing-sensor board, which consists of a separate avionics system that is electrically isolated from the flight control system. The wing-sensor board includes a 2S battery, an STM32 nucleao-144 development kit, and 8 IO-expander boards, each with 3 ADC modules. The system reads and logs 24 strain sensors mounted on the right wing during flight. The software running on the STM32 includes functions for calibration of the strain sensors and live data display. All data during flight is logged to a separate micro-SD card. Strain data needs to be synchronized with flight controller IMU data in post-flight processing in order to correlate wing deflection with estimated aerodynamic forces.

The ground control station is a standard Aurora laptop running Ubuntu 16.04 and QGroundControl. A RFD900 is connected via serial and is used as the link to the aircraft. The wing-sensor system cannot be accessed in flight and logging functions must be started and stopped manually before/after flight. The GCS laptop must be manually connected to the wing-sensor board via serial to access the terminal interface.

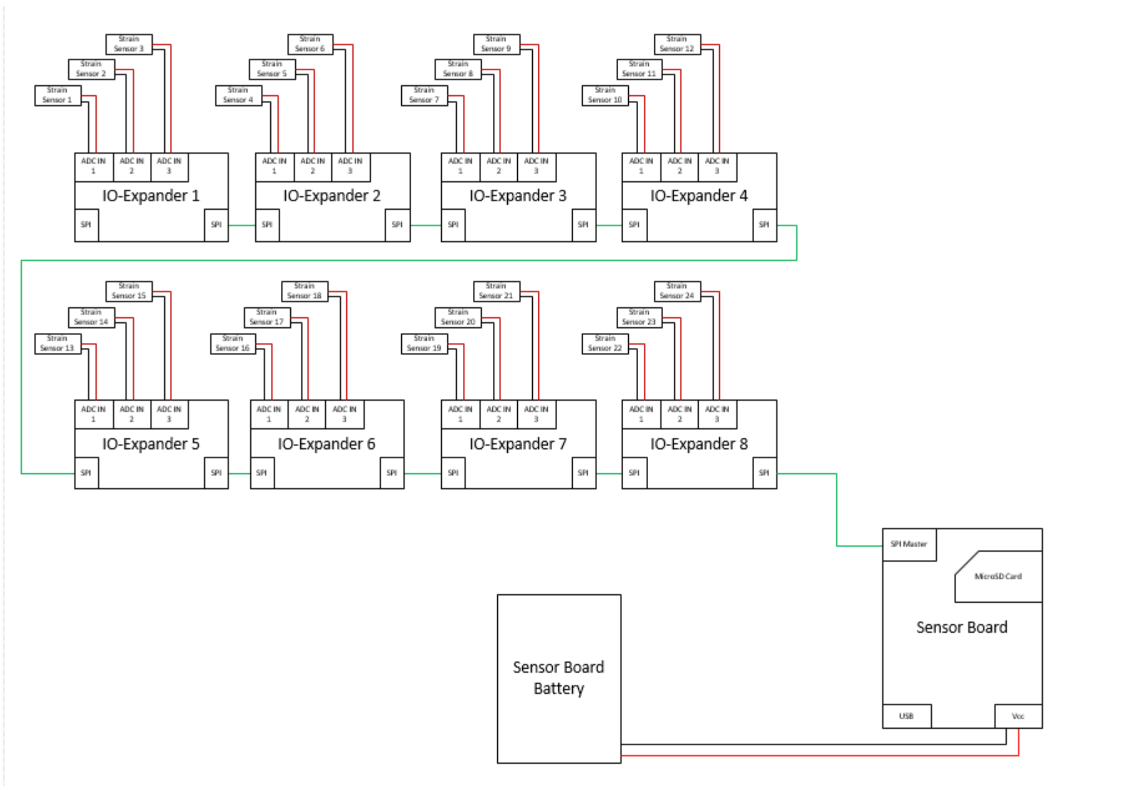

Figure 11. Diagram of wing-sensor avionics system.

5.3 Testing Procedures and Results

5.3.1 Test Procedures

A set of pre-flight checkout procedures – including vehicle assembly and checkout, and transmitter checkout – was developed for the DDDAS testbed system and successfully validated in the first flight test of the vehicle. The pre-flight checklist is provided in Table 3.

Table 3. DDDAS vehicle assembly and pre-flight checkout procedure

Step	Task

Vehicle Assembly	1. Attach left wing: a. Insert 2 carbon rods into holes in upper fuselage above cabin door. b. Verify tubes are centered by aligning the markings with the fuselage side wall. c. Insert left tips of the carbon rods into left wing and slide on, stop at 4 inches from fuselage. d. Connect servo connectors and airspeed sensor. e. Continue sliding left wing until it meets the fuselage while guiding cables into the receptacle. f. Attach A74 bolts inside the fuselage to secure wing. 2. Attach right wing: a. Adjust carbon rods if they shifted during left wing assembly. b. Insert right tips of the carbon rods into right wing and slide on, stop at 4 inches from the fuselage. c. Connect servo connectors and insert sensor board connectors into cable receptacle. d. Continue sliding right wing until it meets the fuselage while guiding cables into the receptacle. e. Attach A74 bolts inside fuselage to secure wing. f. Connect wing sensor cables inside fuselage 3. Install Batteries a. Install 2 avionics batteries on avionics tray. b. Install 1 wing sensor battery on avionics tray. c. Install 2 flight batteries in nose of aircraft.
Vehicle Checkout	4. Mechanical. a. Fuselage, tail assembly, 3 nuts and washers secure. b. Landing gear attached, secured, check wheels, collars, and set screws. c. Wings attached, bolts secure. d. Left outer aileron, servo linkage secure, check travel, smooth operation. e. Left inner aileron, servo linkage secure, check travel, smooth operation. f. Right inner aileron, servo linkage secure, check travel, smooth operation. g. Right outer aileron, servo linkage secure, check travel, smooth operation. h. Left elevator, servo linkage secure, check travel, smooth operation. i. Right elevator, servo linkage secure, check travel, smooth operation. j. Rudder, servo linkage secure, check travel, smooth operation. k. Main motor installed, bolts secure. i. Prop installed, 6 bolts secure. 5. Electrical a. Avionics tray, 8 screws secure. i. Batteries installed, Velcro straps secure. ii. Powerbox installed, connections secure.

