LiPo Battery Energy Studies for Improved Flight Performance of Unmanned Aerial Systems

K. Chang[1], P. Rammos[1], S. A. Wilkerson[2], M. Bundy[2], and S. Andrew Gadsden[1]
1 University of Maryland, Baltimore County (UMBC), Baltimore, MD, USA 21250;
2 United States Army Research Laboratory, Aberdeen Proving Ground, MD, USA 21001

ABSTRACT

Energy storage is one of the most important determinants of how long and far a small electric powered unmanned aerial system (UAS) can fly. For years, most hobby and experimentalists used heavy fuels to power small drone-like systems. Electric motors and battery storage prior to the turn of the century were either too heavy or too inefficient for flight times of any usable duration. However, with the availability of brushless electric motors and lithium-based batteries everything has changed. Systems like the Dragon Eye, Pointer, and Raven are in service performing reconnaissance, intelligence, surveillance, and target acquisition (RISTA) for more than an hour at a time. More recently, multi-rotor vehicles have expanded small UAS capabilities to include activities with hovering and persistent surveillance. Moreover, these systems coupled with the surge of small, low-cost electronics can perform autonomous and semi-autonomous missions not possible just ten years ago. This paper addresses flight time limitation issues by proposing an experimental method with procedures for system identification that may lead to modeling of energy storage in electric UAS'. Consequently, this will allow for energy storage to be used more effectively in planning autonomous missions. To achieve this, a set of baseline experiments were designed to measure the energy consumption of a mid-size UAS multi-rotor. Several different flight maneuvers were considered to include different lateral velocities, climbing, and hovering. Therefore, the goal of this paper is to create baseline flight data for each maneuver to be characterized with a certain rate of energy usage. Experimental results demonstrate the feasibility and robustness of the proposed approach. Future work will include the development of mission planning algorithms that provide realistic estimates of possible mission flight times and distances given specific mission parameters.

Keywords: Battery energy management, flight performance, modeling, unmanned aerial system

1. A BRIEF INTRODUCTION

Lithium-based batteries present advantageous characteristics, such as high charge and discharge rates, longevity, high energy density, and affordable cost accompanied with a lightweight structure [1, 2, 3, 4]. Nonetheless, only small improvements in lithium-based batteries have occurred over the past ten years with the biggest improvement being the reduction of price. Even with the most advanced lithium-based batteries, electric multi-rotor UAS mission plans are often dictated by the flight time (and consequently path) of the vehicle [5]. In most scenarios, this is generally limited to approximately thirty minutes before battery protection measures activate and the craft must land. However, lithium-based batteries are still affected by charge and discharge rates, life cycles, temperature, and their capacity rating [1]. These issues need to be considered when operating battery powered unmanned air systems. Currently, lithium-based battery characteristics offer the best power supply for small UAS' where reliability and weight power density are of importance [6].

Considerable research efforts are focused on the topic of developing models for lithium polymer (LiPo) battery discharge and life cycles [7]. Generally, these models include autonomous batteries, in controlled environments (e.g. bench testers), as well as models specifically derived for the usage of battery packs in vehicles with variable power requirements [7]. The derivation of a battery mathematical model constitutes a complex task due to the complicated structure of a battery, as well as its nonlinear characteristics. Distinct battery models are utilized, such as electrochemical models, which take into consideration the internal processes within the cell, or statistical methods that derive model parameters using collected sampled data [7, 8, 9]. It is common practice to combine modeling methods, in order to obtain more accurate and robust models [7]. In addition, a majority of research is focused on the design of battery management systems (BMS), which are crucial to the needs of UAS powered by sources such as LiPo batteries. These algorithms can estimate the state of charge (SOC) of a battery, which is one of the most important parameters that reflects the battery performance; and gives the user information about its remaining capacity. In UAS platforms, the battery shut-off criteria relies on the terminal voltage, which is directly related to the battery's SOC [8, 9]. Therefore, a BMS can improve the flight time of a UAS, since it can provide a better estimate of the available capacity and allows the vehicle to fly longer (and perhaps more efficiently), depending on the load requirements. Examples of common techniques used for this purpose include application of the extended Kalman filter and Bayesian inference frameworks [10, 11].

