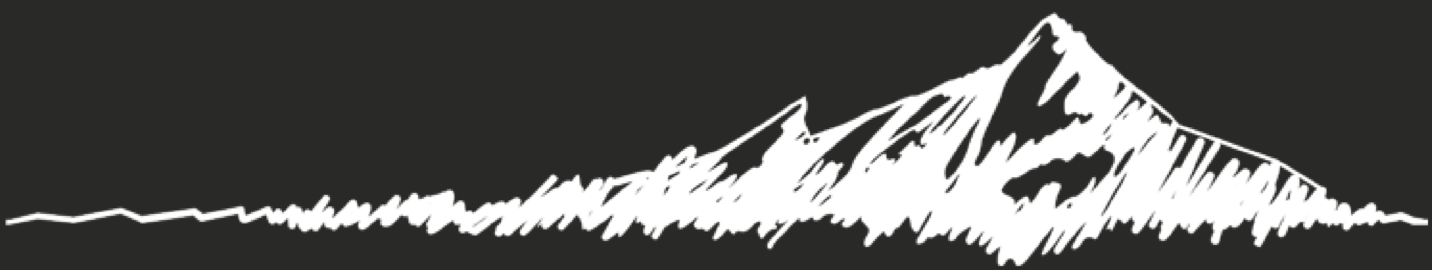
BlackSwift
TECHNOLOGIES

WHITE PAPER

ADVANCED APPLICATIONS OF MACHINE LEARNING FOR UAS

Improved UAS Robustness Through Augmented Onboard Intelligence



THE ISSUE AT HAND

Catastrophic unmanned aircraft system (UAS) failures occur at a much higher rate than manned aircraft; on the order of hundreds of times worse than general aviation aircraft. This is a major concern when considering integration of UAS into the national airspace system (NAS). This high failure rate is due to the lack of onboard monitoring, systematic maintenance, or an onboard pilot. While monitoring systems are prevalent in most manned aircraft, small UAS suffer from a dearth of subsystem state information; critical components such as servos are often open-loop and unmonitored.

Manned aircraft require maintenance and checks by certified mechanics to minimize the chances of equipment failure, and greatly benefit from the presence of a skilled pilot onboard. These pilots, who sometimes have thousands of hours of experience, can prevent failures by noticing ice buildup on wings or navigating without GPS or other electronic navaids. UAS failures - caused by the absence of these factors - are not only expensive in terms of the value of the lost vehicle, avionics, and payload, but also can create potentially dangerous situations if suffered above populated areas or beyond visual line of sight.

CONTENTS

INTRODUCTION

Black Swift Technologies LLC (BST) is working to dramatically improve the reliability of small UAS by using machine learning techniques to both predict critical maintenance and detect hazardous faults in real-time. Accurate prediction of component failure is essential for routine flights to mitigate risk to property or personnel, and can be used to set a schedule for routine maintenance on components that are currently largely ignored until they fail.

BST is working to make these predictions fully autonomous, so maintenance can be accomplished without the need of an expert technician, significantly reducing operating costs. In addition to tracking maintenance needs, BST is employing machine learning algorithms to continuously monitor for faults like icing, propeller damage, and wireless communications failure.

These machine learning algorithms will complement a highly capable avionics subsystem designed, implemented and maintained entirely by BST. This modular system consists of networked onboard monitoring nodes capable of observing subsystem performance in a distributed manner.

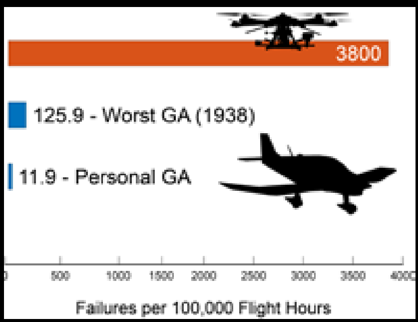
Automation of the detection of these common flight hazards will allow for proper diagnosis and resolution of issues during flight, without requiring the hundreds of hours of experience typically needed for an operator to perform at an equivalent level.

BACKGROUND

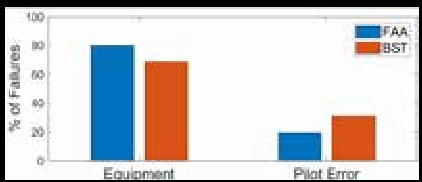
MODULAR BY DESIGN

IMPROVED UAS ROBUSTNESS THROUGH AUGMENTED ONBOARD INTELLIGENCE

UAS failures occur at a much higher rate than manned aircraft



Comparison of Personal General Aviation and UAS accident rates.[1]