	iii. Pixhawk installed, connections secure. iv. RFD900 installed, FTDI secure. v. Wing sensor board installed, connections secure. b. Flight batteries installed, connections secure. c. Spectrum receiver installed, secure. d. Voltage probe connected to main ESC, AR6600T secure.
Transmitter Checkout	6. Vehicle Powered on. a. Connect avionics batteries b. Connect wing sensor battery c. Connect flight batteries d. Verify transmitter voltage reading 7. Flaps switch position A. a. Transmitter roll – all ailerons, check movement b. Transmitter pitch – elevators, check movement. c. Transmitter yaw – rudder, check movement. d. Transmitter Dial – inner ailerons, no movement. 8. Flaps switch position B a. Transmitter roll – outer ailerons, check movement. b. Transmitter Pitch – elevators, check movement c. Transmitter yaw – rudder, check movement. d. Transmitter dial, - inner ailerons, check movement 9. Thrust test, a. Main motor ESC powered b. Main motor spin direction correct. c. Transmitter thrust – motor, check spin. 10. Wing sensor board a. Powered, logger running, check messages for output.

The communications architecture of the DDDAS testbed system is shown in Figure 12. A standard 2.4 GHz RC transmitter and redundant receiver are used to manually control the aircraft during flight (when the onboard autopilot is disabled or for backup in the case of an in-flight autopilot malfunction); the signal quality of the telemetry is downlinked to this transmitter from the aircraft. A 915 MHz transmitter onboard the aircraft (Pixhawk 2.1) is used for data telemetry during the flight, specifically to downlink aircraft state data, including battery voltage information, aircraft positional information, and flight mode status.

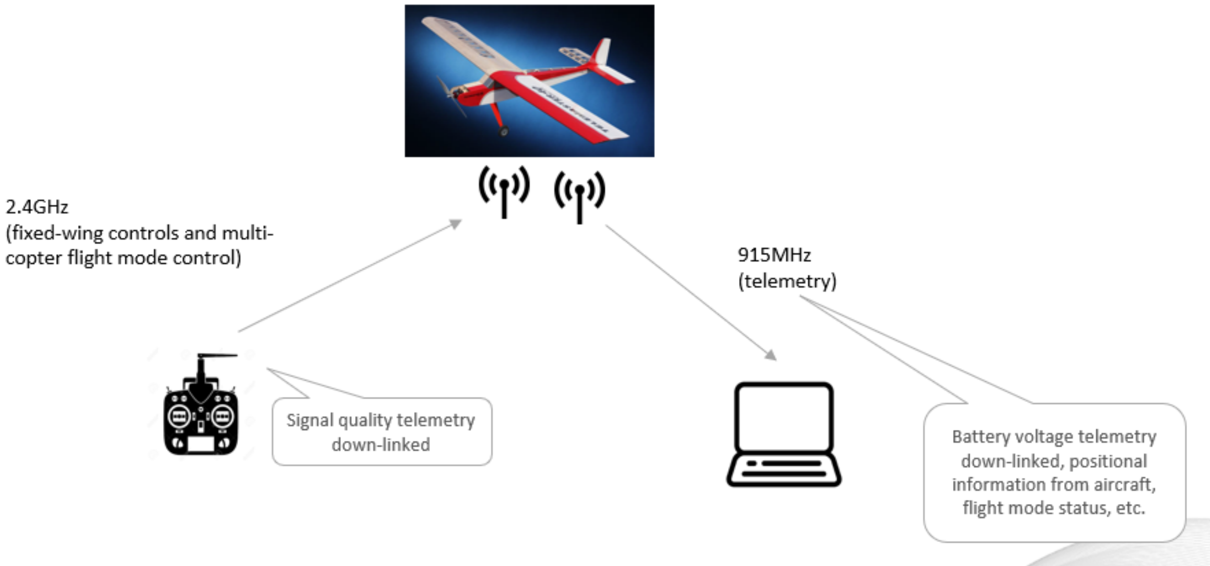

Figure 12. DDDAS testbed aircraft communications setup. A single 2.4 GHz RC transmitter and redundant receiver for manual control of the aircraft and a 915 MHz data telemetry for downlink of aircraft state data were used.

