Verification of Prognostic Algorithms to Predict Remaining Flying Time for Electric Unmanned Vehicles

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Abstract

This paper addresses the problem of building trust in the online prediction of a battery powered UAV’s remaining available flying time. A series of ground tests is described that make use of an electric unmanned aerial vehicle (eUAV) to verify the performance of remaining flying time predictions. The algorithm verification procedure described is implemented on a fully functional vehicle that is restrained to a platform for repeated run-to-functional-failure (charge depletion) experiments. The vehicle under test is commanded to follow a predefined propeller RPM profile in order to create battery demand profiles similar to those expected during flight. The eUAV is repeatedly operated until the charge stored in powertrain batteries falls below a specified limit threshold. The time at which the limit threshold on battery charge is crossed is then used to measure the accuracy of the remaining flying time prediction. In our earlier work battery aging was not included. In this work we take into account aging of the batteries where the parameters were updated to make predictions. Accuracy requirements are considered for an alarm that warns operators when remaining flying time is estimated to fall below the specified limit threshold.
1. Introduction

Improvements in battery storage capacity have made it possible for general aviation vehicle manufacturers to consider electrically-powered solutions. The development of trust in battery remaining operating time estimates, however, is currently a significant obstacle to be overcome when considering adoption of electrical propulsion systems in aircraft (Patterson, German & Moore, 2012). There are several ways in which predicting remaining operating time is more complicated for battery-powered vehicles than it is for vehicles with a conventionally-powered liquid-fueled combustion system. Unlike a liquid-fueled system, where the fuel tank’s volume remains unchanged over successive refueling procedures, a battery’s charge storage capacity will diminish over time. Another complicating feature of a battery system is the time-varying relationship between battery output power and battery current draw. Whereas a conventional liquid combustion system uses an approximately constant amount of liquid fuel to produce a given motive power, the power from a battery system is equal to the product of battery voltage and current. Thus, as batteries are discharged, their voltages drop lower, and they will lose charge at a faster rate.

Our previous papers introduced several new tools for battery discharge prediction onboard a small electric aircraft. One paper described a battery equivalent circuit model to simulate battery state (Bole, Teubert, Quach, Hogge, Vazquez & Goebel, 2013). The model’s battery capacity, internal resistance and other parameters were identified through two laboratory experiments that used a programmed load. The batteries were slowly discharged in one experiment. In the other experiment a repeated pulsed loading was done. Current and voltage profiles logged during flights of a small electric airplane further tuned the battery model (Quach, Bole, Hogge, Vazquez, Daigle, Celaya, Weber & Goebel, 2013). The use of a flight plan with upper and lower uncertainty bounds on the required energy to complete the mission successfully was presented along with an approach to identify additional parasitic battery loads (Bole, Daigle & Gorospe, 2014). Another paper introduced a verification testing procedure that is intended to build trust in predictions of remaining flying time prior to actual flight testing (Hogge, Bole, Vazquez, Celaya, Strom, Hill, Smalling & Quach, 2015). This article is a further discussion of the verification testing of remaining flying time prior to flight testing. The philosophy behind the testing procedure described here is to translate system performance and safety goals into requirements for an alarm that warns system operators when the estimated remaining flying time falls below a certain threshold. Ground testing of the actual vehicle provides the closest possible testing conditions short of actual flight and captures some of the variation that the powertrain hardware and that the pilot may introduce while avoiding the risks inherent in flight. For instance, the batteries may be drained to a lower capacity during testing of the remaining flying time prediction without danger of vehicle loss.