The goal of this paper was to create a set of baseline data that allowed each flight maneuver to be characterized with a certain rate of energy usage. Experimentation results demonstrate the feasibility and robustness of the proposed approach. Future work will include the development of a rudimentary energy consumption model that will serve as a basis for future studies. By understanding how a UAS consumes energy whilst performing various actions, it is possible to get more accurate estimates of how much energy a UAS mission will require. Furthermore, having an understanding of a mission's energy requirements provides insight into the possibility of optimizing missions by either prioritizing having more mission objectives or ensuring that the UAS returns to the operator.

This paper is organized as follows. In Section 2, materials and equipment used for the experimental measurements are presented. All of the procedures followed before, during, and after the experimental flights are also described in Section 2. In Section 3, figures of acquired data for different flight paths are presented followed by a discussion on the result. Additional data and results are provided in the appendix. The results provided in this paper are preliminary, and will be expanded upon in the future. The paper is summarized with conclusions and future work.

2. EXPERIMENTAL SETUP

2.1 Materials and Equipment

It would be a very difficult task to write a report that accurately addressed every variable in any given small-UAS or 'drone'. What we attempt to do here is to provide a baseline set of tests from which to build additional tests look at individual parameters governing a specific drones baselined performance characteristics and capabilities. Clearly when we add additional batteries we can extend the mission of the drone in terms of time in the air and distance traveled. However, in doing so we add weight such that we reduce the effective payload of the drone while also increasing the energy demands from the batteries. The additional weight will affect the speed at which the drone can fly, as well as its aerodynamic performance. We choose as our two test drones a standard do-it-yourself (DIY) system from 3D Robotics and a DJI system [12]. Both are of similar size. We use the PixHawk control system to navigate both systems under GPS control during the tests [13]. However, the 3D Robotic system has a sturdy metal frame and slightly larger motors leading to slightly greater demands on battery power and less performance in terms of time in the air. Our two baseline systems are shown below in Figure 1.

Other parameters within our control affecting the UAS' performance are listed here as well. In future testing, we will examine some of these additional parameters from our baseline tests. There are numerous parameters that affect the overall performance of these two copters. In fact, there are too many to mention, nonetheless we will mention a few. The pitch and size of the props are related to the amount of lift, speed motor, overall speed, and amount of energy it will use. Many of these parameters are understood well enough that they can be estimated without testing. Additionally, the motor size and speed control size coupled with these parameters will determine some of the performance characteristics of a particular system. However, one of the parameters that is not fully understood for any given system is the overall time limitations imposed by speed, transitional lift characteristics, and wind speed. Therefore, in our baseline test we examine both of these quadcopters flying the exact same mission at different speeds with little or no wind speed. Furthermore, we conduct these tests with a stripped-down version of the quadcopter eliminating energy use from video transmitters cameras and other devices that might skew our results. Only the results from the 3D Robotics platform are included here. Results from both systems were similar with the DJI being far more efficient due to its lighter frame and smaller motor sizes.

Figure 1. 3D Robotics and DJI test vehicles [12].

Additionally, six identical Turnigy Nanotech 4,000 mAh 4-cell 25-50 C lithium polymer batteries (LiPo) [10], shown in Figure 2, were procured to reduce variance in battery energy output due to different brands. Also, by using higher quality batteries such as the Turnigy Nanotech product line, manufacturing tolerances are more consistent and the higher C rating allows for the battery to be more resistant to voltage sagging [10]. In the future, these batteries will be tested for charge and discharge characteristics at the U.S. Army Research Laboratory's Communications-Electronics Research, Development and Engineering Center (CERDEC). Lastly, the Pixhawk 4 hardware was used as the flight controller for this experiment [13]. The Pixhawk 4 is capable of autonomous flight using user pre-programmed mission directives. This was especially important to address the possibility of user generated flight variations due to imperfect piloting. Additionally, Pixhawk 4 was chosen for its comprehensive data logging capabilities as well. Beside acquisition of basic data, such as accelerometer or gyroscope data, Pixhawk 4 is also capable of colleting current, speed, and voltage measurements, which are all essential to the experiment.