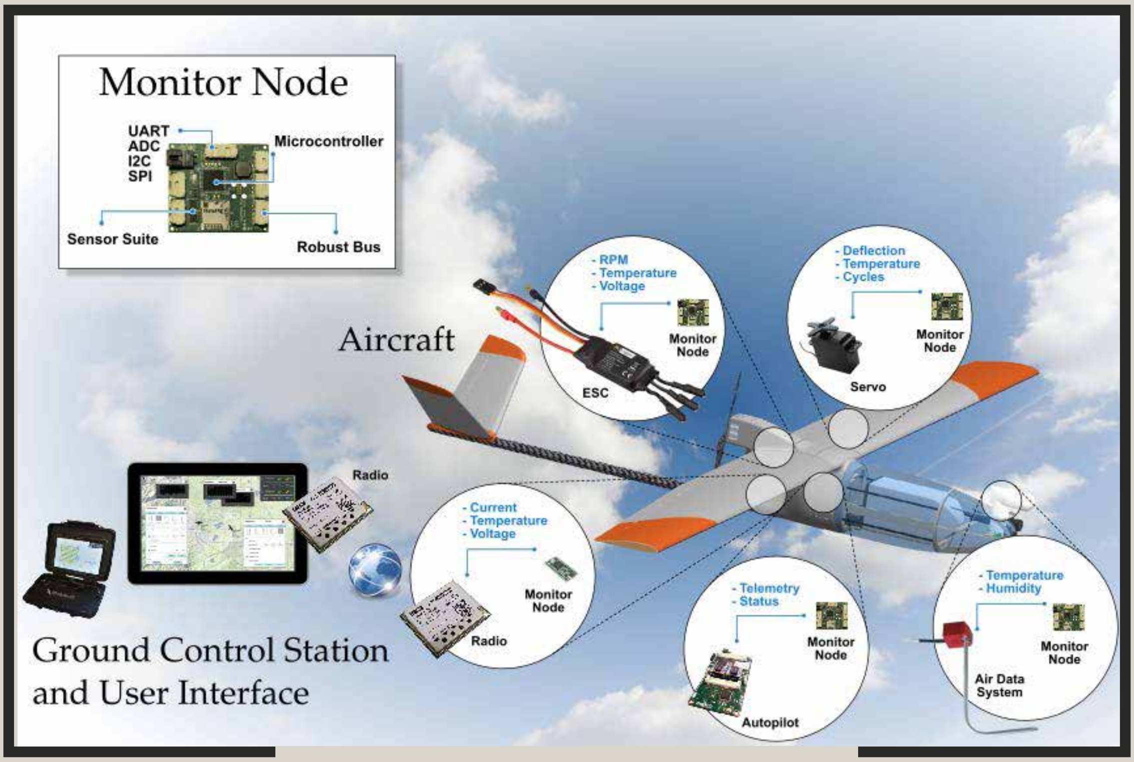


Breakdown of failures, showing that both the internal BST and the FAA database agree that over 2/3's of failures are related to equipment rather than pilot error.

This high failure rate is due to the lack of onboard monitoring, systematic maintenance, or an onboard pilot. While monitoring systems are prevalent in most manned aircraft, small UAS suffer from a dearth of subsystem state information; critical components such as servos are often open-loop and unmonitored.

Manned aircraft require maintenance and checks by certified mechanics to minimize the chances of equipment failure, and greatly benefit from the presence of a skilled pilot onboard. These pilots sometimes have thousands of hours of experience that in itself can prevent failures by noticing ice buildup on wings or being capable of navigation without GPS or other electronic navaids. UAS failures caused by the absence of these factors and are not only expensive in terms of the value of the lost vehicle, avionics, and payload, but also can create potentially dangerous situations if suffered above populated areas or beyond visual line of sight.

[1] R. Matyáš, "Introduction of enhanced vision system and its application for general aviation," MAD-Magazine of Aviation Development, vol. 3, no. 16, pp. 29–31, 2015.



