Predicting Battery Life for Electric UAVs

Bhaskar Saha[1]
Mission Critical Technologies, Inc. (NASA ARC), 2041 Rosecrans Ave., Ste 220, El Segundo, CA 90245

Edwin Koshimoto[2]
NASA Dryden Flight Research Center, Edwards, CA 93523

Cuong C. Quach[3] and Sixto L. Vazquez[4]
NASA Langley Research Center, 1 S. Wright St., Hampton, VA 23681

Edward F. Hogge[5]
Lockheed Martin Corporation (NASA LaRC), 1 S. Wright St., Hampton, VA 23681

Thomas H. Strom[6]
ATK Space Systems (NASA LaRC), 1 S. Wright St., Hampton, VA 23681

Boyd L. Hill[7]
Vigyan Inc (NASA LaRC), 30 Reseach Dr, Hampton VA 23681

and

Kai Goebel[8]
NASA Ames Research Center, Moffett Field, CA 94035

This paper presents a novel battery health management technology for the new generation of electric unmanned aerial vehicles powered by long-life, high-density, scalable power sources. Current reliability based techniques are insufficient to manage the use of such batteries when they are an active power source with frequently varying loads in uncertain environments. The technique presented here encodes the basic electrochemical processes of a Lithium-polymer battery in an advanced Bayesian inference framework to simultaneously track battery state-of-charge as well as tune the battery model to make accurate predictions of remaining useful life. Results from ground tests with emulated flight profiles are presented with discussions on the use of such prognostics results for decision making.

Nomenclature

E	=	battery voltage
ΔE	=	voltage drop
E^0	=	theoretical output voltage
x	=	state variable
y	=	measurement

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[1] Research Scientist, Intelligent Systems Division, NASA ARC, MS 269-3, non-AIAA Member.
[2] Aerospace Engineer, Aerodynamics & Propulsion Branch, NASA DFRC, non-AIAA Member.
[3] Research Engineer, Safety-Critical Avionics Systems Branch, NASA LaRC, non-AIAA Member.
[4] Research Engineer, Safety-Critical Avionics Systems Branch, NASA LaRC, non-AIAA Member.
[5] Contractor, Safety-Critical Avionics Systems Branch, NASA LaRC, non-AIAA Member.
[6] Contractor, Safety-Critical Avionics Systems Branch, NASA LaRC, non-AIAA Member.
[7] Contractor, Safety-Critical Avionics Systems Branch, NASA LaRC, non-AIAA Member.
[8] Senior Scientist, Intelligent Systems Division, NASA ARC, Senior AIAA Member.

t = time
Δt = time delay between consecutive discrete time staps
θ = model parameter

I. Introduction

WITH electric UAVs (unmanned aerial vehicles) we are witnessing the dawn of a new era in aviation. They are being increasingly deployed in military, civilian and scientific missions all over the globe. However, like ground vehicles, battery powered electric UAVs suffer from uncertainties in estimating the remaining charge and hence most flight plans are highly conservative in nature. The amount of usable charge of a battery for a given discharge profile is not only dependent on the starting state-of-charge (SOC), but also other factors like battery health and the discharge or load profile imposed. This is because in most battery powered propulsion systems, the battery shut off criteria are based on the terminal voltage. This voltage is related to the SOC of the battery, but it is a highly non-linear relation, which is further complicated by a sharp drop off of the terminal voltage as the battery SOC nears empty. This problem is more pronounced in battery powered electric UAVs since different flight regimes like takeoff/landing and cruise and changing environmental factors like wind velocity impose different power requirements and a dead stick condition (battery shut off in flight) can have catastrophic consequences.

In this paper, a detailed battery discharge model is presented for the Lithium-polymer (Li-Poly) cells and verified using ground tests of the Edge 540, a subscale aerobatic UAV powered by four 18.5V 6000mAh Li-Poly battery packs. This model was then used in a Particle Filter based prognostic framework to accurately predict the remaining useful life (RUL) for the batteries. Particle Filters are a class of Sequential Monte Carlo methods that not only use the information available from system measurements but also incorporate any models available for system behavior. This technique also has the ability to tune non-stationary model parameters simultaneously with state estimation, which combined with the representation of state space as multiple weighted particles, makes it ideal for state tracking and prediction. Given stochastic estimates of future usage, the RUL estimates generated can facilitate intelligent flight plan reconfiguration, which can be vital in assuring system safety. Some initial results were published earlier[1]; this paper is intended as the next step in the approach presented. The main contributions of this paper are the advances in battery modeling and the statistical evaluation of prognostic performance.