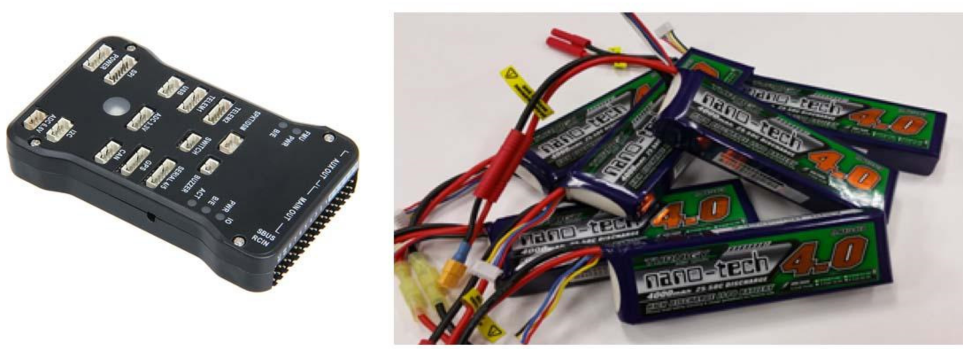

Figure 2. PixHawk control system and a pile of Turnigy 4000 mAh batteries [13, 14].

2.2 Experiment Location

For our initial experiments we chose a standard 3D Robotics quad that uses the Pixhawk autopilot system and ArduCopter/APM:Copter firmware [15, 13]. The quadcopter was stripped of excess weight and power drains like cameras, telemetry, and video transmitters. The flight body weighed 1.875 kg and the 4,000 mAh batteries used in the experiments weighed an additional 0.420 kg. There are numerous choices for props, motors, speed controllers which all have some effect on the efficiencies, duration of flight, and energy use. For these experiments, we used the baseline 3D Robotics system with 11-4.7 APC props (shown Figure 1). The experiments were conducted at each condition to include varying speeds and flight conditions: hover, and horizontal speeds of 1, 3, 6, 9, 12, 15, 20 m/s. Each of these tests were repeated three times to assure repeatability of the results. As shown in Figure 3, the flight path was approximately 1,500 feet long which allowed the aircraft to maintain speed and altitude for an extended period. Data collection was performed at the Sandy Hook flying field in Harford County Maryland, on a partly cloudy day with mild wind gusting. A generator was brought on site to facilitate battery charging during the experiment. Fresh batteries were used for every flight regardless of flight parameters.

Figure 3. Sandy Hook flying field and location of experiment [16].

For the initial estimate of power consumption, 23 flight tests were conducted ranging in time from approximately 10 minutes to just short of three minutes. Due to the nature of the tests conducted, it was not feasible to find a location where the test could be conducted inside a controlled environment with no wind disturbance. Therefore, to account for the effect of wind on the experiment, the wind speed was recorded at the start of each flight. During these tests, the wind was gusting between 3 and 5 mph leading to some transitional lift during the hover and free flight conditions. Nonetheless, throughout most of the testing, the steady wind speed was found to be very low (assumed to be zero). It was found that the effects due to these wind velocities were negligible. Tests were performed at an altitude of 40 m above a flat and level field with temperatures varying between 5 and 10 degrees Celsius. Furthermore, it is important to note that prior to running the experiments, all batteries were new and fully charged.

2.3 Experimental Protocol

The UAS was tested under eight different speed conditions starting from 1 m/s. The maximum allowable speed that the UAS could maintain a steady altitude was 20 m/s. All tests were conducted at an altitude of approximately 40 meters over a straight path measuring. Takeoffs and landings were handled by the Pixhawk 4 flight controller autopilot.

For this study, the experimental protocol begins with using mission planning software to create a simple and easily reproducible flight paths [14, 15, 13]. In this case, the flight path was simply a straight line 1,500 feet between two arbitrary points. This defined flight path was then used for all of the tests. In addition to programming the autonomous flight, the operator's transmitter had to be configured to be able to initiate autonomous mode; this was done using the mission planning software. Prior to each flight, a pre-flight check to make sure the UAS was flight worthy was performed [17]. It was important to ensure that the test vehicle would not fail after taking off to an altitude of 40 meters. Next, a fully charged battery was connected to the UAS. From this point, the procedure was relatively simple. The UAS was brought to an unobstructed location and the autonomous mode was activated. The UAS then proceeded to take-off, fly the path, and land by itself; while collecting a multitude of data. In order to improve the reliability of the data and results, three trials were conducted at each speed condition (the results of which were averaged).