A large electric unmanned aerial vehicle (eUAV) was used in this study. The eUAV is a 33% sub-scale version of the Zivko Aeronautics Inc. Edge 540 T tandem seat aerobatic aircraft as seen in Fig. 1. This vehicle has been actively used by researchers at NASA LaRC to facilitate the rapid deployment and evaluation of remaining flying time prediction algorithms for electric aircraft since 2010. Examples of prior works using this platform are found in the following papers: (Saha, Koshimoto, Quach, Hogge, Strom, Hill, Vazquez & Goebel, 2011),
Remaining flying time prediction algorithms focus on the prediction of battery charge depletion over an eUAV flight. A lower-bound on the battery state of charge (SOC) that is considered safe for flight is set at 30% in this work. Flying the vehicle with batteries below 30% SOC is considered to be a high-risk mode of operation. Policy and guidelines are set according to the rulings and the engineering judgment of the NASA Langley UAS Operations Office and the NASA Langley Airworthiness and Safety Review Board. Such violations of operating guidelines are referred to here as a functional failure of the vehicle’s mission. The primary use case for remaining flying time predictions is to warn system operators when landing procedures must be initiated to avoid aircraft batteries becoming too depleted. It was determined that initiating landing procedures when the eUAV batteries reach 30% SOC would provide a sufficient energy buffer for at least two “missed approach” maneuvers without risk of exceeding battery current limits and any associated excessive heating based upon ground tests. The predictive element to be tested in this work is an alarm that warns system operators when the powertrain batteries are two minutes from reaching the 30% SOC threshold under normal operating conditions. This should allow the pilot sufficient time to prepare for landing without exceeding a moderate work load.

The accuracy of onboard remaining flying time estimation algorithms is tested in this work. A series of controlled run-to-functional-failure (charge depletion) experiments were conducted. The vehicle under test was strapped down to a platform and commanded to follow an RPM profile that created battery demand profiles similar to those expected for flight while a ground station operator monitored the battery health parameters.

The time it takes for powertrain batteries to reach 30% SOC establishes a truth value for the functional failure time. Unlike actual flight tests, powertrain batteries can be repeatedly run down to their lower-limits in the ground-based testing described here to verify the accuracy of remaining flying time predictions.

The defined performance requirements were then verified by repeating ground based run-to-functional-failure tests a specified number of times. The performance requirement testing procedure used here was originally introduced in Saxena, Roychoudhury, Lin and Goebel (2013).

Section 2 of this paper provides an overview of the Edge 540T powertrain. Algorithms used for onboard battery state estimation and remaining flying time predictions are summarized in Section 3. The process used to verify onboard remaining flying time predictions through ground testing and experimental results are described in Section 4. Finally, concluding remarks are given in Section 5.

2. **Overview of Edge 540T Powertrain**

A wiring diagram for the vehicle powertrain is shown in Fig. 2. The aircraft has two 3-phase tandem motors that are mechanically coupled to the aircraft propeller. Powertrain batteries are arranged in two pairs of series connected battery packs. A switchable parasitic load $R_p$
injects a fault to test the robustness of the remaining flying time estimation algorithms to changes in battery loading demand. The other symbols in Fig. 2 identify the location of current and voltage sensors.

Remaining flying time predictions are generated by propagating a number of estimates of the battery charge forward. Forward propagation of the present battery state estimate is performed using an estimate of the future powertrain demand that will occur over the known flight plan. These future loads include propeller loads and parasitic loads. The prognostic tools make use of the known flight plan to inform future load predictions, but no prior information is assumed to be available regarding when a parasitic load may be injected.

3. Remaining Flying Time Prediction

Battery discharge prediction is described here in terms of the following components; (i) online battery state estimation; (ii) prediction of future battery power demand as a function of an aircraft flight plan; (iii) online estimation of additional parasitic battery loads; and (iv) prediction of battery discharge over the future flight plan. The assumptions and algorithms used for each of these steps are summarized in this section.

3.1. Online Battery State Estimation

Our previous papers (Quach et al., 2013) and (Bole et al., 2014), described the use of an equivalent circuit model and an unscented Kalman filter (UKF) (Julier & Uhlmann, 1997, 2004) to update battery state estimates based on observations of current and voltage at the battery output terminals. This approach is also summarized here for convenience. Figure 3 shows an equivalent circuit battery model that is used to represent battery output voltage dynamics as a function of battery current. It is similar to models presented in (Chen & Rincon-Mora, 2006, and Ceralo, 2000). The basic model is based on Thevenin’s theorem to model the current and voltage profile of the battery as a black box input-output device. We make the first-approximation assumption that the battery state can match a linear electrical network with voltage and current sources and only resistances. Thevenin states that the black box can be replaced at the input output terminals by an equivalent voltage source in series connection with an equivalent resistance. To better match standard battery phenomenon, such as internal resistance voltage drops and hysteresis effects, additional pairs of series connected RC parallel circuits are added to the model. The $R_p$, $C_p$ pair are added for the internal resistance drop and the $R_{C_p}$, $C_{C_p}$ pair are added for the concentration polarization effect. The correspondence of these RC circuits to actual battery chemical phenomena is only notional. Models that better account for the electrochemical behavior and aging effects are being considered for future work. (Daigle and Kulkarni, 2013). See section 4.3 for further discussion. In the equivalent circuit model, some of the components were made to vary according to the bulk charge stored in $C_p$ as described in (Zhang and Chow, 2010). The State of Charge (SOC) is a battery charge estimate of the bulk charge. The battery input-output voltage dynamics will change as a function of this bulk charge estimate. Battery SOC is defined here as:
\[
SOC = 1 - \frac{q_{\text{max}} - q_b}{C_{\text{max}}}
\]

