Optimizing Battery Life for Electric UAVs using a Bayesian Framework

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Abstract—**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. For electric UAVs (unmanned aerial vehicles) the variation in the load profile can be very unpredictable. This paper presents a model parameter augmented Particle Filtering prognostic framework to explore battery behavior under these future load uncertainties. Stochastic programming schemes are explored to utilize the battery life predictions generated as a function of load, in order to infer the most optimal flight profile that would maximize the battery charge utilized while constraining the probability of a dead stick condition (i.e. battery shut off in flight).**

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1. 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. While an impressive technical feat themselves, these UAVs are but stepping stones to the full-scale electric and hybrid aircraft of the future. EADS (European Aeronautic Defense and Space Company) has been testing a battery electric-powered ultra-light aircraft for the last year, and recently introduced a series-hybrid motor glider as well as an ambitious future concept for an all-electric, 50-seat passenger plane powered by superconducting drive motors. In 2010, Boeing released details of the SUGAR Volt (Subsonic Ultra Green Aircraft Research) twin-engine future concept airliner. The 737-size transport would be powered by hybrid propulsion system that would combine gas turbine and battery/electric motor technology.

However, with the electric car still trying to find its niche, battery powered propulsion is a bigger hurdle for aircraft. This is because of the large disparity between the energy densities of batteries versus jet-fuel. Though some of that can be negated by the higher efficiency of electric motors than combustion-based engines, the energy and power densities of batteries would have to increase several fold to make electric propulsion commercially feasible. As important as finding better battery materials is to this effort, it is equally imperative to utilize the available energy to the optimal extent possible, thus reducing the need for bigger, heavier batteries.

Like ground vehicles, battery powered electric aircraft suffer from uncertainties in estimating the remaining charge and hence most flight plans are highly conservative in nature, using only a fraction of the available battery energy. 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. Just as for an electric car the future power draw may be inferred from the intended route, speed, and terrain data, the variables of interest for a pilot controlled UAV include wind speed and direction, air temperature and density, as well as the duration and velocity of different flight segments like climb, cruise, turns and descent.

Previous work in battery prognostics for UAVs has relied on assuming knowledge of these future load conditions. [5] But given the unpredictable nature of UAV load patterns, it is preferable that the system operator not only receive prognostics information based on expected load induced on the system, but also information about a range of load levels, including the extreme load levels (i.e. the maximum and minimum loads). Knowledge of how these varying load profiles affect the remaining useful life (RUL) of the battery provide the operator with a complete picture of how the battery charge may be depleting. In this paper a model parameter augmented Particle Filtering prognostic framework is used to explore these future load uncertainties. Stochastic programming schemes are explored to utilize the RUL distributions generated as a function of the loads, in order to infer the most optimal flight profile. Such a profile would maximize the battery charge utilized while constraining the probability of a dead stick condition (i.e.

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battery shut off in flight), which can have catastrophic consequences.

In this paper our application platform is a subscale aerobatic UAV, the Edge 540, powered by four 18.5V 6000mAh Lithium-polymer (Li-Poly) battery packs. For prognostics, a detailed discharge model was developed for the Li-Poly cells and verified using hardware-in-the-loop as well as flight tests of the Edge 540. This model was then used in a Particle Filter (PF) based prognostic framework that combines state estimation with model adaptation to accurately predict the remaining battery charge. This information is used in conjunction with stochastic estimates of future usage to give remaining run time for the UAV. This paper also discusses how these predictions may be used to increase operational safety, optimize mission plans and extend battery life.

2. BATTERY BEHAVIOR

Batteries are energy storage devices that facilitate the conversion, or *transduction*, of chemical energy into electrical energy, and vice versa [3]. The characteristics of a Li-Poly battery have also been explained in [5], but some information is repeated here to motivate the modeling approach. 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:

Ohmic Drop

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, where IR denotes the product of current (I) and resistance (R). For a given load current this drop usually decreases with time due to the increase in internal temperature that increases ion mobility. However, when we have step changes in the load, a higher load level followed by a lower one presents a period of relaxation for the battery. During this period the voltage does not immediately jump up but gradually rises which can be modeled by an exponential function. A similar effect can also be observed for a step increase in current level. These effects can be reconciled by considering the battery impedance as an RC equivalent circuit [7]. Henceforth, this drop is referred to as ΔE_{IRC}, given by

$$\Delta E_{IRC}(t_k) = \Delta I_{-1}\alpha_{1,k}\left(1-\exp\left(-\alpha_{2,k}\left(t_k - t_{\Delta I_{-1}}\right)\right)\right) - \alpha_{3,k}t_k \quad (1)$$

where t_k is any time instant, ΔI_{-1} is the last step-change in load current, $t_{\Delta I_{-1}}$ is the time instant of that change, and the $\alpha_{i,k}$'s are model parameter values at t_k. More details about the formulation of Eq. (1) can be found in [5].