II. UAV Platform

The test UAV platform for this research is a COTS 33% scale model of the Zivko Edge 540T as shown in Fig. Figure 1. Details of this platform have been presented in[1], but are also repeated here for the sake of readability. The UAV is powered by dual tandem mounted electric out-runner motors capable of moving the aircraft up to 85 knots using a 26 inch propeller. The gas engine in the original kit specification was replaced by two electric out runner motors which are mounted in tandem to power a single drive shaft. The motors are powered by a set of 4 Li-Poly rechargeable batteries. The batteries are each rated at 6000 mAh. The tandem motors are each controlled by separate motor controllers.

The battery health management (BHM) system is designed to be a relatively low cost analog-to-digital data acquisition system. There are three major elements to the BHM system - a signal conditioning board, an analog-to-digital acquisition board, and an embedded processor board. There are 12 channels of data (4 battery voltages, 4 battery currents, and 4 battery temperatures) to be recorded at rates up to 30 samples per second. The signal conditioning board processes the analog sensor signals for the analog-to-digital acquisition board. The analog-to-digital acquisition board feeds the processed signal data into an embedded processor board running a Gumstix Overo(™) computer-on-module (COM) system, where the data are fed into the battery prognostics algorithm. The battery prognostic algorithm leverages POSIX threading for speed and efficiency. Finally the embedded processor board outputs the battery prognostics algorithm results on an RS-232 data stream.

Figure 1. ⅓-scale Edge 540 UAV.

III. Battery Modeling

The characteristics of a Li-Poly battery have also been explained in[1, 2]. For the purposes of this paper it will suffice to say that the internal chemical processes of the battery were broken down into three basic electrochemical processes:

Mass transfer: This refers to the diffusion process through which Li-ions migrate to the cathode via the electrolytic medium. The internal resistance to this ionic diffusion process is also referred to elsewhere as the *IR drop*.[2] For a given load current this drop usually decreases with time due to the increase in internal temperature that results in increased ion mobility, and is henceforth referred to as ΔE_{IR}.

Self-discharge: Self-discharge is caused by the residual ionic and electronic flow through a cell even when there is no external current being drawn. The resulting drop in voltage has been modeled to represent the *activation polarization* of the battery, referred to from now on as ΔE_{AP}. All chemical reactions have a certain activation barrier that must be overcome in order to proceed and the energy needed to overcome this barrier leads to the activation polarization voltage drop. The dynamics of this process is described by the Butler–Volmer equation. This process was represented by an exponential function in[1]. However, a log function is a more accurate representation, as abstracted from the Butler–Volmer equation.[3]

Reactant depletion: This process represents the voltage loss due to spatial variations in reactant concentration at the electrodes. This is mainly caused when the reactants are consumed by the electrochemical reaction faster than they can diffuse into the porous electrode, as well as due to variations in bulk flow composition. The consumption of Li-ions causes a drop in their concentration as along the cell, which causes a drop in the local potential near the cathode.[3] This voltage loss is also referred to as *concentration polarization*, represented in this paper by the term ΔE_{CP}. The value of this factor is low during the initial part of the discharge cycle and grows rapidly towards the end of the discharge or when the load current increases. An exponential function is used to represent this process.

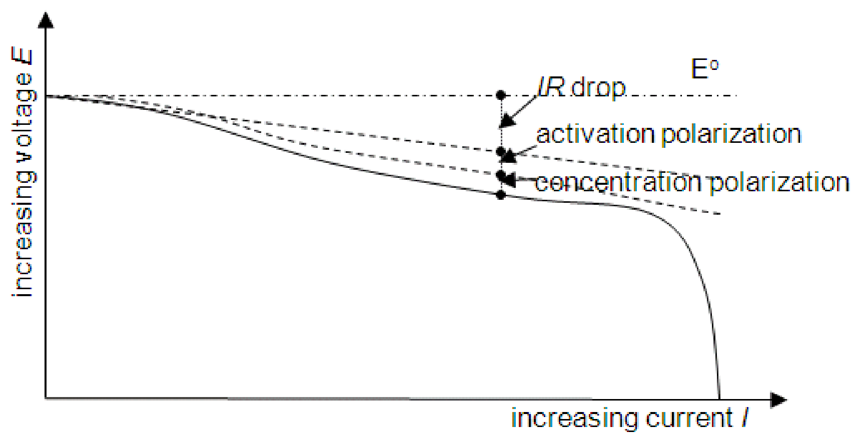

Figure 2. Typical polarization curve of a battery.