Flight test procedures are depicted in Figure 13. Once the pre-flight checklist is complete and the flight test is to be initiated, the flight test procedure can begin. The flight test procedure is as follows:

1. Start Sensor Log
    a. Connect wing sensor battery to wing sensor board
    b. Connect GCS laptop to wing sensor board via USB
    c. Open minicom and connect to device /dev/ttyACM# (usually /dev/ttyACM0)
    d. Execute "wing_sensors top" command to verify operation
    e. Start logging module
    f. Disconnect logging board from GCS laptop
2. Arm vehicle by applying right yaw
3. Takeoff, perform test
4. Landing
5. Disarm vehicle by applying left yaw
6. Stop Sensor Log
    a. Connect GCS laptop to wing sensor board via USB
    b. Open minicom and connect to device /dev/ttyACM#
    c. Stop logging module
    d. Disconnect logging board from GCS laptop
    e. Disconnect all batteries

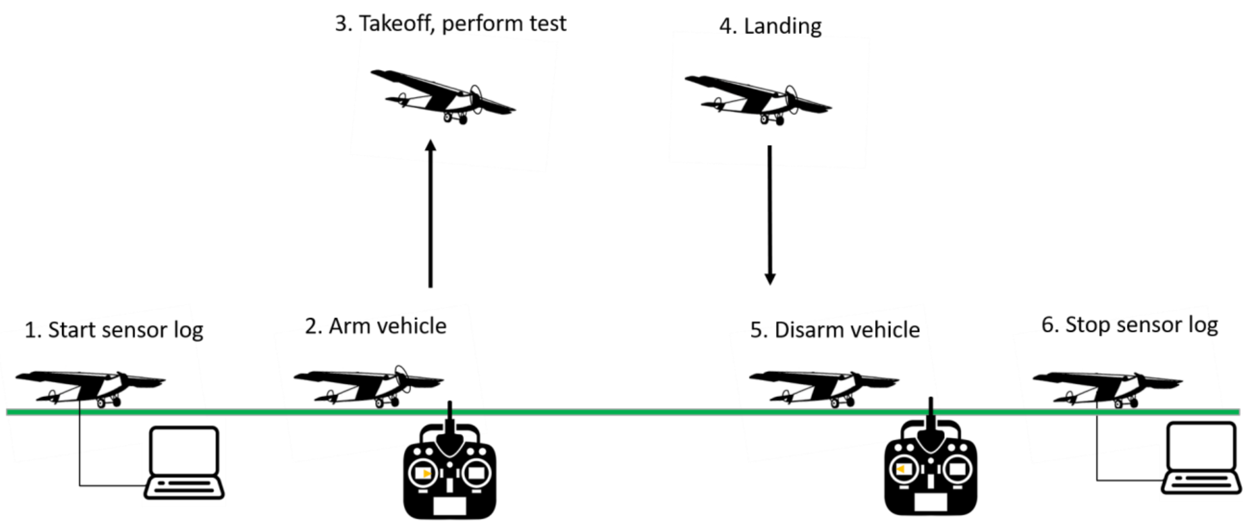

Figure 13. Flight test procedure diagram.

Post-flight procedures for the testbed aircraft system require the wing sensor board and Pixhawk logs to be downloaded and synchronized using custom-developed software. Once the data has been retrieved, post-processing can occur.

5.3.2 Flight Test 1

The first flight test conducted for the DDDAS testbed aircraft consisted of a full system assembly and checkout at the field, as well as a maiden flight. The flight test thus served multiple purposes: 1.) to verify that the full aircraft system was properly integrated, and all subsystems were functioning properly; 2.) to verify that the aircraft was fully controllable and performed in-flight as expected; and 3.) to collect an initial set of strain data for verification of sensing architecture and to supplement computational models of wing strain for use in DDDAS algorithm development.

To fully verify that all systems were properly functioning, three specific ground tests were performed pre-flight: flight control system calibration, range test of RC link, and verification of lost signal control actions. The three ground test cards for all pre-flight checkout activity are shown in Figure 14 through Figure 16 while the flight test card is shown in Figure 17. Several photographs showing pre-flight checkout procedures – including checkout of the sensor board via the bottom wing skin access panels and checkout of the vehicle power system – as well as a view of the fully assembled, flight-ready aircraft system are shown in Figure 18.

Pilot: Juha Turalba	Location: Bridgewater SSRCC Field	Day: Day 1

Test name: FCS calibration before flight.		Test number: 1
Check	**Sequence of steps**	**Configuration**
	1. Power on aircraft. 2. Power on the RC controller. 3. Press the Arm/Disarm button, located on the vehicle, until it is flashing rapidly. 4. Arm system by applying right yaw input until vehicle is armed. 5. Control surface movement direction check. • Right Roll • Left Roll • Positive Pitch • Negative Pitch • Right Yaw • Left Yaw 6. Perform Compass, IMU, Accelerometer, and RC calibration if neccisairy. 7. Disarm the vehicle by applying left yaw input. 8. Disconnect all batteries. 9. Save all logs as Ground Test Card 1, the date, and vehicle.	• Propeller removed • Sensors located within wings connected and functional. • Controller Switch Positions (Spektrum DX18) • 3-position switch: Manual / Acro / Stabilized to be used as needed. • 3-position switch for flap control to be used as needed. • 2-position switch: One position has the motor in the “off” position and another, where the motor can be controlled. **Success criteria** • Control direction is correct for all control surfaces. • Compass, IMU, Accelerometer, and RC calibration is complete.
Notes		
Review FCS data after each test.		

Figure 14. Ground Test Card 1. Calibrate and confirm functionality of the FCS.