Activation Polarization

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. The resulting drop in voltage has been modeled as shown in Eq. (2) to represent the activation polarization of the battery, referred to from now on as ΔE_{AP}.

$$\Delta E_{AP}(t_k) = \alpha_{4,k} \ln(1 + \alpha_{5,k} I_k t_k) \quad (2)$$

where I_k is the instantaneous load current and $\alpha_{i,k}$'s are model parameter values at time t_k. The effect of ΔE_{AP} is most pronounced when the electrode reaction is controlled by electrical charge transfer at the electrode and not by the mass transfer to or from the electrode surface from or to the bulk electrolyte.

Concentration Polarization

Concentration polarization 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 the volumetric or bulk flow of the ions. The consumption of Li-ions causes a drop in their concentration along the cell, between the electrodes, which causes a drop in the local potential near the cathode. This voltage loss is also referred to as concentration polarization, represented in this paper by the term ΔE_{CP}.

$$\Delta E_{CP}(t_k) = \alpha_{6,k} \exp(\alpha_{7,k} I_k t_k) \quad (3)$$

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.

The output current plays a big role in determining the losses inside a battery and is an important parameter to consider when analyzing battery performance. The term most often used to indicate the rate at which a battery is discharged is the *C-Rate* [3]. The discharge rate of a battery is expressed as *C*/*r*, where *r* is the number of hours required to completely discharge its nominal capacity. The terminal voltage of a battery, as also the charge delivered, can vary appreciably with changes in the C-Rate. Furthermore, the amount of energy supplied, related to the area under the discharge curve, is also strongly C-Rate dependent. Figure 1 shows the typical discharge of a battery and its variation with C-Rate. Each curve corresponds to a different C-Rate or *C*/*r* value (the lower the *r* the higher the current) and assumes constant temperature conditions.

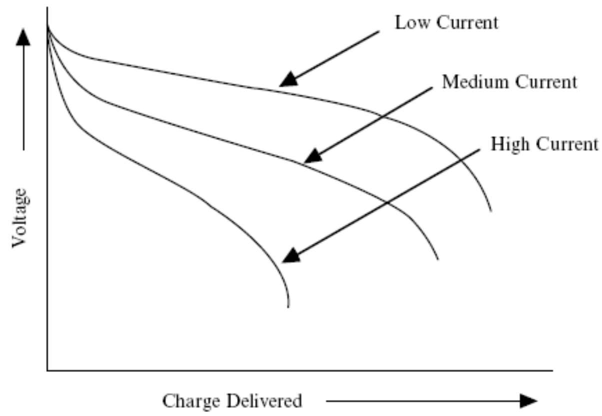

Figure 1 – Schematic drawing showing the influence of C-Rate upon the discharge curve (reproduced from [3])

Thus the higher the demand on the battery, the lesser the amount of usable charge delivered. This is a key point, since for electric UAVs some maneuvers impose a higher C-Rate than others. Consequently, when optimizing the future flight profile for a constrained remaining battery charge, the expected load current and time duration corresponding to each flight maneuver need to be taken into consideration.