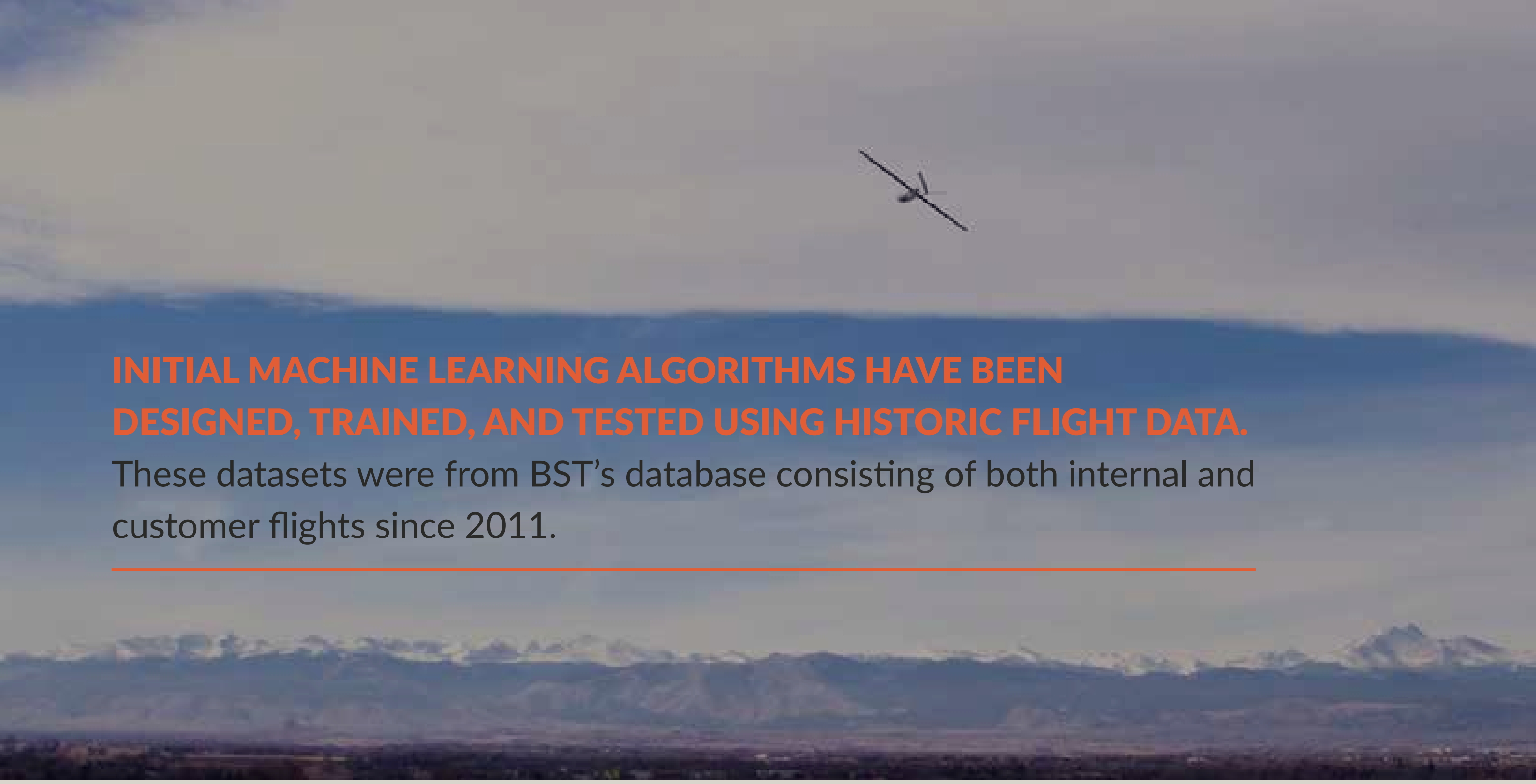
MODULAR BY DESIGN

BST is employing machine learning algorithms to continuously monitor for faults like icing, propeller damage, and wireless communications failure. Automation of the detection of these common flight hazards will allow for proper diagnosis and resolution of issues during flight, without requiring the hundreds of hours of experience typically needed for an operator to perform at an equivalent level.

These machine learning algorithms will complement a highly capable avionics subsystem designed, implemented and maintained entirely by BST. This modular system consists of networked onboard monitoring nodes capable of observing subsystem performance in a distributed manner. These boards—while computationally powerful—are small, lightweight, and consume low power to avoid significantly impacting the performance of the aircraft while minimizing cost. Furthermore, the networked devices can communicate with each other as well as the autopilot, allowing for vehicle wide information to contribute to a high degree of awareness of the aircraft's well-being.

THIS TECHNOLOGY IS BEING DEVELOPED UNDER A NASA SMALL BUSINESS INNOVATION RESEARCH (SBIR) GRANT AND HAS BEEN APPROVED FOR A TOTAL OF $875K IN FUNDING[1].

[1] https://sbir.nasa.gov/SBIR/abstracts/16/sbir/phase2/SBIR-16-2-S3.04-8077.html



INITIAL MACHINE LEARNING ALGORITHMS HAVE BEEN DESIGNED, TRAINED, AND TESTED USING HISTORIC FLIGHT DATA. These datasets were from BST's database consisting of both internal and customer flights since 2011.

01

Working with NASA on this is very important for the overall viability of this technology since NASA and the FAA are leading the effort for the long term integration of UAS into the NAS. Additionally, the SBIR program allows BST to receive up to $875K in a 1:1 match of any additional external funding that should result from the work.

By the end of next year, BST will be providing NASA a system that will enable ubiquitous operations of UAS in the NAS. This technology has the potential to be far reaching as it plays a critical role in beyond-line-of-sight operations, flights over populated areas, and fully autonomous operations without direct human oversight. Furthermore, the overarching vision of ubiquitous use of UAS will require many new technology advancements such as collision avoidance capabilities, GPS denied navigation, and significant improvements in overall system reliability and robustness.

02

It is essential that these operational goals are accomplished using technology that is low cost and lightweight to realize the economic benefits of these autonomous systems. The specific technology gap addressed in this effort is focused on improving reliability, subsystem failure tolerance, and automated diagnostics. To be trusted to operate in the entirety of the NAS, these systems must approach the reliability of manned aircraft without the aid of a skilled pilot. Advanced machine learning techniques are capable of providing that reliability at a low price point.