Thus the overall voltage of the battery, as shown by the polarization curve in Fig. Figure 2, is given by the equation:

$$E(t) = E^0 - \Delta E_{IR}(t) - \Delta E_{AP}(t) - \Delta E_{CP}(t) \tag{1}$$

where t is the time variable during a discharge cycle and E^0 is the Gibbs free energy, i.e. the theoretical outut potential for the given chemistry. The variations in E^0 with internal temperature are not explicitly modeled, but accounted for by the adaptive powers of the prognostic framework described later. For a constant current discharge case, the individual voltage drops are modeled based on empirical evidence as follows:

$$\Delta E_{IR}(t) = \Delta E_{\Delta I} - a_1 t \tag{2}$$

$$\Delta E_{AP}(t) = a_2 \ln(1 + a_3 t) \tag{3}$$

$$\Delta E_{CP}(t) = a_4 \exp(a_5 t) \tag{4}$$

where $\Delta E_{\Delta I}$ indicates the change in the *IR drop* due a change in load current. The parameters $a_{1\ldots5}$ are unknowns that must be learnt by the prognostic algorithm.

However, it must be noted that in the case of the electric UAV, as in most other battery-powered applications, the load is not constant. Figure 3 shows a typical flight profile of the UAV indicating that typical flight loads are short pulses of widely differing current levels or *C-Rate*. Additionally, for most batteries the voltage as well as the charge delivered, varies considerably with changes in the *C-Rate*.[3]

This necessitates two changes to the battery model described by Eqs. (2)–(4). Firstly, the parameters of the model must be *C-Rate* or load dependent. We model this by making $\Delta E_{\Delta I}$, a_3, and a_5 proportional to the load current I. Secondly, when we have step changes in the load, a higher load level followed by a lower one presents a peiod of relaxation for the battery. During this period the voltage does not immediately jump up as per Eqn (2), but gradually rises which can be modeled by an exponential function.[6] A similar effect can also be observed for a step increase in current level as can be seen in Figure 4. These effects can be reconciled by considering the battery impedance as an RC equivalent circuit.[4] We can thus replace the ΔE_{IR} term by the ΔE_{IRC_1} and ΔE_{IRC_2}terms as follows:

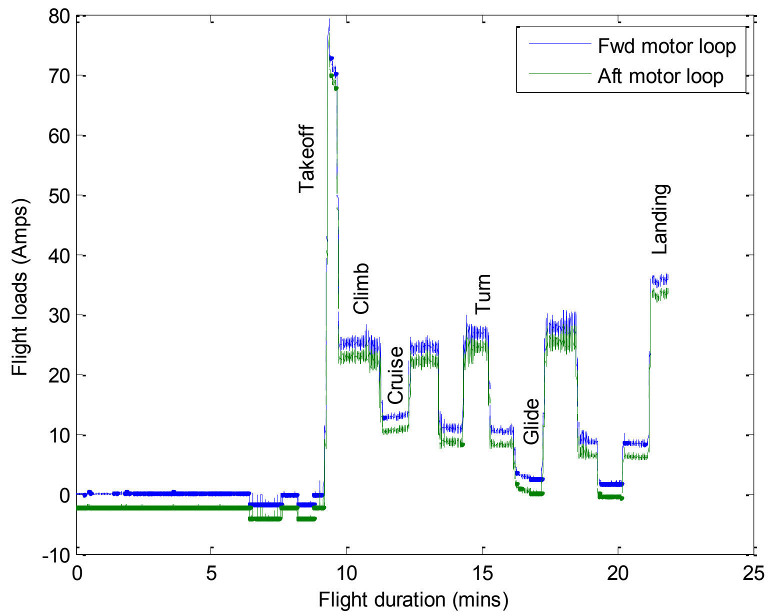

Figure 3. Typical flight load profile for the UAV.