3. PROGNOSTIC FRAMEWORK

The formulation of a model, though, is just a part of the solution. As mentioned above there are a number of unknown parameters that need to be identified. Even after identification, they may not be directly applicable to any given test run since the values may differ from one battery to another, or for the same battery from one cycle to the next. Furthermore, for any given cycle the parameter values may be non-stationary. In general, the task of tracking the battery voltage (denoted as the state variable x_k) and estimating the unknown model parameters $\alpha_{i,k}$'s can be cast as a *filtering* problem. The state equations with additive zero-mean Gaussian noises can be written as

$$\begin{aligned} x_k &= \mathrm{f}\left(x_{k-1}, \alpha_{i,k-1}\right) + \omega_{k-1} \\ \alpha_{i,k} &= \mathrm{g}\left(\alpha_{i,k-1}\right) + \vartheta_{i,k-1} \\ z_k &= \mathrm{h}\left(x_k\right) + \nu_k \end{aligned} \tag{4}$$

A variety of filtering techniques is applicable here since manually piloted flight patterns differ from each other and so do the atmospheric flight conditions. However, keeping the uncertainties inherent to our problem in mind, a Particle Filtering (PF) framework is chosen. Particle Filters [2] are a novel class of non-linear filters that combine Bayesian learning techniques with importance sampling to provide good state tracking performance while keeping the computational load tractable. The idea is to represent the system state as a probability density function (pdf) that is approximated by a set of particles (points) representing sampled values from the unknown state space, and a set of associated weights denoting discrete probability masses. The particles are generated from an *a priori* estimate of the state pdf, propagated through time using a nonlinear process model, and recursively updated from measurements through a measurement model. The main advantage of PFs here is that model parameters are included as a part of the state vector to be tracked, thus performing model identification in conjunction with state estimation [4]. Figure 2 shows a flowchart for this filtering process.

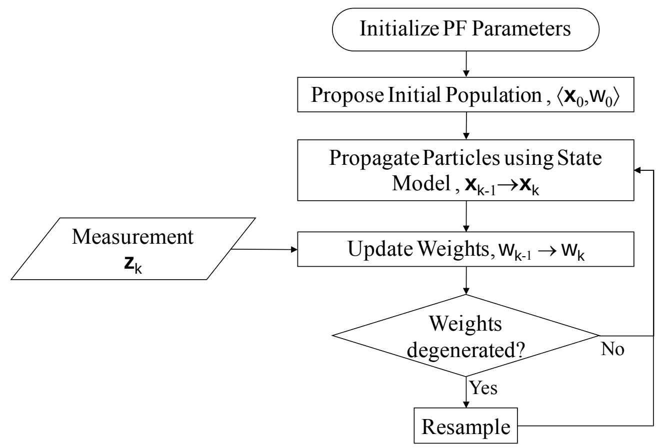

Figure 2 – Particle filtering flowchart (reproduced from [5])

After the model has been tuned to reflect the dynamics of the specific system being tracked, it can then be used to propagate the particles up to the failure threshold (e.g. 0% SOC for the battery or when the voltage per cell reaches the cutoff limit) to give the RUL pdf [4], as shown in Figure 3. The EOL (end-of-life) threshold refers to the EOD threshold, which in our case is the minimum allowable battery voltage (EEOD).

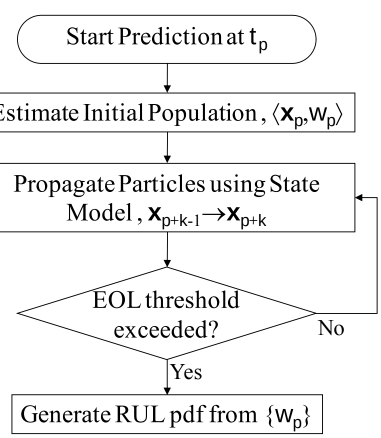

Figure 3 – Prediction flowchart (reproduced from [5])

The details of the particle filter equations are given in [5]. Here it will suffice to say that

$$x_k \equiv E\left(t_k\right) = E^{\circ} - \left\{\Delta E_{IRC}\left(t_k\right) + \Delta E_{AP}\left(t_k\right) + \Delta E_{CP}\left(t_k\right)\right\} \tag{5}$$

where $E(t_k)$ or E_k denotes the estimated terminal voltage of the battery. The measurement z_k is the measured terminal voltage, denoted by $E^*(t_k)$ or E^*_k.

$$z_k \equiv E^*(t_k) = E(t_k) + \nu_k \quad (6)$$

If t_p be the time instant when a prediction of remaining battery life is desired, then there are N state trajectories projected forward in time, corresponding to the N particles, until the EOD threshold is reached, i.e. $E_n(t_{p+k})<E_{EOD}$, where n is the particle index. The RUL pdf at t_p, denoted by $p(t_{RUL,p})$, is constructed by fitting a mixture of Gaussian kernels to the weighted distribution of the individual RUL values, $\{(t_{n,EOD} - t_p), w_{n,p}\}$, $n = 1,\ldots,N$, where $w_{n,p}$ is the particle importance weight at t_p and $t_{n,EOD}$ is the predicted time where the nth particle trajectory crosses the EOD threshold.