3. DATA COLLECTION AND RESULTS

Current consumption data was matched with the corresponding velocity data during a period of time when the velocity was relatively constant. The data was then filtered and averaged using a script created in MATLAB. Finally, the velocities were averaged between different trials to reduce variation.

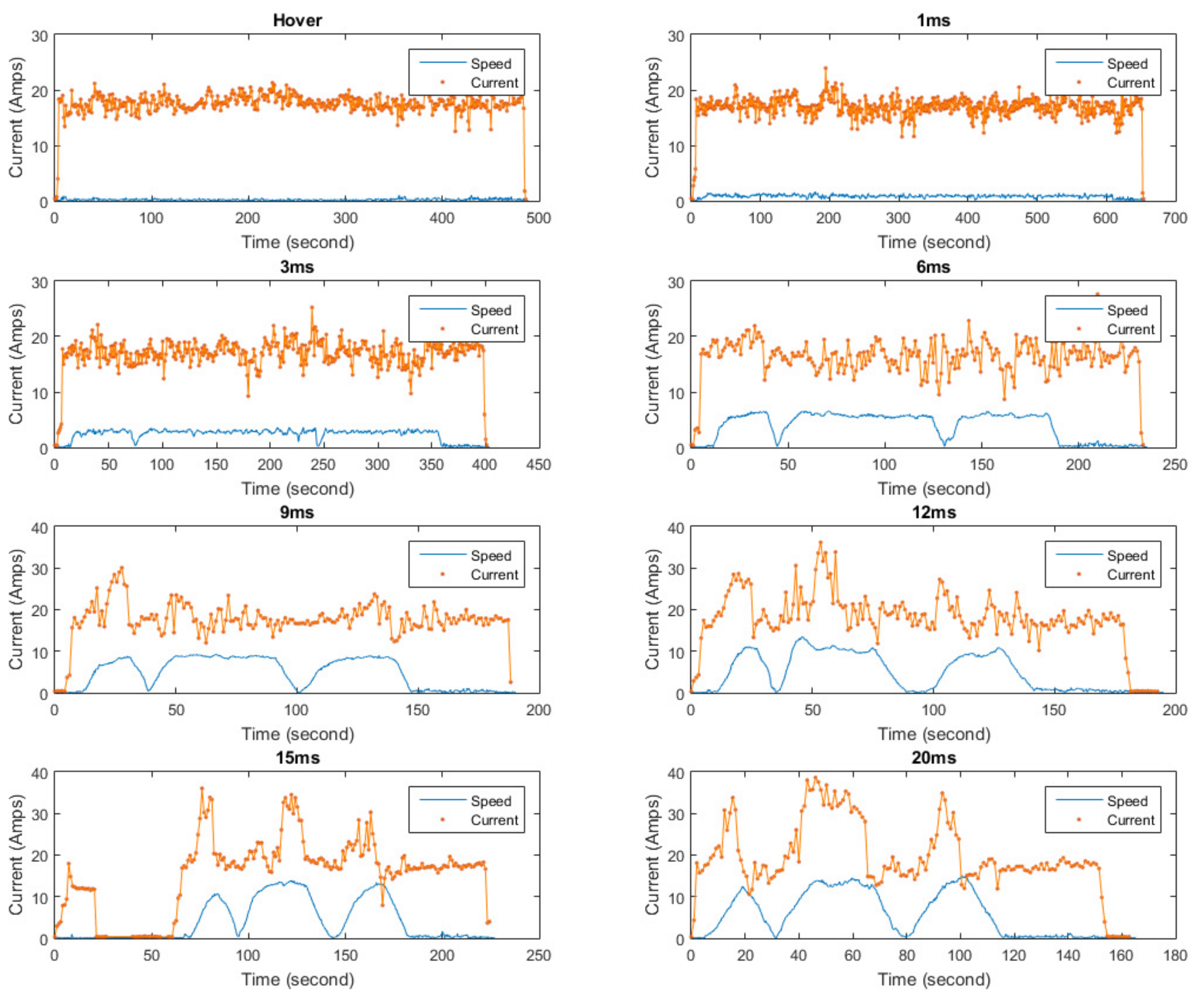

Figure 4. Average speed and current draw for each trial.