$$\Delta E_{IRC_1}(t) = \Delta I.\, \theta_1\big(1 - \exp\big(-\theta_2(t - t_{\Delta I})\big)\big) \tag{5}$$

$$\Delta E_{IRC_2}(t) = -\theta_3 t \tag{6}$$

where ΔI is the step change in current at time $t_{\Delta I}$. The model parameters are now expressed as θs. Similarly, Eqs. (3) and (4) can be rewritten as:

$$\Delta E_{AP}(t) = \theta_4 \ln(1 + \theta_5 I t) \tag{7}$$

$$\Delta E_{CP}(t) = \theta_6 \exp(\theta_7 I t) \tag{8}$$

Thus the overall battery voltage equation, represented earlier by Eq. (1) now becomes:

$$E(t) = E^0 - \Delta E_{IRC_1}(t) - \Delta E_{IRC_2}(t) - \Delta E_{AP}(t) - \Delta E_{CP}(t) \tag{9}$$

IV. Prognostic Framework

To ensure that the model works well, the model's parameters need to be properly identified and tuned. Tuning needs to be done on an individual basis because generic parameters do not take into consideration the differences between different batteries or even the differences that appear between cycles of operation of the same battery. Indeed, parameter values may change even within a single cycle as the battery goes through the range of SOC. Tracking a state variable and predicting future values can be cast as a filtering problem. There is a large literature body delineating different filtering techniques where each techniques sports certain performance advantages over others. In battery prognostics we are interested in predicting EOD (end-of-discharge) and EOL (end-of-life). Here, we need to reconcile non-exact, non-linear non-stationary models with non-Gaussian noise and future load uncertainties.

A Particle Filtering (PF) based framework provides the capabilities for tracking and future state prediction. At the same time, it allows the explicit representation and management of these uncertainties. Particle Filters are non-linear filters that have the promise of good state tracking performance[5] by combining Bayesian learning techniques with importance sampling. At the same time, the computational load remains tractable. System states (such as battery SOC, voltage or capacity) are represented as probability density functions (pdf) that are approximated by a set of points (the so-called "particles"). These represent sampled values from the unknown state space. The particles have a set of associated weights that denote discrete probability masses. The particles are generated from an a priori estimate of the state pdf. They are propagated through time via a nonlinear process model, and they are recursively updated from measurements through a measurement model. Model parameters can be included as a part of the state vector to be tracked. This means that model identification can be performed in conjunction with state estimation.[6] When the model has been tuned to sufficiently reflect the specific system dynamics, it can then be used to propagate the particles forward to the failure threshold which it crosses as a pdf. In case of battery prognostics, the failure threshold is either EOD or EOL. The difference of the time at which the particle filter crosses the failure threshold minus the time at which the prediction is made is the RUL.[6] It should be noted that the RUL is also expressed as a pdf.

For the application at hand, the EOD estimation problem needs to be expressed in the PF framework, for which the battery discharge model represented by Eqn (8) has to be recast in the discrete-time state-space form. The first step in that process in to define the state variables, x_is:

$$x_1 = \Delta E_{IRC_1}(t) \tag{10}$$

$$x_2 = \Delta E_{IRC_2}(t) \tag{11}$$

$$x_3 = \Delta E_{AP}(t) \tag{12}$$

$$x_4 = \Delta E_{CP}(t) \tag{13}$$

$$x_5 = E^0 - x_1 - x_2 - x_3 - x_4 \tag{14}$$

Thus, differentiating w.r.t. time we get:

$$\frac{dx_1}{dt} = \theta_2(\Delta I\theta_1 - x_1) \tag{15}$$

$$\frac{dx_2}{dt} = -\theta_3 \tag{16}$$

$$\frac{dx_3}{dt} = \frac{\theta_4 . \theta_5 I}{\exp\frac{x_3}{\theta_4}} \tag{17}$$

$$\frac{dx_4}{dt} = \theta_7 I x_4 \tag{18}$$

$$\frac{dx_5}{dt} = -\frac{dx_1}{dt} - \frac{dx_2}{dt} - \frac{dx_3}{dt} - \frac{dx_4}{dt} \tag{19}$$