4. The Electric UAV Platform

The test vehicle used for this research is a COTS 33% scale model of the Zivko Edge 540T. 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 motors are powered by a set of 4 Li-Poly rechargeable batteries. The batteries are each rated at 7800 mAh. The tandem motors are each controlled by separate motor controllers.

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 and Figure 5 show the currents and voltages during a typical flight profile.

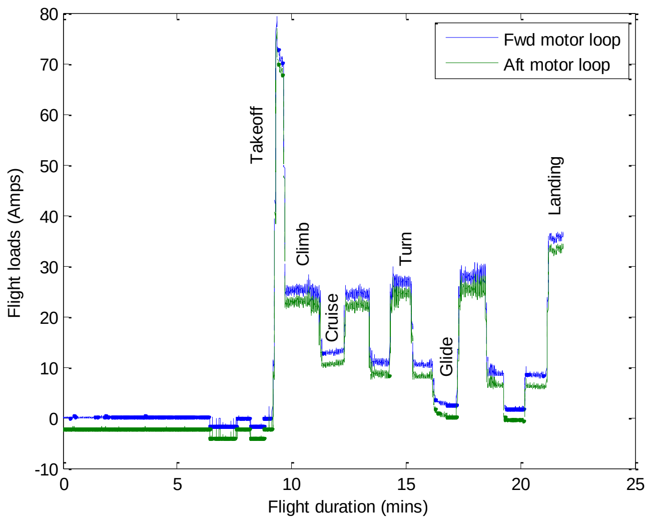

Figure 4 – Load currents during a typical flight profile

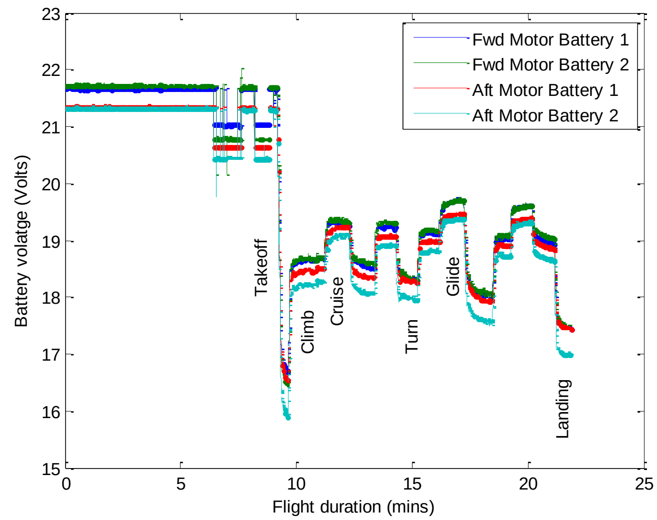

Figure 5 – Battery voltages during a typical flight profile

Based on the data generated by several such tests, the nominal values for the model parameters $\alpha_{i,k}$'s are learned. Furthermore, for the sake of computational tractability, only $\alpha_{5,k}$ and $\alpha_{7,k}$ are selected to be non-stationary after a model sensitivity analysis. The corresponding state updates are simply modeled as Gaussian random walks.

$$\begin{aligned} \alpha_{5,k} &= \alpha_{5,k-1} + \vartheta_{5,k-1} \\ \alpha_{7,k} &= \alpha_{7,k-1} + \vartheta_{7,k-1} \end{aligned} \quad (7)$$

Additionally, we fit Gaussian kernels to the load (I) distribution for different flight maneuvers. Table 1 shows a list of the mean, standard deviation, minimum and maximum values (rounded off to the nearest integer) for the load current (I_μ, I_σ, $I_>$, $I_<$, respectively) and duration ($\tau_\mu, \tau_\sigma, \tau_>, \tau_<$, respectively) corresponding to each maneuver.