Pilot: Juha Turalba	Location: Bridgewater SSRCC Field	Day: Day 1

Test name: Range test of RC link before flight.		Test number: 2
Check	**Sequence of steps**	**Configuration**

	1. Power on aircraft.
	2. Power on the RC controller.
	3. Press the Arm/Disarm button, located on the vehicle, until it is flashing rapidly.
	4. Arm system by applying right yaw input until vehicle is armed.
	5. Move RC controller a distance of 30 paces from the aircraft (90 feet).
	6. Face the model with the transmitter in the normal flying position and place the transmitter into Range Test mode / push the trainer button to reduce the power output.
	7. Operate the controls. Spotter to visually verify that movement is seen on the aircraft and link correct using the GCS.
	8. Disarm the vehicle by applying left yaw input.
	9. Disconnect all batteries.
	10. Save all logs as Ground Test Card 2, the date, and vehicle.
		• Propeller removed
		• Sensors located within wings connected and functional.
		• Controller Switch Positions (Spektrum DX18)
		    • 3-position switch: Manual / Acro / Stabilized to be used as needed.
		    • 3-position switch for flap control to be used as needed.
		    • 2-position switch: One position has the motor in the “off” position and another, where the motor can be controlled.
		
		Success criteria
		• At a distance of 30 paces. small frame losses. Investigate remote receiver placement if over 50.
		• At a distance of 30 paces. no holds.

Notes		
Review FCS data after each test.		

Figure 15. Ground Test Card 2, Range Test

Pilot: Juha Turalba	Location: Bridgewater SSRCC Field	Day: Day 1

Test name: Verification of lost signal control actions.		Test number: 3
Check	**Sequence of steps**	**Configuration**

	1. Power on aircraft.
	2. Power on the RC controller.
	3. Press the Arm/Disarm button, located on the vehicle, until it is flashing rapidly.
	4. Arm system by applying right yaw input until vehicle is armed.
	5. Power off the RC controller and verify that the proper lost link procedure is engaged.
	6. Disarm the vehicle by applying left yaw input.
	7. Disconnect all batteries.
	8. Save all logs as Ground Test Card 3, the date, and vehicle.
		• Propeller removed
		• Sensors located within wings connected and functional.
		• Controller Switch Positions (Spektrum DX18)
		  • 3-position switch: Manual / Acro / Stabilized to be used as needed.
		  • 3-position switch for flap control to be used as needed.
		  • 2-position switch: One position has the motor in the “off” position and another, where the motor can be controlled.

		Success criteria
		1. The Pixhawk flight controller shall be configured in such a way that in the event that signal is lost, the air vehicle will return to the home waypoint, which is defined as the location of the pilot-in-command, and shall orbit.
Notes		
Review FCS data after each test.		

Figure 16. Ground Test Card 3, Lost Signal Verification

Pilot: Juha Turalba	Location: Bridgewater SSRCC Field	Day: Day 1

Test name: Maiden flight on aircraft.		Test number: 4
Check	**Sequence of steps**	**Configuration**

	1. Power on aircraft.
	2. Power on the RC controller.
	3. Press the Arm/Disarm button, located on the vehicle, until it is flashing rapidly.
	4. Arm system by applying right yaw input until vehicle is armed.
	5. Move aircraft to takeoff location.
	6. Takeoff and climb to 300 ft.
	7. General racetrack pattern, banks limited to 30-degrees.
	8. Landing.
	9. Disarm the vehicle by applying left yaw input.
	10. Disconnect all batteries.
	11. Save all logs as Flight Test Card 1, the date, and vehicle.
		• Propeller attached.
		• Flight batteries and avionics batteries connected and secure.
		• Sensors located within wings connected and functional.
		• Controller Switch Positions (Spektrum DX18)
		    • 3-position switch: Manual / Acro / Stabilized to be used as needed.
		    • Slider switch for flap control to be used as needed.
		    • 2-position switch: One position has the motor in the "off" position and another, where the motor can be controlled.
		
		Success criteria
		• No holds encountered during the flight.
		• Aircraft performs as expected.

Notes
1. Review FCS data after each test. 2. Perform an inspection of the aircraft after the first flight to ensure that all components are secure.

Figure 17. Flight Test Card 1, General flight pattern (maiden flight on)

Figure 18. (Top) Pre-flight assembly of the aircraft sensor board and checkout of the aircraft power system. (Bottom) Fully assembled flight-ready aircraft system.

The maiden flight of the testbed aircraft was primarily used to verify that all flight hardware functioned properly in-flight and to verify that the aircraft flew as anticipated. Thus, a relatively benign flight path was flown – takeoff and climb to 300 ft AGL, fly general racetrack patterns with banks limited to 30 degrees for up to 6 minutes of flight time, and a typical descent and landing. Figure 19 shows the flight path collected from onboard telemetry and overlaid on the actual airfield.

Figure 20 shows the respective strain gauge and IMU data collected during the maiden test flight. The data generally shows higher strains across the wing for high-acceleration maneuvers in the range of absolute strain values predicted by the FEA, which was the primary goal of the flight test. Follow-on work is needed to further calibrate the sensors and collect additional data to fully understand the system.

Figure 19. Flight Test 1 Path.