Where \(q_b\) represents the charge stored in capacitor \(C_b\), \(q_{\text{max}}\) is the maximum charge that the battery can hold, and \(C_{\text{max}}\) is the maximum charge that can be drawn from the battery in practice. This battery model contains six electrical components that are tuned to recreate the observed current-voltage dynamics of the Edge-540T battery packs. The following SOC parameterizations \((\text{Bole et al., 2014})\) were used to model the bulk charge influence on the \(C_b\), \(C_{cp}\) and \(R_{cp}\) circuit elements of Fig. 3:

\[
C_b = C_{Cb3} + C_{Cb2}SOC + C_{Cb1}SOC^2 + C_{Cb0}SOC^3
\]

\[
C_{cp} = C_{Cp0} + C_{Cp1}\exp(C_{Cp2}(SOC))
\]

\[
R_{cp} = R_{Cp0} + R_{Cp1}\exp(R_{Cp2}(SOC))
\]

These parameters \((C_{\text{max}}, R_s, R_{Cp0}, R_{Cp1}, R_{Cp2}, C_{Cp0}, C_{Cp1}, C_{Cp2})\) were identified by fitting a pulsed discharge lab experiment voltage profile shown in Fig. 4 with a Nelder-Mead downhill simplex method solution search that minimizes the error between the modeled and actual voltage profile \((\text{Nelder & Mead, 1965})\).

These identified parameters are associated with a selected battery from a batch of batteries of a given chemical formulation. These parameters are assumed to be unvaried across all similar battery packs of a given batch. Any differences in individual batteries due to manufacturing variation is accounted for by adaptation of the battery charge capacity term \(C_{\text{max}}\) of the \(C_b\) capacitor in the equivalent circuit model. \(C_{\text{max}}\) is identified by running a slow discharge lab experiment for each battery pack as shown in Fig. 5.

During this low current discharge test, the voltage across the \(C_b\) capacitor plays a dominate role. Thus, this experiment allows the \(C_{\text{max}}\) parameter in the equivalent circuit model to be fitted in isolation, also through use of the Nelder-Mead simplex method \((\text{Bole et al., 2014})\). According to the SOC definition \((\text{equation 1})\) \(C_{\text{max}}\) will always be less than \(q_{\text{max}}\), due to electrochemical side-reactions that make some portion of a battery’s charge carriers unavailable. As the battery ages more of its internal charge will become unavailable because of these side reactions. The \(C_{\text{max}}\) parameter must be refitted periodically to capture this effect \((\text{we use 10 recharge cycles between refits})\). The \(C_{\text{max}}\) and \(R_s\) parameters obtained were used in a simulation run using the current profile from a chamber run. The SOC battery plots were examined to see if the SOC estimates remained constant while the battery voltage recovered in the recorded rest period after the run. If they remained nearly constant, they were used. If estimated SOC was seen to rise during the rest period, it indicated that \(R_s\) was too low and needed to be increased. Likewise, if SOC was seen to fall, then \(R_s\) was too high and needed to be decreased. This \(R_s\) selection was repeated until the SOC estimates remained constant after a run.
3.2. Unscented Kalman Filter

Once all battery parameters are fitted, the UKF is used to update model projections of the battery output voltage with past measurement data in a tracking mode. The UKF takes in the measured battery current and voltage, and gives probability distributions for the charge states of each of the three capacitors in the equivalent circuit model as components of a state vector.