Transforming into the discrete time domain, integrating over the time interval Δt_{k-1} between two time instants t_{k-1} and t_k, and adding noise terms, we get the following state-space form:

$$x_{1,k} = \Delta I\theta_1 - \frac{\Delta I\theta_1 - x_{1,k-1}}{\exp(\theta_2 \Delta t_{k-1})} \tag{20}$$

$$x_{2,k} = x_{2,k-1} - \theta_3 \Delta t_{k-1} \tag{21}$$

$$x_{3,k} = \theta_4 \ln\left(\exp\left(\frac{x_{3,k-1}}{\theta_4}\right) + \theta_5 I \Delta t_{k-1}\right) \tag{22}$$

$$x_{4,k} = x_{4,k-1} \exp(\theta_7 I \Delta t_{k-1}) \tag{23}$$

$$x_{5,k} = E^0 - x_{1,k} - x_{2,k} - x_{3,k} - x_{4,k} + \omega_{x_5,k} \tag{24}$$

where k is the discrete time index and $\omega_{x_5,k}$ is a zero-mean Gaussian random noise. Note that we are not assuming that the system noise is Gaussian, but merely that in the Particle Filtering framework the distribution approximated by the Gaussian kernels over each particle is sufficient to represent the true state pdf. As mentioned before, it is critical in health management applications to adapt the model parameters to a changing system. In the context of this paper, this corresponds to making all the θ terms additional state variables to be tracked. Since this would significantly increase the state-space dimension, thus making the filtering problem intractable, we take the approach of identifying the θ terms from testing data. However, a sensitivity analysis of the model shows that small changes in the parameters θ_5 and θ_7 have a significant effect on the battery voltage variable x_5, hence we include them in our state vector $X = [x_1\ x_2\ x_3\ x_4\ x_5\ \theta_5\ \theta_7]^T$. The state transition logic for the parameters is simply chosen to be a Gaussian random walk around the initial starting point learnt from data:

$$\theta_{5,k} = \theta_{5,k-1} + \omega_{\theta_5,k} \tag{25}$$

$$\theta_{7,k} = \theta_{7,k-1} + \omega_{\theta_7,k} \tag{26}$$

Ideally, one would track the internal impedances as an indicator for battery depletion, This would necessitate making measurements from which those impedances can be estimated. However, measurement techniques, like electrochemical impedance spectroscopy (EIS), are somewhat impractical for onboard deployment. Instead, most battery powered systems use a cut-off based on battery voltage instead of a cut-off based on SOC. In addition, the relation between terminal voltage and SOC, as given by the manufacturer, does not hold throughout the full life of the battery or under extreme load and temperature conditions. It is therefore advantageous for the prediction tasks to track the variable on which system EOL is determined and we are therefore using terminal voltage, $E(t)$, as an indicator of battery life instead of the SOC. Thus, our measurement equation becomes:

$$E_k \equiv y_k = x_{5,k} + \nu_{y,k} \tag{27}$$

where $\nu_{y,k}$ is also a zero-mean Gaussian noise sample.

V. Prediction Results

Testing on the Edge 540 UAV platform was carried out with the airframe restrained on the ground. The propeller was run through various RPM (revolutions per minute) regimes indicative of the intended flight profile (takeoff, climb, multiple cruise, turn, and glide segments, descent and landing). Figure 4 shows the voltages during a typical flight. It is desired to predict when the battery will run out of charge. i.e. the EOD event indicated by the end of the voltage plots after landing.