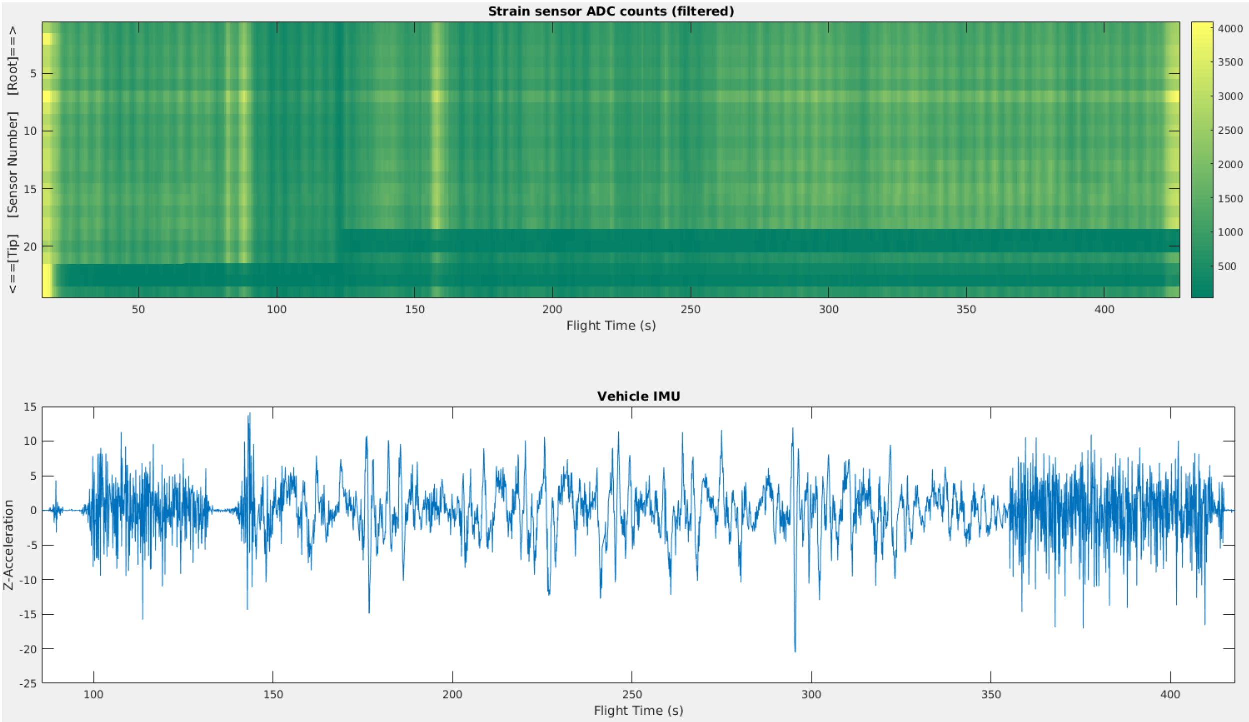

Figure 20. (Top) Strain gauge data collected during the flight test and (bottom) the corresponding IMU measurements.

6 Publications

Journal papers

1. Kapteyn, M., Knezevic, D., Huynh D, Tran, M., and Willcox, K., Data-driven physics-based digital twins via a library of component reduced-order models. Under revision for *International Journal for Numerical Methods in Engineering*, 2020.

2. Burrows, B. and Allaire, D., Nonlinear Kalman filtering via measure change, *American Society of Mechanical Engineers (ASME) Journal of Dynamic Systems, Measurement, and Control* 142(2):021006, 2020.

3. Swischuk, R., Mainini, L., Peherstorfer, B. and Willcox, K., Projection-based model reduction: Formulations for physics-based machine learning, *Computers and Fluids*, Vol. 179, pp. 704-717, January 2019.

4. Swischuk, R. and Allaire, D., A machine learning approach to aircraft sensor error detection and correction, *American Society of Mechanical Engineers (ASME) Journal of Computing and Information Science in Engineering*, 19(4):041009, 2019.

5. Kapteyn, M., Willcox, K. and Philpott, A., Distributionally Robust Optimization for Engineering Design under Uncertainty. *International Journal for Numerical Methods in Engineering*, Vol. 120, Issue 7, pp. 835-859, July 2019. An earlier version of this work appeared in Proceedings of 2018 AIAA Non-Deterministic Approaches Conference, AIAA SciTech Forum, Kissimmee, FL, January, 2018. (AIAA 2018-0666)

6. Singh, V. and Willcox, K., Engineering Design with Digital Thread. *AIAA Journal*, Vol. 56, No. 11, pp. 4515-4528, 2018. Also in proceedings of 2018 AIAA Scitech Forum, Kissimmee, FL, January, 2018.

7. Singh, V. and Willcox, K., Methodology for path planning with dynamic data-driven flight capability estimation, *AIAA Journal*, Vol. 55, No. 8, pp. 2727-2738, 2017.

8. Burrows, B., Isaac, B, and Allaire, D., A conjunctive filtering approach to multi-task aircraft capability estimation in dynamic data-driven application systems, *American Institute of Aeronautics and Astronautics (AIAA) Journal of Aerospace Information Systems*, Vol. 14, No. 12, pp. 625-636, 2017.

9. Mainini, L. and Willcox, K., Data to decisions: Real-time structural assessment from sparse measurements affected by uncertainty, *Computers and Structures*, Vol. 182, pp. 296-312, 2017.

10. Burrows, B., Isaac, B., and Allaire, D., Multitask Aircraft Capability Estimation Using Conjunctive Filters, *Journal of Aerospace Information Systems*, Vol. 14, No. 12 (2017), pp. 625-636.

11. Ulker, F., Allaire, D. and Willcox, K., Sensitivity Guided Decision Making for Wind Farm Micro-Siting, *International Journal for Numerical Methods in Fluids*, Vol. 83, Issue 1, pp. 52-72, 2017.

Conference papers

1. Kapteyn, M., Knezevic, D., and Willcox, K., Toward predictive digital twins via component-based reduced-order models and interpretable machine learning. In Proceedings of 2020 AIAA SciTech Forum & Exhibition, Orlando FL, January, 2020. (Best student paper award.)