The UKF is a tool for computing probabilistic belief in system state estimates based on stochastic models of the system’s dynamics. The UKF assumes a general nonlinear form of the state and output equations, and efficiently propagates model and state uncertainties. The UKF employs an unscented transform using a minimal set of weighted samples, called sigma points, whose mean and covariance are preserved once transformed by the unscented transform and the nonlinear battery model function (Julier & Uhlmann, 1997, 2004). The UKF takes battery current as a controlling input to the system, and the measured battery voltage from the previous time step. The UKF gives a probability distribution for the future voltage state as system output. The SOC distribution can be directly derived from this. The number of sigma points required is minimal as compared to particle filters that require an order of magnitude more random variable sampling. The future system state must be simulated until a given cut-off threshold is reached for each sampled particle. (Daigle et al., 2012). Readers interested in the application of UKF to the estimation of battery SOC are referred to our previous papers (Bole et al., 2013; Daigle et al., 2012) and the references therein. The Bayesian use of actual past system behavior makes the model-based filtering approaches such as UKF much less susceptible to initialization and measurement errors than the coulomb counting method currently used in many battery monitoring systems (Dai et al., 2006).

3.3. Prediction of Motor Power Demand as a Function of Aircraft Flight Plan

After estimating battery state, the next step towards predicting remaining flying time is the estimation of motor power demand over the remainder of a given flight plan. The aircraft’s flight plan is assumed here to be specified in advance in terms of a set of segments of fixed airspeed. Each segment includes a desired vehicle airspeed along with an expected duration or other ending condition. An example flight plan is defined here as:

1. Takeoff and climb to 200 m:
   Set airspeed to 25 m/s, hold for 1.0 min
2. Maintain altitude, airspeed:
   Set airspeed to 23 m/s, hold for 3.0 min
3. Maintain altitude, increase airspeed:
   Set airspeed to 25 m/s, hold for 2.0 min
4. Maintain altitude, decrease airspeed:
   Set airspeed to 20 m/s, hold for 2.0 min
5. Maintain altitude, increase airspeed:
Set airspeed to 23 m/s, hold until landing is called by monitors on the ground.

6. **Remote control landing:** airspeed and duration may vary widely depending on pilot behavior and environmental conditions.

The energy needed for an aircraft to fly the remainder of a given flight plan will necessarily be uncertain due to random variation in pilot behavior and environmental conditions. A minimum, maximum, and median motor power demand for each remaining segment of the flight plan is used in this work to represent prediction uncertainty. These three power estimates can then be integrated to form predictions of the minimum, maximum, and median motor energy consumption over the remaining flight plan.

Figure 6 shows sample predictions of future motor power and energy demand over segments 1–5 of the given flight plan. Here, segment 5 of the flight plan is shown to extend out indefinitely (20 min.), representing the intent to continue flying until the ground team calls for a landing. The median motor power demand is estimated for each flight plan segment using a previously developed reduced order powertrain and aerodynamics model, discussed in Bole et al. (2013) and Bole et al. (2014). A plus or minus 20% error margin around the median motor power demand estimate was used to generate the minimum and maximum predictions shown in Fig. 6.

A constraint on the minimum battery SOC required for safely landing the aircraft is considered to limit the aircraft’s maximum safe flying time. Prediction of available flying time remaining can thus be considered as the time until the battery SOC reaches 30%, assuming that a landing will not be called until the last possible moment. A triplet of minimum, maximum, and median remaining flying time estimates will ultimately be produced by estimating when the battery SOC threshold would be reached for each of the minimum, maximum, and median motor power profiles.

3.4. **Online Estimation of Additional Parasitic Battery Loads**

Parasitic demands on the battery system that cannot be known in advance are simulated with a resistive load that may be injected in parallel with the aircraft batteries at any time during flight. This parasitic load is denoted as \( R_p \) in Fig. 2. The magnitude of the parasitic load is assumed to be unknown. An online filtering routine, described in Bole et al. (2014), was shown to rapidly converge on estimates of parasitic load using data from the current and voltage sensors shown in Fig. 2. A battery current profile and parasitic load estimates from a sample aircraft data set is shown in Fig. 7. Here, a 5.5 \( \Omega \) parasitic load is injected in parallel with the aircraft batteries at 5 minutes into the run. The time at which the parasitic load is injected is shown with a dashed line on the third column of plots in Fig. 8. At the time the load is injected the battery current is seen to become notably higher than the motor current. The estimated parasitic load is then seen to rapidly converge to approximately 5.5 \( \Omega \).