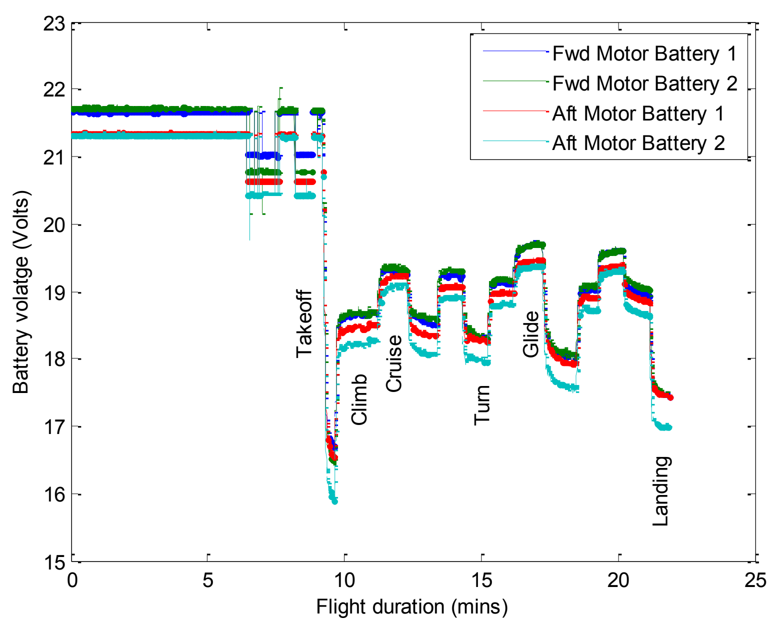

Figure 4. Battery voltages during a typical flight.

In order to evaluate the prognostic algorithm we make multiple predictions at the time instants 13, 15, 17 and 19 minutes. It is not desired to make predictions till the end of the flight since there needs to be some tme for the UAV pilot to land the aircraft with some safety margin on the remaining battery life. One example prediction is shown in Figure 5, where the prediction is made 13 minutes into the flight. The predicted

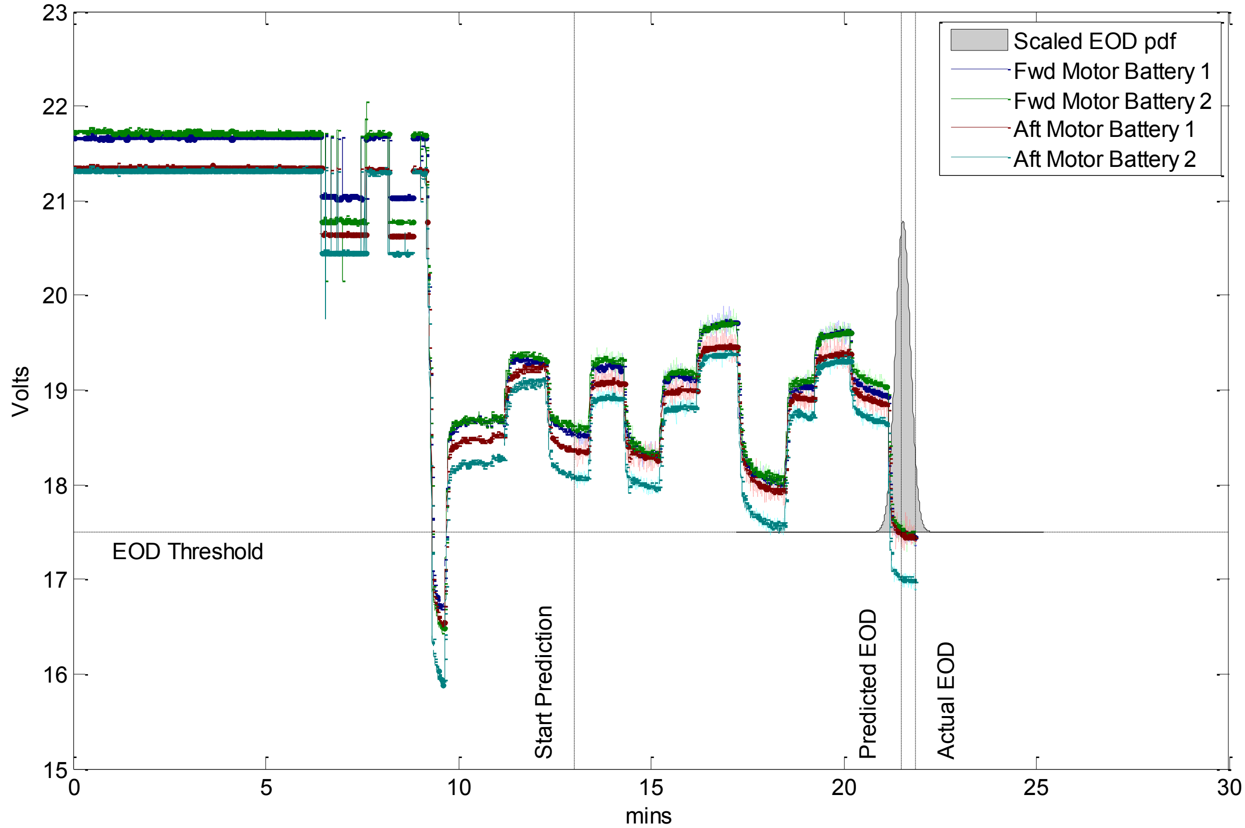

Figure 6. Predicted battery voltages with prediction means shown in dotted lines.