2. Burrows, B., and Allaire, D. Analysis of uncertainty quantification techniques for vehicle capability in damaged composite aircraft, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, AIAA-3663-2019, Dallas, TX, 2019.

3. Sanghvi, M., Honarmandi, P., Attari, V., Duong, T., Arryoave, R. and Allaire, D., Uncertainty propagation via probability measure optimized importance weights with application to parametric materials models, American Institute of Aeronautics and Astronautics (AIAA) SciTech Forum, AIAA-0967-2019, San Diego, CA, January, 2019.

4. Swischuk, R. and Allaire, D., A machine learning approach to aircraft sensor error detection and correction, American Institute of Aeronautics and Astronautics (AIAA) Science and Technology Forum, AIAA-1164-2018, Kissimmee, FL, January, 2018.

5. Burrows, B. and Allaire, D., A comparison of nave Bayes classifiers with applications to self-aware aerospace vehicles, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, AIAA-3819-2018, Denver, CO, June, 2017.

6. Thomison, W.D. and Allaire, D., A model reification approach to fusing information from multifidelity information sources, American Institute of Aeronautics and Astronautics (AIAA) Science and Technology Forum, AIAA-1949-2017, Grapevine, TX, January, 2017.

7. Burrows, B., Isaac, B., and Allaire, D., A dynamic data-driven approach to multiple task capability estimation for self-aware aerospace vehicles, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, AIAA-2016-4125, Washington, D.C., June, 2016.

8. Korobenko, A., Pigazzini, M., Singh, V., Kim, H., Allaire, D., Willcox, K., Marsden, A., and Bazilevs, Y., Dynamic data-driven damage prediction in aerospace composite structures, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, AIAA-2016-4126, Washington, D.C., June, 2016.

9. Isaac, B., and Allaire, D., A dynamic data-driven approach to optimal offline learning for online flight capability estimation, American Institute of Aeronautics and Astronautics (AIAA) Science and Technology Forum, AIAA-2016-1444, San Diego, CA, January, 2016.

10. Mainini L., Structural assessment and sensor placement strategy for self-aware aerospace vehicles, Structural Health Monitoring 2017: Real-Time Material State Awareness and Data-Driven Safety Assurance, IWSHM 2017, vol. 1, p. 1586-1594

11. Allaire D., Kapteyn M., Kays C., Mainini L., Singh V., Willcox K. Towards Low-Cost Attritable Aircraft Technology via Dynamic Data-Driven Application Systems, Infosymbiotics/DDDAS 2017, Cambridge, MA, 7-9 August, 2017

12. Mainini L., Model order reduction for real time decisions from incomplete and uncertain measurements, QUIET 2017 – Quantification of Uncertainty: Improving Efficiency and Technology, International School for Advanced Studies, Trieste, Italy, July 18-21, 2017. Invited

13. Mainini L., Willcox K., Sensor placement strategy to inform decisions, AIAA 2017-3820, In Proceedings of 18th AIAA/ISSMO Multidisciplinary Analysis and Optimization Conference, AIAA Aviation Forum, Denver, CO, June 5-9, 2017

14. V. Singh and Willcox, K., Engineering Design with Digital Thread, IWSHM 2017 11th International Workshop On Structural Health Monitoring, Stanford University, CA, September 12-14, 2017

7 Presentations

- Willcox, K. A technology roadmap towards Digital Thread. Invited talk, Panel on Multidisciplinary Design Optimization & Model-based Systems Engineering, AIAA Scitech Forum, Orlando, FL, January 2020

- Willcox, K. Toward predictive digital twins via component-based reduced-order models and interpretable machine learning. Invited talk, Institute of High Performance Computing, A*STAR, Singapore, January 2020.

- Willcox, K. Big Decisions need more than just Big Data. Invited Keynote Lecture. 23rd International Conference on Modelling and Simulation (MODSIM), Canberra, Australia, December 2019.

- Willcox, K. Predictive data science: From model reduction to scientific machine learning. Invited Keynote Talk, SC19, Denver, CO, November 2019.

- Willcox, K. Predictive Data Science for Physical Systems: From Model Reduction to Scientific Machine Learning. Invited Lecture, International Congress on Industrial and Applied Mathematics (ICIAM), Valencia, Spain, July 2019

- Willcox, K. Predictive Data Science for Physical Systems: From Model Reduction to Scientific Machine Learning. Invited talk, ONERA Laboratories, Toulouse, France, July 2019

- Willcox, K. Data-driven reduced models, model adaptation, and Digital Twins. Invited talk, Lockheed Martin Aeronautics Internal Workshop on Digital Strategy, Fort Worth, TX, June 2019

- Willcox, K. Predictive Data Science for Physical Systems: From Model Reduction to Scientific Machine Learning. Keynote Talk, New York Scientific Data Summit, New York, NY, June 2019

- Willcox,K. Data to Decisions: Computational Methods for the Next Generation of Engineering Systems. Keynote Talk, SIAM Central Valley Regional Student Conference, University of California, Merced, April 2019

- Willcox, K. Projection-based model reduction: Formulations for Physics-based Machine Learning. Charlemagne Distinguished Lecture, RWTH Aachen, April 2019

- Burrows, B. Analysis of uncertainty quantification techniques for vehicle capability in damaged composite aircraft, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, Dallas, TX, June, 2019.