Online parasitic load estimates are directly incorporated into battery discharge predictions. This results in an immediate shift in battery discharge predictions each time the parasitic load estimate is updated. This immediate shift in discharge predictions is demonstrated in the following subsection.
3.5. Predicting of Battery Discharge Over a Flight Plan

Figure 8 shows plots of measured and predicted battery current, voltage, and SOC at three sample times over the battery discharge run. The minimum, median, and maximum predictions are plotted from each sample time until the predicted SOC reaches 30%. The predictions made at the first two sample times occur prior to parasitic load injection. These predictions are seen to under-estimate the future battery current loads, resulting in over-estimates of future battery voltage and SOC. The parasitic load has been detected by the third sample time, and the predictions at that time are seen to be much more closely centered on the measured evolutions of battery current, voltage, and SOC.

Figure 9 shows predictions of remaining flying time for the example run shown in Fig. 8. The solid line in Fig. 9 indicates the true flying time remaining. The dashed line in Fig. 9 represents the median remaining time prediction. The bars in Fig. 9 represent the interval between the minimum and maximum remaining time prediction. Here, the true flying time remaining is found by subtracting the current time from the time at which the lowest battery SOC crossed 30%. The predictions are seen to overestimate remaining flying time until the parasitic load is detected at about 5 minutes into the run. After the parasitic load is detected the remaining flying time predictions are immediately shifted down.

4. Ground Test Verification of Remaining Flying Time Prediction

The ground-based verification testing of Edge 540 T hardware and software was performed by strapping the vehicle down in the LaRC Electromagnetics and Sensors Branch High Intensity Radiated Fields (HIRF) test chamber. More information about the HIRF Chamber can be found in a report of an earlier UAS radio frequency emissions test in (Ely, Koppen, Nguyen, Dudley, Szatkowski, Quach, Vazquez, Mielnik, Hogge, Hill & Strom, 2011). The airplane was placed upon expanded-polystyrene blocks centered within the chamber, as seen in Fig. 10. The aircraft powertrain with propeller was operated with the vehicle anchored using a steel cable to the chamber wall. Its motor and actuators were operated from another room using the same remote control radio that will be used in flight tests.

Measured aircraft states, battery SOC estimates, and remaining flying time estimates were broadcast to a ground station over a wireless downlink. The ground station also had an uplink interface that enables the aircraft’s autopilot to autonomously follow a given flight plan in chamber testing. This autopilot hardware-in-the-loop interfacing capability is discussed in (Bole et. al., 2013).

Only manual control was used for the test results described in this paper, although the autopilot interface is expected to be used in future work. Aircraft propeller RPM, estimated battery SOC, and predicted flying time remaining were displayed to system operators by the ground station in near real-time. The motor throttle was commanded using the control radio by a manual operator, who read the RPM display from the ground station. The operator adjusted the remote control throttle to maintain the target values for the time duration as determined by the flight plan described in Section 3.2. The test proceeded until a 28% SOC condition was indicated on the ground station display for the lowest battery. Battery current draw was then stopped and powertrain batteries were allowed to rest for approximately one
hour. The battery terminal voltages at rest were used compute an empirical approximation of ending battery SOC.

Onboard data logging during the experiment runs was performed by the data system described in (Hogge, 2011). After the conference paper that described the 2014 chamber runs, some additional runs were completed during 2015.

4.1. Test experience and lessons learned.

During analysis of the test results it was noticed that the chamber runs had been run at too low an equivalent energy to match flight. When the RPM was increased to match the electrical power drawn during past flight maneuvers, motor heating became an issue. Our subject matter expert indicated that the motor was overheating because the static test air flow is not representative of that of flight. Temperature monitoring was done to verify that motor winding temperature limits were not exceeded.

This is a limitation of this technique. The motor, ESC, and batteries can be damaged from overheating because of the reduced airflow during static testing. Use of a temperature monitor was found to be important to prevent this type of damage.

4.2. On-line code disagreement with off-line analysis code

During preparation of figures based on the off-line battery model simulation and those from the on-line battery state estimation a discrepancy was noticed in the SOC and remaining flying time estimated values. The off-line battery model code was more trusted when there was a disagreement and implementation errors were suspected. A search for coding discrepancies revealed the following:

- The simulation iteration step number of the input current for the propagation of sigma points through the transition function differed.
- The iteration step number of the input current used to produce battery model output values differed.
- The temperature input was changed from that measured by the data system to be a constant 30 deg. C. to match that used during the lab experiments when the model was developed.