Table 1 – Maneuver characterization (I's in Amps; τ's in secs)

	I_μ	I_σ	$I_>$	$I_<$	τ_μ	τ_σ	$\tau_>$	$\tau_<$
M1:Takeoff	80	7	70	100	60	10	50	75
M2:Climb	30	5	22	40	120	10	90	140
M3:Cruise	15	3	10	22	90	10	70	115
M4:Turn	35	5	25	47	120	10	100	145
M5:Glide	5	1	2	8	90	10	75	120
M6:Landing	40	5	30	53	60	10	40	80

5. Prognostic Results

The first step to optimizing battery use is the estimation and prediction of remaining battery charge. In order to evaluate the prognostic algorithm we make several predictions as shown in Figure 6.

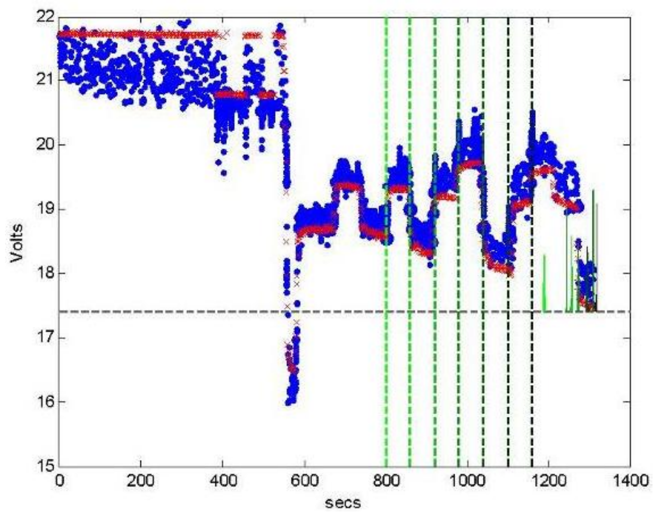

Figure 6 – Battery voltage prediction using Particle Filter

The red crosses show the measured voltage values while the blue dots indicate the PF state values. The time instants when the predictions are made are shown in green vertical dashed lines, with lighter shades indicating earlier predictions. The corresponding end-of-discharge (EOD) pdfs are shown in green patches on the 17.4 V EOD threshold voltage line (shown in dashed gray).

In order to validate the learned prognostic model several flight tests were conducted using the UAV with randomized flight profiles. The prediction performance was accurate to within 2 minutes, i.e. $|t_{EOD} - \bar{t}_{RUL,p}| < 2$ mins, over multiple flights of durations between 15 to 25 minutes. Figure 7 shows one such prognostic exercise.

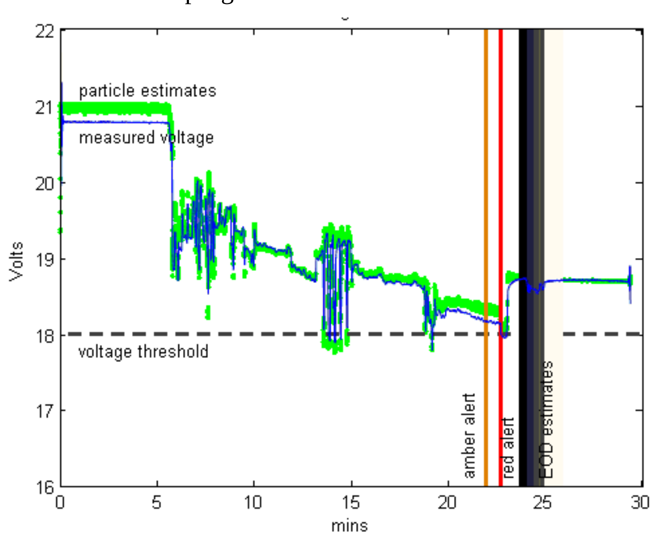

Figure 7 – Battery voltage prediction using Particle Filter during flight test

The blue line indicates the measured voltage while the green dots indicate the state values of the PF. The grey lines denote the $\mu_{RUL,p}$ values plotted every second, while the amber and red lines represent early alerts for the pilot to land the plane before the dead stick condition.