03

BST has already begun development of these machine learning techniques, and has demonstrated the value of their routine use in UAS. The effort began with an analysis of BST flight records which revealed the most common failure modes for BST manufactured aircraft, as shown in the following table.:

Overall Severity	
Result	Measured
Success	80.40%
Partial Failure	15.20%
Catastrophic Failure	3.80%

Failure Breakdown	
Failure Type	Measured
Lost Communication	4.40%
Payload Failure	3.20%
Landing Failure	2.20%
GPS Outage	1.90%
Loss of Propulsion Power	1.90%
In-flight Airframe Failure	1.30%
Launch Failure	1.30%
Inclement Weather	0.60%
User Error	0.60%
Loss of Onboard Power	0.60%

04

These failures correlate well with data from FAA databases, and accurately represent expected failure by subsystem. Given this data, algorithms were then proposed to autonomously monitor for specific faults associated with common failure modes. Examples of these faults include, but are not limited to:

1. Monitoring the wireless communication subsystem to reduce the possibility of lost communication events.

2. Automatically tracking the performance of the actuators and motors to recommend maintenance or replacement before failures occur.

3. Monitoring the overall aircraft performance and environmental conditions to detect hazards such as icing.

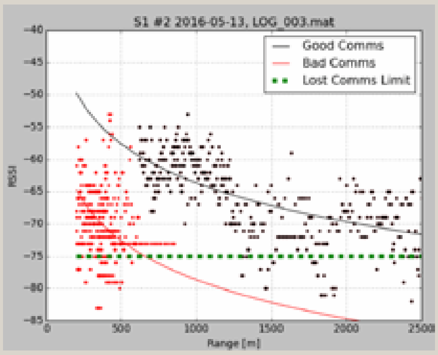
4. Analyzing all onboard data to locate outliers or off-nominal performance that point to potential hazardous failures on-board.

05

An example of the value of these algorithms can be shown through an examination of the wireless communication subsystem. Our implementation allowed for simplified access to data of interest, enabling the system to scan through hundreds of hours of past flights and quickly identify cases of reduced comm performance. These performance issues could then be characterized into a suspected cause, such as using incorrectly selected antennas for the radio system or the operator forgetting to deploy the ground station antenna.

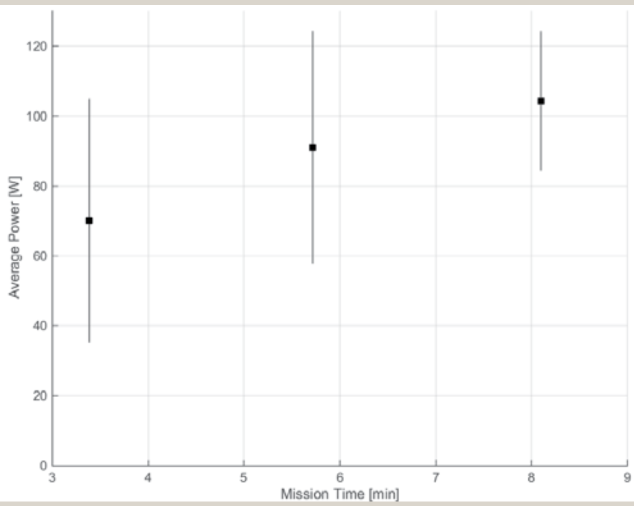
The next figure shows one such flight that started out with bad communications caused by leaving the ground station on the ground without the antenna deployed. This was corrected in-flight, resulting in much improved communication range. If the machine learning algorithms had been on board, the aircraft operator would have been alerted before takeoff.

06



Data showing reduced comms (in red) with a range of less than 600m and improved comms (black) with a range of almost 3km.

Another example was related to tracking the performance of the propulsion system. Running the algorithms on the large set of historic flight data found very consistent performance of the efficiency of the propulsion system across similar systems. Several major outliers corresponded to conditions like flying much heavier payloads or even aircraft icing. The graph below shows the degradation of the propulsion system as rime ice builds up on the wing of a BST S1 and the photograph shows the ice buildup on a winter flight of an S2.



Data showing increased power requirements as icing forms on a fixed wing UAS.

Clear ice build-up on a wing of an S2 after a high altitude test flight in the winter.