Once the on-line and offline code matched these conditions, the on-line SOC matched the 27% off-line SOC check case value at the end of the run instead of the more conservative 19% given in error. (Experiment target was 28%) The Fig. 11 originally reported in Hogge et al. (2015) had a problem with the method used to characterize the battery capacity parameters used in estimating the remaining flying time. This biased the SOC estimation error and the two-minute alarm cumulative plot. Two-minute alarms calculated from the corrected battery capacity values are in Fig. 12. The incorrect capacity came from a fit to the voltage profile from the high current chamber runs instead of from a fit to the low current (2A) slow discharge bench battery characterization test. This violated the equilibrium condition required to separately identify the capacity parameter. This was corrected through the use of the capacity parameters obtained from the low current characterization. The alarm criteria was made more conservative by using a coefficient of 1.09 to increase the velocity...
input to the drag model. This was based on preliminary flight experience to compensate for wind gusts and pilot variation in the trim of the aircraft. When a coefficient of 1.0 was used to adjust the velocity input to the drag model, the pilot’s increased use of speed during gusty winds and the pilot’s difficulty in trimming the eUAV for optimum flight led to late alarm predictions. These late alarm predictions violated the safety criteria set by the operators.

4.3. Battery parameter deterioration with age

Evidence of deterioration in the results is seen in Fig. 13 when ten additional ground test runs were added to the earlier plot. The increase seen in the dispersion of the remaining useful life estimate for the 2015 series of runs has some runs failing early and some runs failing late. Another issue discovered was that the battery aging had changed the capacity parameters significantly, but the year-old characterization runs had overestimated the battery capacity $C_{\text{max}}$ used in the later runs (2015). This deficiency was mitigated through use of revised battery capacities (June 2015) to recalculate the data off-line (Fig. 14). Even though the improvements were made to the capacity parameter estimates, the number of runs that exceeded the two-minute alarm bound has an increasing trend. The increased failures in the later runs may be due to the batteries approaching the end of their service life as stated by the manufacturer as being 80% of their initial capacity. These issues resulted in an additional operational requirement to repeat the bench capacity characterization after 10 recharge cycles to update the $C_{\text{max}}$ and $R_s$ parameters. The equivalent circuit models are not able to track any battery degradation unless the battery parameters are updated. This is one of the main drawbacks of the model where it cannot track aging efficiently. Additionally, more detailed models of the electrochemical processes that are still computationally efficient enough could be used and are currently under review for possible use. (Daigle & Kulkarni, 2013).

4.4. Performance Requirements

The specification of performance requirements for ground verification of remaining flying time predictions is described next. The predictive element to be tested in this work is an alarm that warns system operators when the powertrain batteries are two minutes from reaching 30% SOC under normal operations.

Accuracy requirements for the two minute warning were specified as (Saxena, Roychoudhury, Celaya, Saha, Saha, & Goebel, 2012):

1. The prognostic algorithm shall raise an alarm no later than two minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.

2. The prognostic algorithm shall raise an alarm no earlier than three minutes before the lowest battery SOC estimate falls below 30% for at least 90% of verification trial runs.

3. Verification trial statistics must be computed using at least 20 experimental runs.

4. At the end of the 2 minute warning period the pilot must have an option of doing 2 go- Rounds before the aircraft must land.
5. After the 2 minute warning it is advisable that the pilot not gain altitude.

6. The ending SOC estimation error as identified from the resting battery voltage must be less than 5% for at least 90% of verification trial runs.

Requirement one, the late alarm prediction bound, the alarm (two minute) is biased to occur early rather than late since the landing becomes unsafe if not enough charge reserve is present. Requirement two, the early alarm prediction bound, (three minute) limits the “opportunity cost” of unnecessarily denied flying time (Saxena et al., 2012). Requirement three is an attempt to define a number to use to calculate quantified confidence limits. Requirement four is an energy reserve safety requirement to allow repeated landing attempts before battery exhaustion. Requirement five is a constraint on unplanned maneuvers close to the 30% SOC minimum energy for landing state to insure prognostic estimates for decision making will be reliable. Requirement six is an accuracy constraint on the diagnosis of the battery charge state.