6. STOCHASTIC PROGRAMMING

Given this prognostic capability, it is possible to use the RUL pdfs in a decision-theoretic framework to optimize battery use. In general, many decision problems can be modeled using mathematical programs, which seek to maximize or minimize some objective which is a function of the decisions. The possible decisions are constrained by limits in resources, minimum requirements, etc. Decisions can take many forms. For our application they can be a temporally ordered set of maneuvers, e.g. {M1, M2, M3, M4, M3, M4, M5, M2, M4, M5, M3, M6}, executing a flight plan.

The general form of a mathematical program is

$$\begin{aligned} &\text{minimize}\, \psi(u,v) \\ &\text{subject to}\, \phi(u,v) \le 0 \\ &u \in \mathbf{U} \end{aligned} \tag{8}$$

Where u and v are system variables, ψ is the objective function, ϕ is the constraint function, and $\mathbf{U}$ is the set of constraints. The constraints can be quite general, but linear constraints are sufficient in many cases to capture the essence of the model. Stochastic programs [6] are mathematical programs where some of the data incorporated into the objective or constraints is uncertain. Uncertainty is usually characterized by a probability distribution on the parameters. Although the uncertainty is rigorously defined, in practice it can range in detail from a few scenarios (possible outcomes of the data) to specific and precise joint probability distributions.

When some of the data, say v, is random, then solutions and the optimal objective value to the optimization problem are themselves random. A distribution of optimal decisions is generally computationally intractable. There are several simplification strategies that can be applied in such a scenario.

Worst-case Analysis

If the value of ψ is uncertain, worst-case analysis or robust optimization tries to minimize the maximum possible value of ψ. Similarly, the constraint criteria needs to be satisfied by the maximum value of the constraint function ϕ. The problem formulation in Eq. (8) then changes to

$$\begin{aligned} &\text{minimize } \max \psi(u,v) \\ &\text{subject to } \max \phi(u,v) \le 0 \\ &u \in \mathbf{U} \\ &v \in \mathbf{V} \end{aligned} \tag{9}$$

where $\mathbf{V}$ is an "uncertainty set" to be specified in advance.

Expected Value Model

Here, the expected value of the functions ψ and ϕ are used in lieu of the functions themselves. The resulting formulation is given below.

$$\begin{aligned} &\text{minimize } \overline{\psi}(u,v) \\ &\text{subject to } \overline{\phi}(u,v) \le 0 \\ &u \in \mathbf{U} \end{aligned} \tag{10}$$

where $\overline{\psi}$ and $\overline{\phi}$ denote the respective expected values. This scheme can be considered optimization on average.

Probabilistic Model

Here, the expected value of the functions ψ and ϕ are used in lieu of the functions themselves. The resulting formulation is given below.

$$\begin{aligned} &\text{minimize } \psi(u,v) \\ &\text{subject to } p(\phi(u,v) \le 0) \ge p \\ &u \in \mathbf{U} \end{aligned} \tag{11}$$

where p denotes some probability value, $0 \le p \le 1$.

7. Optimization Strategy

For the UAV flight tests under consideration, the goal is to maximize the number of maneuvers without exceeding the charge available from the battery. Decisions can thus be represented as flight plans that include a temporally ordered set of maneuvers $u \equiv \{u_m;\ m = 1, \ldots, M\}$, where M is the number of maneuvers and $u_m \in$ {M1, M2, M3, M4, M5, M6}, which denotes the set $\mathbf{U}$ in this case. There are some obvious constraints like u_1 will be M1 and u_M will be M6. The objective then is to find the optimal flight plan given by $\{u_m;\ m = 2, \ldots, M-1\}$. There are other constraints like the requirement of keeping the UAV within controllable range and having an approximately even mix of flight maneuvers. We enforce this by mandating that no two consecutive maneuvers be the same, i.e. $u_m \ne u_{m-1}$, and the maneuver following any two consecutive non-turn actions will be a turn, i.e. $u_{m-2} \ne \text{M4} \wedge u_{m-1} \ne \text{M4} \Rightarrow u_m = \text{M4}$. Thus we can define the set of constraints by

$$\mathbf{U} \cong \begin{cases} u_m \in \mathcal{U}\{\text{M2, M3, M4, M5}\}, \\ u_m \ne u_m, \\ u_{m-2} \ne \text{M4} \wedge u_{m-1} \ne \text{M4} \Rightarrow u_m = \text{M4}. \end{cases} \tag{12}$$

where $\mathcal{U}$ denotes a uniform distribution over { M2, M3, M4, M5}.