THE VALUE OF ALGORITHMS

PROOF OF CONCEPT

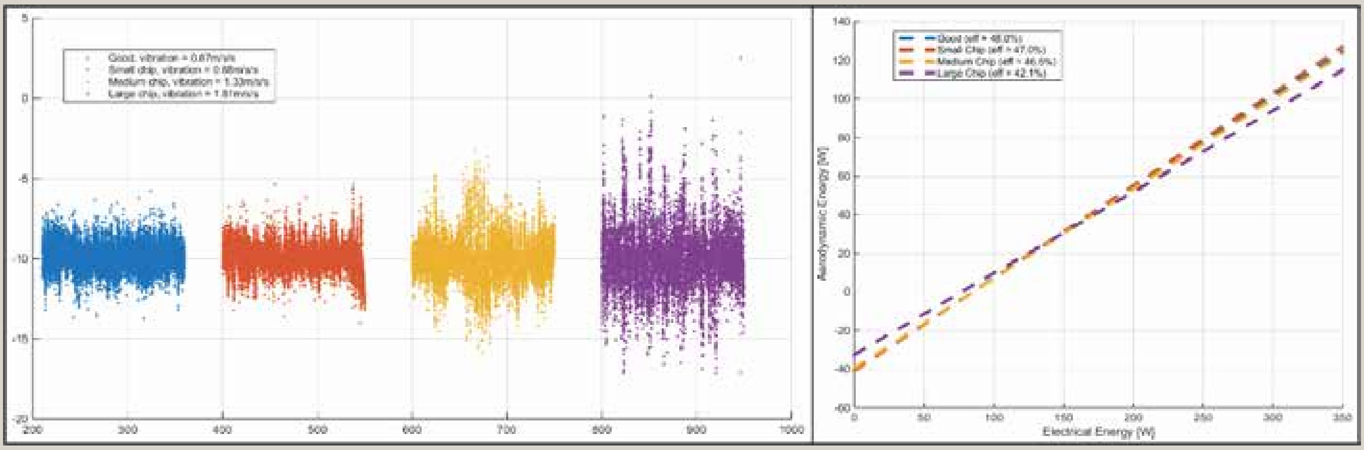
AS A DEMONSTRATION TO THE VALUE OF THE ALGORITHMS FOR DETECTING OFF-NOMINAL SITUATIONS —EVEN THOSE THEY ARE NOT TRAINED SPECIFICALLY FOR— AN ANALYSIS OF THE FLIGHT USING THE SAME ALGORITHMS DEVELOPED TO DETECT ICING FOUND THE PROPULSION SYSTEM EXPERIENCED REDUCED EFFICIENCY AND INCREASED VIBRATION.

In addition to the historic flight database, specific failure modes have been simulated and tested to collect data for developing detection algorithms.

For example, the propeller on a BST UAS was purposely damaged and flight tested to gather data on the effects of a compromised propulsion system. Chipped or damaged propellers are a common issue that can be caused by a hard landing or debris strike. Propeller damage can be catastrophic not only to flight time, but also to the vehicle in the case of a multi-rotor platform. Characterization was performed initially using an undamaged propeller followed by a series of tests after the propeller had been chipped by an increasing amount.

Image of controlled propeller chipping.

Between the undamaged and most damaged flights, the algorithms computed a 108% increase in vibration and a 5.9% reduction in propulsion efficiency (refer to graphic on next page). Vibration change is a strong indicator of propeller damage that a real-time algorithm can use to automatically detect propeller damage.

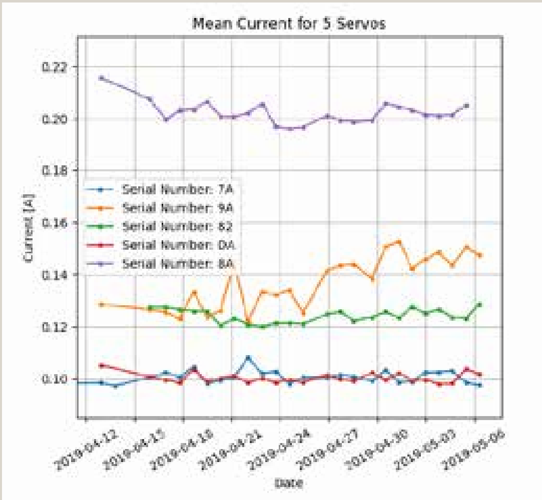


Left: Z-axis acceleration profiles of increasing propeller chipping. The vibration increased by 108% between the undamaged and most damaged propeller. Right: Aerodynamic efficiency curves for increasing propeller chipping. The efficiency decreased by nearly 6% between the undamaged and most damaged flights.

In addition to the real-time fault detection algorithms, preventative maintenance algorithms are being developed to help detect imminent failures in hardware subsystems. The BST avionics are modular and distributed. This is a key design feature in that 1) the failure of one node generally doesn't cause the failure of the whole system and 2) electronics can be paired with subsystems such as servos and motors to allow for them to be uniquely identified and tracked over their lifetime. To this end, BST has outfitted critical hardware components with sensors and a protocol has been developed to exchange data over a robust network bus. This has allowed the team to begin tests to gather data on hardware faults, and for bench testing to be performed on isolated subsystems for failure analysis. This testing includes both an examination of long-term wear and tear as well as transient, destructive failures. Tests are currently being conducted on the control servos, motors, and batteries - totaling in the hundreds of hours for some subsystems.