- Willcox, K. Projection-based model reduction: Formulations for Physics-based Machine Learning. Invited talk, Department of Mathematics, Southern Methodist University, March 2019
- Willcox, K. Projection-based model reduction: Formulations for Physics-based Machine Learning. Invited talk, Department of Mathematics, University of Texas at Dallas, March 2019
- Willcox, K. Projection-based model reduction: Physics-based approaches to learn low-dimensional models. Invited Colloquium Talk, Department of Mathematics, University of Houston, February 2019.
- Allaire, D. Uncertainty propagation via probability measure optimized importance weights with application to parametric materials models, American Institute of Aeronautics and Astronautics (AIAA) SciTech Forum, San Diego, CA, January, 2019.
- Willcox, K. Multifidelity Models and Methods: Fusing models and data to achieve efficient design, optimization, and uncertainty quantification. Invited Tutorial, Science at Extreme Scales: Where Big Data Meeting Large-Scale Computing, Institute for Pure and Applied Mathematics, September 2018.
- Willcox, K. Model Order Reduction: Approximate yet accurate surrogates for large-scale simulation. Invited Tutorial, Science at Extreme Scales: Where Big Data Meeting Large-Scale Computing, Institute for Pure and Applied Mathematics, September 2018.
- Willcox, K. Data to Decisions: Towards the next generation of engineering systems. Design Innovation Workshop, University of Auckland, New Zealand, July 2018.
- Allaire, D. What Next? Sequentially value-optimal engineering tasking for analysis and design, Computational Methods for Design and Control of Next-Generation Engineered Systems Workshop, Singapore University of Technology and Design (SUTD), Singapore (May, 2018).
- Willcox, K. Data-driven operator inference for learning physics-based low-dimensional models. Engineering Systems Design Distinguished Speaker Seminar, Singapore University of Technology and Design, April 2018.
- Willcox, K. Data-driven operator inference for learning physics-based low-dimensional models. Aachen Institute for Advanced Study in Computational Engineering Science, RWTH Aachen, Germany, April 2018.
- Willcox, K. Data to Decisions: Computational methods for the next generation of aerospace systems. Temasek Laboratories, Singapore, May 2018.
- Willcox, K. Data-driven operator inference for learning physics-based low-dimensional models. Hong Kong University, Hong Kong, May 2018.
- Willcox, K. Data to Decisions: Computational methods for the next generation of engineering systems. Institute of High Performance Computing A*STAR, Singapore, March 2018.
- Willcox, K. Data to Decisions: Computational methods for the next generation of engineering systems. Engineering Product Development Research Seminar Series, Singapore University of Technology and Design, February 2018.
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- Willcox, K.. Multi-fidelity Methods for Design, Optimization and Uncertainty Quantification, Embraer MDO Community of Practice, November 2017.
- Willcox, K.. Managing Multiple Information Sources of Multi-Physics Systems, AvTechSymposium Dayton, OH, October 2017.
- Willcox, K.. Computational Methods for the Next Generation of Aerospace Systems. GALCIT Colloquium, Caltech, October 2017.
- Willcox, K.. Data to Decisions: Multifidelity and Surrogate Modeling for Next-Generation Engineering Systems. Aerospace Engineering Seminar, University of Michigan, September 2017.
- Allaire, D. Design for dynamic data-driven self-aware systems, American Society of Mechanical Engineers International Design Engineering Technical Conferences and Computers and Information in Engineering Conference (IDETC/CIE), 43rd Design Automation Conference KEYNOTE on Data-Driven Engineering Design, Cleveland, OH (August, 2017).
- Willcox, K.. Data-Driven Operator Inference for Non-Intrusive Projection-based Model Reduction Workshop on Mathematical Foundations of Data Assimilation and Inverse Problems, Foundations of Computational Mathematics, Barcelona, Spain, July 2017.
- Willcox, K.. Data to Decisions via Adaptive Reduced Models and Multifidelity Modeling. In MATRIX Workshop on Inverse Problems, Melbourne, Australia, June 2017.
- Burrows, B. A comparison of nave Bayes classifiers with applications to self-aware aerospace vehicles, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, Denver, CO, June, 2017.
- Willcox, K.. Data to Decisions: Multifidelity and Surrogate Modeling for Next-Generation Engineering Systems. Dr. Joseph E. Flaherty Lecture Series, Rensselaer Polytechnic Institute, May 2017.
- Willcox, K.. Data to Decisions via Adaptive Reduced Models and Multifidelity Uncertainty Quantification. Center for Applied Mathematics Colloquium, Cornell University, May 2017.
- Willcox, K.. Data to Decisions via Multifidelity Modeling and Adaptive Reduced Models. Semi-plenary lecture, 19th International Conference on Finite Elements in Flow Problems, Rome, Italy, April 2017.
- Willcox, K.. Data to Decisions via Adaptive Reduced Models and Multifidelity Uncertainty Quantification. Keynote talk, British Applied Mathematics Colloquium, University of Surrey, April 2017.
- Willcox, K.. Data to Decisions via Adaptive Reduced Models and Multifidelity Uncertainty Quantification. University of Southampton, April 2017.

- Willcox, K.. Multifidelity and Surrogate Modeling for Next-Generation Engineering Systems. 2017 MICDE Symposium, Michigan Institute for Computational Discovery & Engineering, April 2017.

- Willcox, K.. Data to Decisions via Adaptive Reduced Models and Multifidelity Uncertainty Quantification. CMDA Distinguished Lecture Series, Virginia Tech, April 2017.

- Willcox, K.. Data to Decisions: Multifidelity and Surrogate Modeling for Next-Generation Engineering Systems. IAM-PIMS Distinguished Colloquium Series, University of British Columbia, March 2017.