The stochastic variables in this case represent the state variable x_k (denoting the battery voltage $E(t_k)$) and the battery prognostic model parameters $\alpha_{i,k}$'s as given in Eqs. (4), (5) and (7). The objective function ψ is the PF state model, $\mathcal{H}$, which gives the remaining battery life, t_{RUL}, as a function of the battery charge state, the parameters and the planned sequence of maneuvers. The value t_{RUL} has to be minimized in order to maximize the number of maneuvers, M. The constraint function ϕ is given by $-\mathcal{H}$, since t_{RUL} must always be positive to prevent a dead stick condition. Thus, the problem formulation for the UAV optimal flight plan becomes

$$\begin{aligned} &\text{minimize } \mathcal{H}(u_{1\ldots M}, x_k, \alpha_{i,k}) \\ &\text{subject to } \mathcal{H}(u_{1\ldots M}, x_k, \alpha_{i,k}) > \tau_{\text{M6},<} \\ &u \in \mathbf{U} \end{aligned} \tag{13}$$

where u_m can be quantitatively represented by $\{I_m, \tau_m\}$, and $\tau_{\text{M6},>}$ denotes the time for landing.

This optimization routine can be run whenever an RUL prediction is made at any given t_p. Each particle in the PF has a value of $\{x_{n,p}, \alpha_{n,i,p}\}$ at time t_p, where n is the particle index. The model H can use this state information and propagate it under a given flight plan to output the RUL value weighted by the particle weight $w_{n,p}$ at t_p. A schematic of this process is shown in Figure 8.

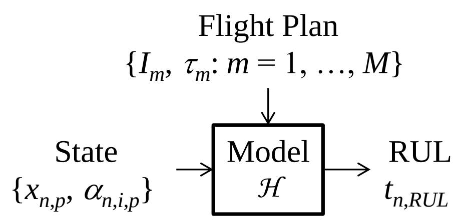

Figure 8 – Schematic of flight plan evaluation

The three different analysis strategies discussed in Section 6 can now be applied. For *worst-case analysis* we need to compute the maximum value of $\mathcal{H}$, hence we need to consider the minimum load current and duration for each maneuver, i.e. $\{I_{m,>},\ \tau_{m,>}\}$. For the *expected value model* we use $\{I_{m,\mu},\ \tau_{m,\mu}\}$, while for the *probabilistic model*, we sample from the distributions of $\{I_m,\ \tau_m\}$ shown in Table 1.

Since this optimization routine needs to be implemented on a resource-constrained embedded computer onboard the UAV, a simple heuristic approach was investigated for the optimization task. The steps involved in this approach are:

i. Start with the particle population of state values $\{x_{n,p},\ \alpha_{n,i,p}\}$ at time t_p.
ii. Generate next maneuver u_m subject to the constraints in $\mathbf{U}$.
iii. Compute corresponding load and duration values $\{I_{m,>},\ \tau_{m,>}\}$ according to the stochastic programming analysis strategies chosen.
iv. Use model $\mathcal{H}$ to estimate the next state and predict RUL t_{RUL}.
v. If $t_{RUL} > \tau_{\text{M6},>}$, then repeat from step ii, else output the sequence of maneuvers except the last one as the optimal sequence.

vi. In case there are more than one flight plans generated by the different particle trajectories (depending on the starting state values at t_p, some particle trajectories may take a few extra maneuvers to exceed the EOD threshold), use the particle weights $w_{n,p}$ to compute the expected optimal plan.

8. Conclusions

In summary, this paper lays a simple flight plan optimization strategy based on the particle filtering framework described in [5]. This is meant as a first step in formalizing computationally tractable stochastic programming techniques to optimally generate flight plans in response to battery life predictions. This approach takes advantage of the PF framework to simultaneously generate the optimal/sub-optimal flight plan simultaneously with predicting the RUL. Several steps lie ahead like a comparative analysis of alternative stochastic models in terms of optimality as well as computational cost. These options will need to be validated by flight tests where robustness to environmental conditions like air temperature and density as well as wind speed can be evaluated. The notion of risk-tolerance can be introduced via appropriate objective functions, thus allowing a non-zero risk of the dead stick condition in order to use more battery power.

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Biography

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