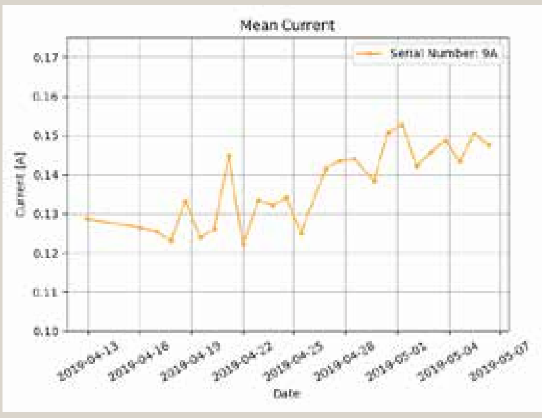
As an example, the servo motors that actuate the control surfaces of BST UAS are currently being tested under representative loading. The servos under test have run for over 3,000 hours combined. The data collected on the first set of servos shows a large variation between different servos of the same make and model.

Current draw among the same type of servo under similar loading can vary by up to 100%. This data allows for the establishment of a baseline performance for servos of the same part number. Tracking data over the lifetime of individual servos allows for an assessment of servo degradation. For example, one servo has been found to steadily increase its current draw over the course of testing.



Mean current draw over 500 hours of testing for five servos of the same make and model.

As servos change over time, clustering algorithms will be explored to automatically make an assessment of in-family and out-of-family performance. Once a significant failure is encountered, algorithms can be developed to help predict such a failure in the future.



Mean current draw over 500 hours of testing for one servo. The observed current draw has been increasing over time.

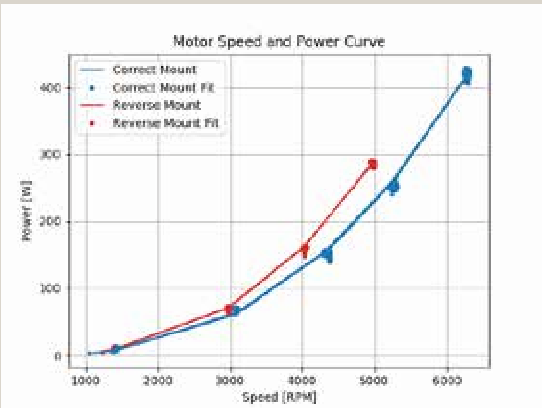
EXTENDING OUR TESTING

MOTORS AND ESC

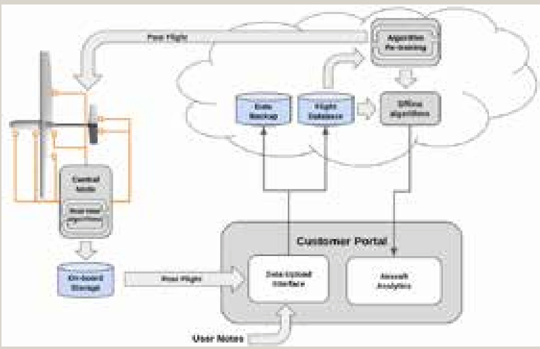
BST HAS OUTFITTED CRITICAL HARDWARE COMPONENTS WITH SENSORS AND A PROTOCOL HAS BEEN DEVELOPED TO EXCHANGE DATA OVER A ROBUST NETWORK BUS.

Similar testing has also begun on the motor and the electronic speed control (ESC) unit that drives it. Common failure modes like a damaged winding or debris in the rotor will be tested to gather data for algorithmic development. Fitting curves to the two trends shows a clear difference in efficiency. The reversed propeller draws far more power to achieve the same motor speed. Similar analysis could be applied to help identify a chipped propeller, and tests to gather this data are planned. By applying a fitted model to the motor data, machine learning tools like support vector machines could be used to separate in-family and out-of-family performance.

The algorithms built to date are just scratching the surface of what can be done with the overall machine learning approach and are already providing value to BST customers. Future work will introduce new algorithms, expand sensing capabilities, and move such capabilities onboard the aircraft. It will result in a greatly improved level of safety through more proactive fault and failure management. As the scope and amount of UAS operations increase, this type of technology will be critical, enabling users to safely operate affordable UAS for commercial and scientific applications.



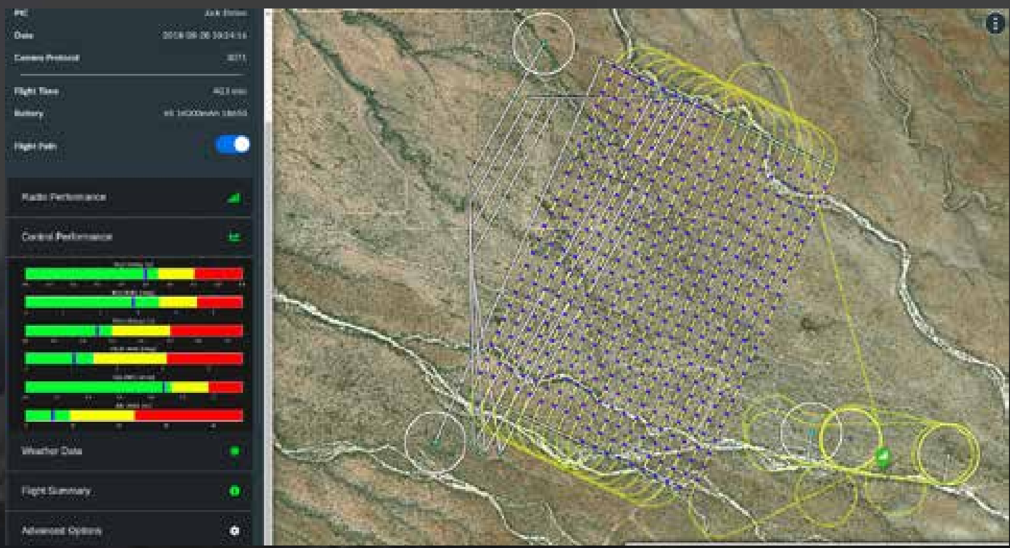
Power consumed by the motor as a function of motor speed.