- Willcox, K.. Multifidelity Monte Carlo Methods for Uncertainty Quantification. In SIAM Computational Science and Engineering 2017, Atlanta, USA, February 2017.

- Thomison, W. A model reification approach to fusing information from multifidelity information sources, American Institute of Aeronautics and Astronautics (AIAA) Science and Technology Forum, Grapevine, TX, January, 2017.

- Willcox, K.. Data to decisions in aerospace systems: Reduced-order modeling and multi-fidelity methods. Presentation to Airbus Group, October 2016.

- Allaire, D. A dynamic data-driven approach to multiple task capability estimation for self-aware aerospace vehicles, American Institute of Aeronautics and Astronautics (AIAA) Aviation Forum, Washington, D.C., June, 2016.

- Willcox, K.. Multifidelity and Surrogate Modeling for Data to Decisions in Engineering Systems. Applied Mathematics Seminar Series, University of Auckland, May 2016.

- Allaire, D. Offline/online data-driven approaches to engineering analysis, National University of Singapore, Department of Mechanical Engineering Seminar Series, Singapore (May, 2016).

- Willcox, K.. Multifidelity Methods for Design and Uncertainty Quantification. Plenary talk, ANZIAM Conference, Canberra, Australia, February 2016.

- Isaac, B. A dynamic data-driven approach to optimal offline learning for online flight capability estimation, American Institute of Aeronautics and Astronautics (AIAA) Science and Technology Forum, San Diego, CA, January, 2016.

8 Awards during project period

Douglas Allaire (TAMU)

- ASME Computers and Information in Engineering Young Engineer Award, 2018

- Texas A&M University Dean of Engineering Excellence Award, 2017

- Texas A&M University J. Mike Walker 66 Department of Mechanical Engineering James J. Cain Graduate Teaching Award, 2017

- Texas A&M University J. Mike Walker 66 Department of Mechanical Engineering Sallie and Don Davis 61 Faculty Fellow I Assistant Professor, 2017

Michael Kapteyn (MIT)

- Southwest Research Institute Student Paper Prize for AIAA Scitech paper "Toward predictive digital twins via component-based reduced-order models and interpretable machine learning."

Renee Swischuk (TAMU)

- Outstanding Presentation Award, 2017 MAA MathFest

Karen Willcox (MIT / UT Austin)

- AIAA Fellow, Class of 2019
- SIAM Fellow, Class of 2018
- Member of the New Zealand Order of Merit, 2017
- Distinguished Alumni Award, University of Auckland, 2016

9 Transitions

- **Methods to industry**: Close collaboration between academic partners (MIT, TAMU) and industry partner (Aurora Flight Sciences). DDDAS methods transitioning to Aurora via implementation on flight test vehicle. Several discussions 2019-20 with Lockheed Martin Aeronautics about transition of Predictive Digital Twin approaches and a possible follow-on collaborative effort.
- **People**: MIT Postdoc Laura Mainini took a position at United Technology Research Center. MIT PhD student Victor Singh took a position at The Boeing Company. TAMU PhD student Brian Burrows took a position at AIR Worldwide. TAMU M.S. student W. Dillon Thomison took a position at Lockheed Martin ADP Skunk Works.
- Project accomplishments featured in Autonomy brief to the Secretary of the Air Force, October 2017.

10 Supported personnel

Aurora Flight Sciences: Alexander Andersen, Ira Benzion, Daniel Campbell, Jeffrey Chambers, Stephen Clark, John Glezellis, Daniel Hurwit, Cory Kays, Aryom Klochkov, Spencer McDonald, Destiny Mora, Thomas Needham, Peter Riley, Benjamin Smith, Theodore Schaefer, Jack Tulloch, Juha Turalba, Joan Vining, Allison Woyak.

Massachusetts Institute of Technology: Graduate Students: Michael Kapteyn (PhD expected 2021), Victor Singh (PhD, 2019, now at Boeing). Postdoctoral Researchers: Laura Mainini (now at UTRC), Benjamin Peherstorfer (now at Courant Institute), Demet Ulker (now at Envision Energy).

Texas A&M: Graduate Students: Brian Burrows (PhD, 2019, now at AIR Worldwide), Meet Sanghvi (M.S., 2019, now a PhD student at TAMU), R. Cory Allen (M.S., 2018. now a PhD student at TAMU), W. Dillon Thomison (M.S., 2017, now at Lockheed Martin), Lalith Peddareddygari (M.S. expected 2020), Arjun Singh (M.S. expected 2020). Undergraduate researcher: Renee Swischuk (Undergraduate Honors Thesis, 2017, now at Caliper Corporation).

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[2] B. J. Burrows, B. Isaac, and D. Allaire, *Multitask aircraft capability estimation using conjunctive filters*, Journal of Aerospace Information Systems, (2017), pp. 625–636.

[3] M. Kapteyn, D. Knezevic, and K. Willcox, *Toward predictive digital twins via component-based reduced-order models and interpretable machine learning*. Paper AIAA-2020-0418, in Proceedings of Scitech Forum & Exhibition, Orlando, FL, 2020.

[4] L. Mainini and K. Willcox, *Data to decisions: Real-time structural assessment from sparse measurements affected by uncertainty*, Computers and Structures, 182 (2017), pp. 296–312.

[5] V. Singh and K. E. Willcox, *Engineering design with digital thread*, AIAA Journal, 56 (2018), pp. 4515–4528.

[6] R. Swischuk and D. Allaire, *A machine learning approach to aircraft sensor error detection and correction*, Journal of Computing and Information Science in Engineering, 19 (2019).