From the experimental results, a trend emerges in energy consumption as a function of system velocity. In fact, it can be seen in Figure 5 that the optimum velocity for this particular quadcopter is around 6 m/s. This plunge in energy consumption is due to a phenomenon called translational lift, which is a characteristic of the rotorcraft [10].

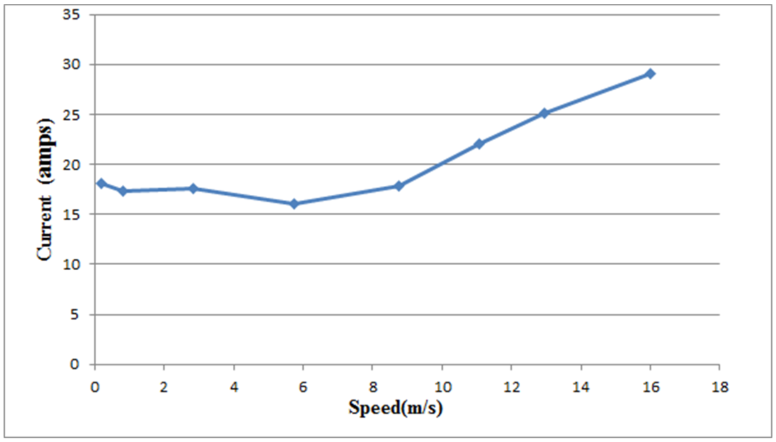

Figure 5. Results of the flights showing current draw versus system speed.

For consistency, an additional six figures that summarize the data from the 23 flights are provided in the Appendix of this paper. Figure A1 shows a typical velocity profile for 12 m/s as the drone traversed its course. In particular, the flight has an up-leg portion where it would fly to the head of the field and position itself at the proper altitude. Afterwards, it would turn and fly at a constant velocity and altitude for slightly over one-quarter of a mile. This allowed us to obtain consistent data at a fixed altitude and speed for a period of time. As shown in Figure A1, the circle indicates the portion of the flight where the data was analyzed. Additionally, we duplicated each flight and path on three separate occasions to show repeatability of data and flights. Figure A2 shows the flight path for two flights at 3 m/s. The data is nearly identical for each flight. Figure A3 shows the same repeatability for flights at 12 m/s; the obtained data was very consistent. Figures of the current drawn during flight and a typical roll-pitch-yaw control plot are also provided in the Appendix. Due to low wind speeds (in other words, noise in the process), the data and parameters measured were very consistent. This will allow for the examination of flight parameters and their effects on battery life, mission length, and other items of interest as influenced by some of the quadcopters design parameters.

4. CONCLUSIONS AND FUTURE WORK

In this paper, an experimental procedure for correlating energy consumption with flight maneuvers was presented. Data collection and preliminary data processing demonstrated a feasibility for expanding to different flight maneuvers and vehicle types. There was a clear trend that indicated the most efficient speed for the UAS that was used. Future directions for this research involves expanding to other flight maneuvers, such as: vertical ascents/descents, turning, banking, and diving. Data collected for this set of flight maneuvers could be aggregated into one large energy consumption model which could be applied to similar classes of UAS' to estimate the energy costs associated with different missions. If the capacity and performance of the battery is known, the operator will be able to estimate the operational range of a particular UAS given a set of input parameters such as flying speed, weight, and desired mission objectives.

In terms of long-term goals, it may be possible to incorporate an energy consumption model into a machine learning algorithm onboard the UAS. The UAS could continuously gather data and learn more about its flight capabilities which would yield more accurate estimates of energy consumption and usage. Furthermore, the UAS could then make intelligent (and autonomous) decisions on how it could modify its flight mission and performance to maximize energy efficiency, flight time, and mission usefulness.

5. APPENDIX: ADDITIONAL DATA AND RESULTS

The following figures are additional data and results included in the paper for completeness.