mean trajectories for the battery voltages are shown by dotted lines. The plot shows good correlation between the predictions and the actual voltages with an accurate and precise (narrow) EOD pdf at the end. Since the PF algorithm need to fit the parameters θ_5 and θ_7 from the measured data, predictions earlier than 13 minutes do not show good convergence.

In order to better quantify the prognostic performance, we calculate the $\alpha - \lambda$ performance metric[7] for the prediction means computed as the weighted sum of the particle populations. The α metric indicates the allowable prediction error, while the λ metric denotes the fraction of remaining life by which the prediction accuracy must be achieved. For our case, we arbitrarily select α to be 0.1 (10% error) and λ to be 0.5 so that we have about 4.5 mins left to perform remedial actions (it takes 2 mins to land the UAV). A more formal specification of the prognostic performance requirements is desired, and is under research. For the sake of statistical significance 100 prediction runs are made and all the trajectories are plotted as shown in Figure 6. The cone with the vertex at 21.85 on the *x-axis* represents the 10% error bounds for RUL. The blue lines represent 100 prediction runs. As an aggregate they can be said to fall within the 10% error cone with about 4.5 minutes of remaining life left (indicated by the vertical dashed line), thus passing the $\alpha - \lambda$ performance criteria. Further improvements in the prognostic algorithm, either in the model

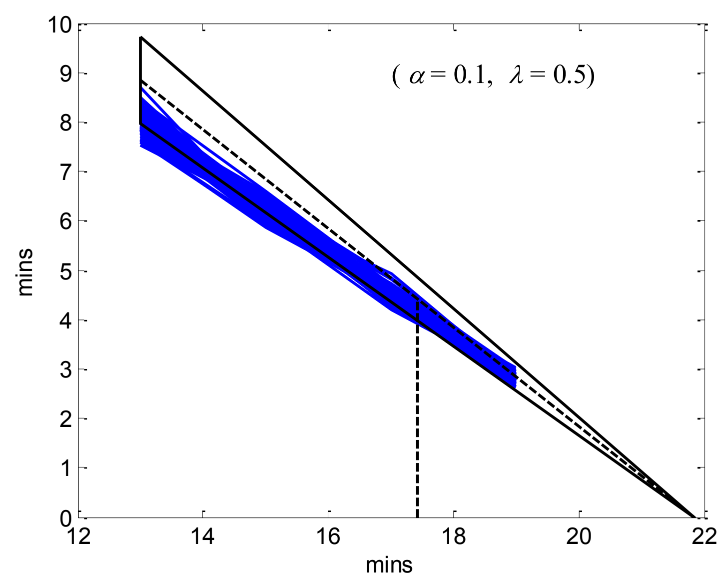

Figure 5. α-λ performance of the PF prognostic framework.

or in the model adaptation, can help bring the prediction trajectories further within the accuracy cone.

VI. Conclusion

In summary, this paper expands on the novel battery health management technique for application onboard an electric UAV presented in[1]. This technique is also readily applicable to small satellites as well as electric vehicles (EVs) on the ground. For over a century now the main hurdle preventing EVs from making the transition to mass adoption has been the uncertainty of running out of battery power on the road. A model-based battery health management approach that is adaptive to environmental as well as system changes, and is capable of producing a battery life prediction output in a pdf form that can be easily integrated into a Bayesian decision making process, is therefore crucial to the success of such battery-powered systems.

In the specific case of UAVs, by creating power profiles for different flight regimes like cruis, turns and landings, we can estimate the mission completion or success probability by calculating the RUL cumulative distribution (cdf) after the intended mission end time. If this value is not 1, i.e.100% success probability, then it can motivate and inform mission replanning activity based on the tradeoff between the amount of risk (1 – success probability) allowed by the operator and the cost of curtailing the mission. The PF prognostic framework can also be used to evaluate the effectiveness of possible mitigation actions, thus acting as a simulation testbed for advanced contingency management technologies.

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