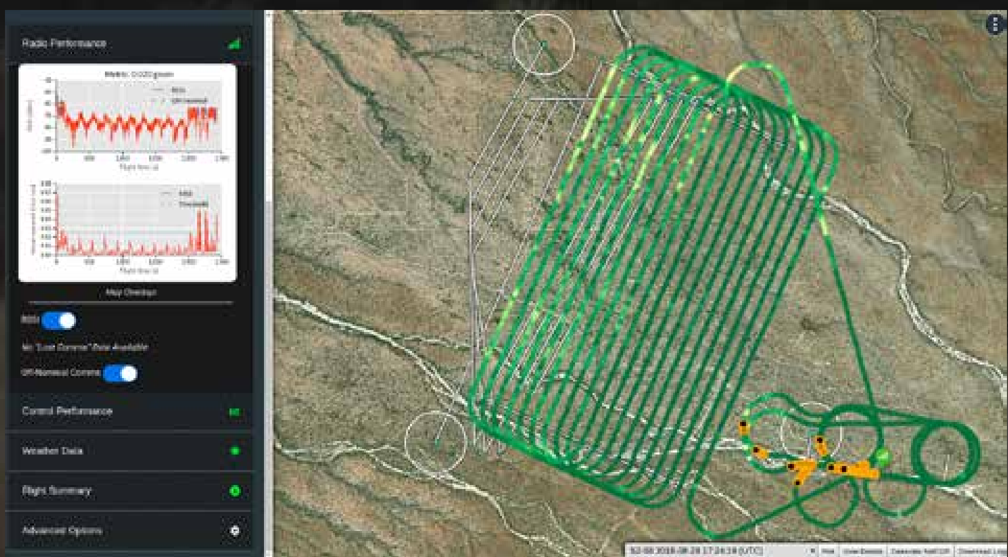
Maintenance workflow and system overview, detailing the currently available setup that transitions flight data into actionable maintenance tasks.

Users can upload new data or browse their historical flight logs for analysis. Historical flights are displayed as thumbnails on a map of the world.

Early validation and commercialization includes an online portal for users of BST aircraft to upload flight logs (above) where the machine learning algorithms will run to assess flight characteristics and recommend maintenance for systems showing degraded performance (below).



Artificial intelligence based analysis algorithms are run on every log and the results are displayed in the sidebar. An automatic analysis of the controls performance is expanded for display in the sidebar. The flight plan and aircraft trajectory are plotted on the map.



Here the AI based analysis of the communications subsystem is displayed in the sidebar. The customer portal now includes geospatial analysis of data. The received signal strength indicator (RSSI) for the flight is plotted over the GPS trajectory in green along with periods of time the AI algorithm flags the radio as off-nominal (in orange and black).

EARLY ADOPTION

Early validation and commercialization includes an online portal for users of BST aircraft to upload flight logs where the machine learning algorithms will run to assess flight characteristics and recommend maintenance for systems showing degraded performance. This incentivizes customers and users of BST UAS to upload their flight data and provides an ever growing database of flight logs that can be used to better train and improve the algorithms over time. The online portal has provided BST with an excellent interface for user interaction and testing on a small scale, and will continue to provide advanced functionality to users of BST systems.

The commercialization strategy for this effort is focused on demonstration and iteration. The top priority is to deploy components of this technology early on with the online portal and gradually start adding the on-board tracking components to both BST aircraft and select customers. The capability to integrate the proposed system with third party aircraft and scalability of the software-based solution will allow BST to quickly grow their user base. In addition, it will drive hardware sales as BST plans on incorporating this technology directly into our commercial offerings. BST plans to utilize revenue from commercial sales to continue adding industry-leading technology into our existing commercial UAS offerings, broadening the information that can be collected from each system and the machine learning capabilities. Commercial transition will also entail a seamless system for providing maintenance recommendations and replacement parts. Customers making use of our portal will be alerted of required fixes or refurbishments, and can make purchases directly from that interface. This is an additional step that further simplifies guaranteeing a well maintained UAS with minimal burden on the company or customer operating the aircraft.