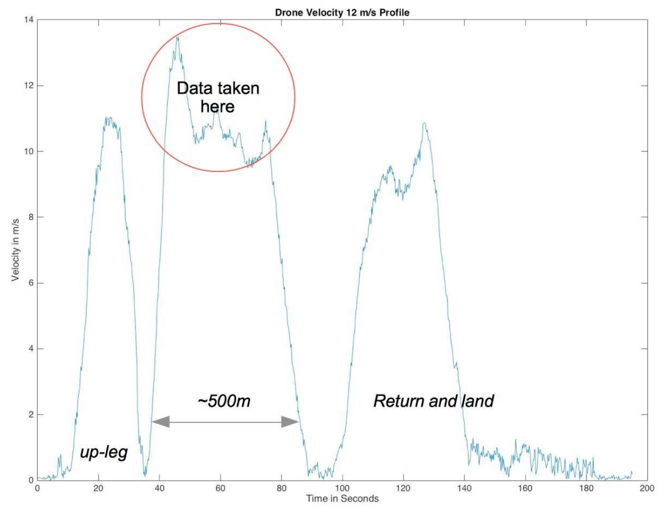

Figure A1. UAS flight profile.

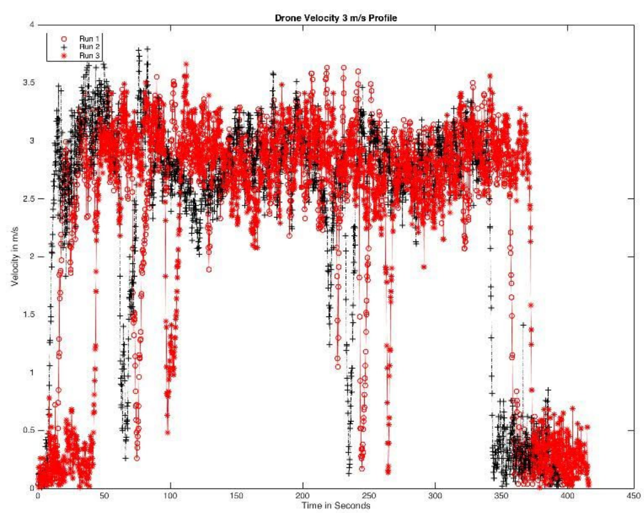

Figure A2. UAS flight profile with velocity of 3 m/s.

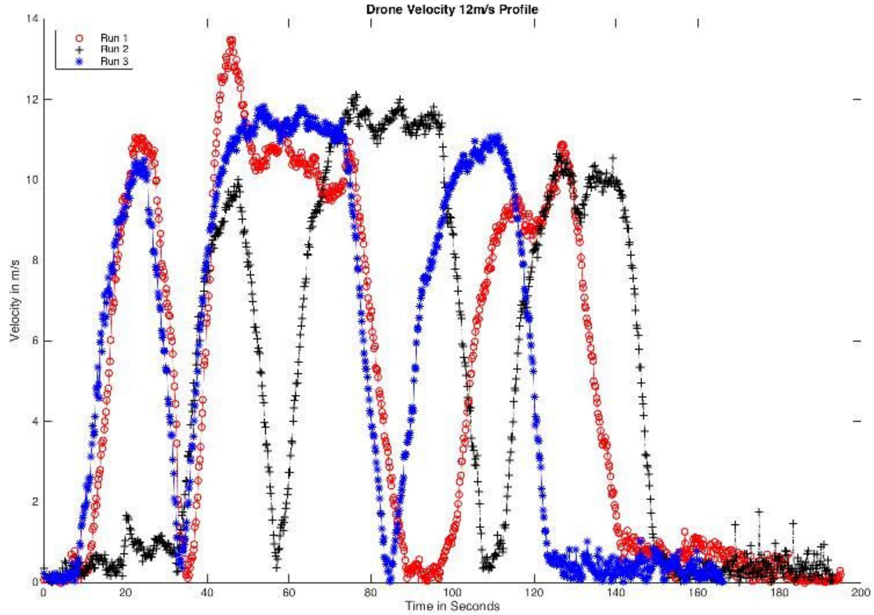

Figure A3. UAS flight profile with velocity ranges of 0 m/s to about 12 m/s.