The requirement definitions above use the term “SOC estimate”, because the UKF state estimation algorithm, described in section 3.2, is relied upon to provide online estimates of battery SOC from measured battery current and voltages. A more direct measurement of battery SOC can be obtained after the experimental run is complete by allowing the batteries to rest until the terminal voltage settles to a constant value. There is a stable, empirical, relationship between resting battery voltage and SOC that can then be used to compute the ending SOC error of the powertrain batteries. The difference between the estimated battery SOC at the end of each experimental run and the measurement of SOC computed from the resting battery voltage is referred to as the SOC estimation error.

4.5. Experimental Results

Figure 14 shows the difference between the time at which the two minutes remaining alarm was raised and the time at which the lowest battery SOC estimate crosses 30% for 36 verification runs. Runs that were performed with and without parasitic load injection are identified. The vertical lines in the Fig. 14 indicate the bounds on acceptable alarm accuracy. 13 verification runs out of the 36 performed are seen to violate requirement two’s accuracy bound. The requirement that 90% of trials pass this benchmark is seen not to be satisfied because of the excessive early predictions.

The SOC error estimation of the first 26 runs performed during the 2014 test series and previously reported is shown in Fig. 15 with corrections made to the battery capacity used to estimate the SOC. These corrections and data set correspond to the two-minute alarm plot of Fig. 12. Figure 16 shows box plots from a combined data set from similar test chamber runs made in 2014 and 2015 (10 additional runs). A total of 36 verification runs were performed. Because each verification run requires 4 powertrain batteries, 144 measurements of SOC estimation error are produced. The overall aspect of the errors are consistent. Only four of these measurements fall outside of the 5% error tolerance specified. Requirement six that 90% of trials pass this benchmark is thus seen to be satisfied.
5. Conclusion

A procedure for verifying the performance of remaining flying time predictions for a small electric aircraft was demonstrated. Aircraft battery packs reaching 30% SOC in flight was defined as high risk operation for our experimental flying vehicle, to be avoided if possible. Ground-based simulated flight testing was shown to enable a safe means of running the aircraft power train to 30% SOC in order to obtain an empirical measurement of the aircraft’s available safe operating time if motor temperature is monitored.

Ground-based testing enables repeatable run-to-functional-failure testing of remaining flying time predictions using the integrated flight vehicle. Repeatable testing such as that described in this paper is necessary to effectively debug, tune, and build trust in prognostic algorithms prior to deployment in mission critical applications.

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Biographies

Edward F. Hogge received a B.S. in Physics from the College of William and Mary in 1977. He has provided engineering services to the government and currently is employed by Northrop Grumman Technology Services. He has recently been supporting aviation safety research through the implementation of electronic systems for subscale remotely piloted aircraft and through commercial aircraft simulation. He is a member of the American Institute of Aeronautics and Astronautics.

Brian M. Bole graduated from the FSU-FAMU School of Engineering in 2008 with a B.S. in Electrical and Computer Engineering and a B.S. in Applied Math. He received M.S. and Ph.D. degrees in Electrical Engineering from the Georgia Institute of Technology. Dr. Bole was recently deceased. Before his death his research interests included: analysis of stochastic processes, risk analysis, and optimization of stochastic systems. He had been investigating the use of risk management and stochastic optimization techniques for
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Sixto L. Vazquez Mr. Vazquez obtained MSEE from Old Dominion University in 1990 and BSEE from the University of Puerto Rico in 1983. He has developed real-time 3D graphical simulations to aid in the visualization and analysis of complex sensory data. He has developed techniques to interactively process, analyze, and integrate sensory data from multiple complex, state-of-the-art sensing technologies, i.e. FMCW Coherent Laser Radar range measuring system, Bragg grating Fiber Optic Strain Sensing system, etc., into simulation. In recent years, he has developed software for the Ardupilot and associated ground station.

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Figure 1.
The Edge 540 T Rapid Evaluation eUAV
Figure 2.
Schematic of electric Powertrain.
Figure 3.
Lithium-Ion battery equivalent circuit model
Figure 4.
Comparison between measured and predicted battery voltage over a pulsed current discharge (Bole et al., 2014) used by permission.
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