The web portal and machine learning algorithms have been developed in such a way to easily adapt them to other UAS systems. The initial online portal was developed using industry standard cloud computing tools that allow for rapid scalability. This allows for a subset of the functionality to be retooled for immediate use by the much larger UAS community, the majority of which make use of systems from other manufacturers. Interfaces provided by these manufacturers to drive many of the cloud-based mapping solutions provide sufficient vehicle information for BST to gathering valuable data about a customer's aircraft. As has already been demonstrated with data from BST aircraft, primary machine learning algorithms can be scaled with the amount of sensor data available on each subsystem, making them useful for the vast majority of UAS. Therefore, with little overhead, BST's proprietary algorithms can be applied to detect and prevent imminent failures before they happen on a wide variety of UAS from different manufacturers. In addition, success shown here can be used to encourage BST's web portal as a value add for manufacturers. BST plans to publish standard data formats to allow for manufacturers to expose additional data about their aircraft, encouraging wider spread use of our system through increased third party compatibility.

NATURE OF ADOPTION

Lastly, a subset of the machine learning algorithms developed as part of this effort make use of specialized data provided by the advanced avionics on BST aircraft. The architecture of these avionics is modular and decentralized, so while some components rely on proprietary BST monitoring circuits, the components themselves can be sold piecemeal to augment third party systems, creating another source of revenue. In turn, the modular nature of the BST system also allows for quick adoption of commercial off the shelf (COTS) components. This will enable BST to accommodate new sensors and subsystems, keeping the system relevant with the rapidly changing UAS technology landscape.

SWIFTCORE AVIONICS

END-TO-END AVIONICS LETTING YOU CONTROL, COMMUNICATE AND COMMAND YOUR UAS FOR FULLY AUTONOMOUS FLIGHT

SwiftPilot™

SwiftPilot is an advanced high-performance autopilot system designed specifically for Unmanned Aerial System (UAS). Enables fully autonomous flight from launch to landing.

- One of the smallest and most powerful autopilot commercially available
- Two dedicated 168 Mhz Cortex-M4 CPU with FPU for autonomous sUAS functionality (core processors) and one (optional) 1 GHz Cortex-A8 processor (payload processor) for customer use
- Modularized CAN-bus hardware architecture, enabling virtually an unlimited number of connectivity options for peripherals/payloads (UART, I2C, SPI, CAN, Ethernet, USB, GPIO, etc.

SwiftTab™

With its intuitive user-focused interface, SwiftTab enables flight planning that is both simple and easy to accomplish. Operators can program their BST UAS in minutes to calculate the area under review and then begin collecting data for immediate analysis and decision-making.

- Runs on a handheld Android™ Tablet as well as Android-based smart phones
- Flight plans can be modified and uploaded mid-flight
- Easily import maps and other geo-referenced data points
- Gesture-based controls enable users to confidently deploy their UAS with minimal training

SwiftStation™

SwiftStation is a tripod-mounted, intuitive ground station that is both highly portable and customizable to support application-specific sensor integrations.

- Incorporates both a 900MHz and a GPS antenna
- Expandable functionality via custom modules
- Multiple radio options available based on customer's specific requirements
- Seamlessly integrates with X-Plane Pro Flight Simulator

ABOUT BLACK SWIFT TECHNOLOGIES

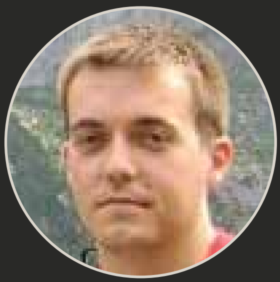
SINCE 2011

Black Swift Technologies (BST) is based in Boulder, CO and has been in operation since 2011. BST is unique is than all UAS sold by BST are built upon it's own SwiftCore^{TM} flight management system (FMS) that includes the autopilot, ground station, user interface, and support electronics. Unlike many competing systems that rely on open-source and low-quality avionics, BST is able to guarantee quality, robustness, and supply of the most critical components of our systems. The SwiftCore FMS was designed by BST from the ground up. This affords control of the critical parts of our products, including the design of all electronics for both the avionics and ground systems, software, mechanical assembly, and the detailed QC process for all outgoing systems. Furthermore, BST uniquely couples avionics expertise with consulting services, and has delivered products and engineering services to many government entities including NASA, NOAA, various universities along with commercial sales to end-users and aircraft integrators.

JACK ELSTON

CEO

Dr. Elston received his Ph.D. from the University of Colorado Boulder based on work that developed a complex meshed network, unmanned aircraft system, and control algorithms for in situ sampling of tornadic supercell thunderstorms. Dr. Elston is also the technical lead on all avionics work at BST including the creation of the highly capable autopilot system that anchors the SwiftCore Flight Management System.



MACIEJ STACHURA

CTO

Dr. Stachura received his M.S. and Ph.D., both in aerospace engineering, from the University of Colorado Boulder. During his time at CU, Dr. Stachura was involved in over 300 fight experiments ranging from multi-aircraft cooperative flight experiments to the VORTEX2 field campaign, which involved the first-ever intercept of a tornadic supercell thunderstorm.

Black Swift Technologies
3200 Valmont Road, Suite 7 • Boulder, CO 80301
https://bst.aero
© 2019 Black Swift Technologies. All rights reserved.