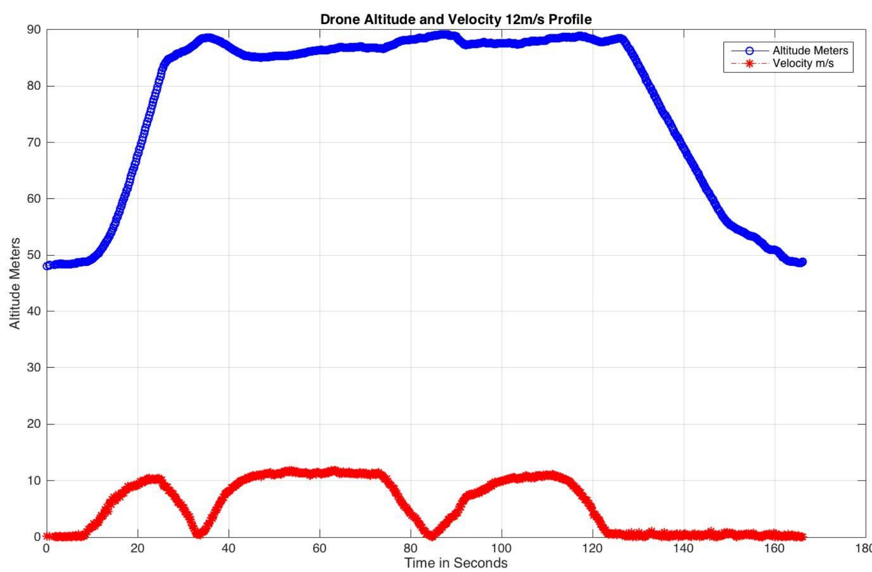

Figure A4. UAS flight profile showing both altitude and velocity.

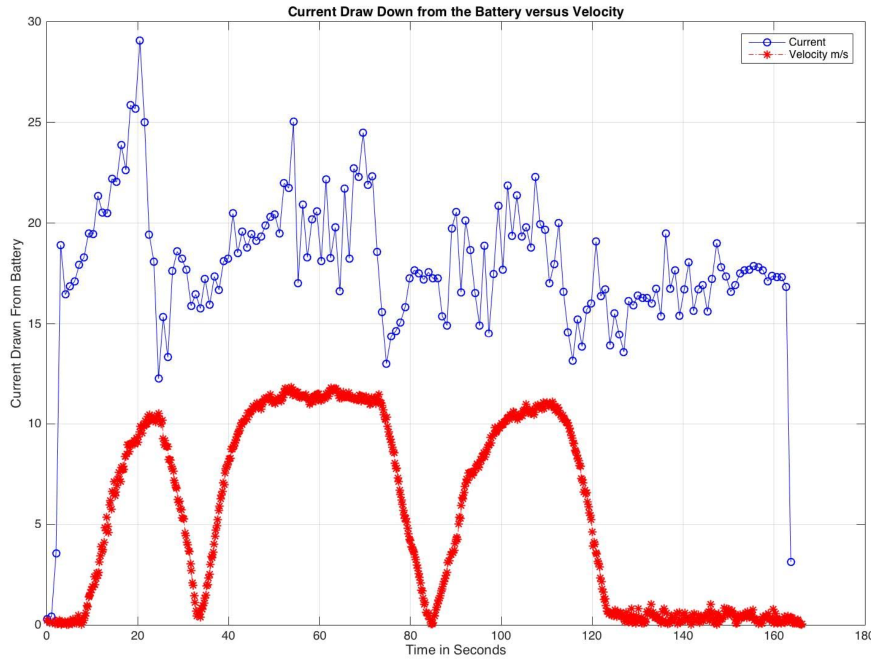

Figure A5. Current drawn from the battery during the flight performance.

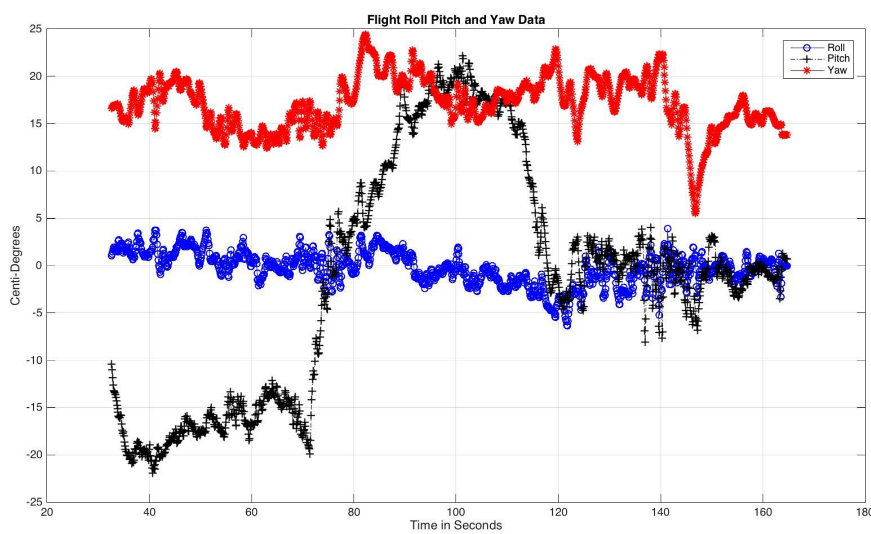

Figure A6. UAS flight profile showing the roll, pitch, and yaw data.

6. REFERENCES

[1] I. Buchmann, "High-Power Lithium-Ion: A New Area in Portable Power," Cadex Electronics Inc., 2006.

[2] L. Beji and A. Abichou, "Trajectory Generation and Tracking of a Mini-Rotorcraft," in *Proceedings of the 2005 IEEE International Conference on Robotics and Automation (ICRA)*, 2005.

[3] J. Gundlach, Designing Unmanned Aircraft Systems, Reston: American Institute of Aeronautics and Astronautics, Inc., 2014.

[4] J. Reuder, M. O. Jonassen and H. Lafsson, "The small unmanned meteorological observer sumo: Recent developments and applications of a micro-UAS for atmospheric boundary layer research," *Acta Geophysica,* vol. 60, no. 5, pp. 1454-1473, 2012.

[5] M. Schwarzbach, M. Laiacker, M. Mulero-Pazmany and K. Kondak, "Remote water sampling using flying robots," in *International Conference on Unmanned Aircraft Systems (ICUAS)*, Orlando, Florida, May 2014.

[6] G. Vachtesevanos, L. Tang, G. Drozeski and L. Gutierez, "From Missiong Planning to Control of Unmanned Aerial Vehicles: Strategies and Implementation Tools," *Annual Reviews in Control,* vol. 29, no. 1, pp. 101-115, 2005.

[7] T. Sarikurt, M. Ceylan and A. Balikci, "A Hybrid Battery Model and State of Health Estimation Method for Lithium-Ion Batteries," in *Proceedings of the IEEE International Energy Conference*, Dubrovnik, Croatia, 2014.

[8] M. Podhrdsky, A. M. Jensen, J. Bone and C. Coopmans, "Small Low Cost Unmanned Aerial Vehicle Lithum-Polymer Battery Monitoring System," in *Proceedings of the ASME International Design Engineering Technical Conferences and Computers and Information in Engineering Conference*, Portland, Oregon, 2013.

[9] B. Saha, E. Koshimoto, C. C. Quach, E. F. Hogge, T. H. Strom, B. L. Hill, S. L. Vazquez and K. Goebel, "Battery Health Management System for Electric UAVs," in *IEEE Aerospace Conference*, Big Sky, Montana, 2011.

[10] B. Saha, E. Koshimoto, C. C. Quach, S. L. Vazquez, E. F. Hogge, T. H. Strom, B. L. Hill and K. Goebel, "Predicting Battery Life for Electric UAVs," in *AIAA Infotech@Aerospace*, St. Louis, Missouri, 2011.

[11] G. R. Plett, "Extended Kalman Filtering for Battery Management Systems of LiPb-Based HEV Packs, Part 1: Background," *Journal of Power Sources,* vol. 134, no. June, 2014.

[12] "3DR-Drone and UAV Technology," 3DR, 2016.

[13] "Pixhawk Autopilot Systems," Pixhawk, 2016.

[14] "Turnigy Power Systems," Turnigy, 2016.

[15] "ArduPilot Documentation," ArduPilot, 2016.

[16] "Google," Google, 2016.

[17] "Rotorcraft Flying Handbook," U.S. Department of Transportation and Federal Aviation Administration, Washington, D.C., 2000.