Remaining Useful Life Prediction of Li-Po Batteries in UAVs Using Extended Kalman Filter

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Abstract: The use of batteries in UAVs (unmanned aerial vehicles) has become common due to some advantages in comparison with internal combustion engines such as weight reduction and better power control. However, in these vehicles it is critical to monitor the RUL (remaining useful life) of the batteries. This information can be used, for instance, as a decision support tool to define which missions could be assigned to the UAV until the next battery recharge. This work presents a methodology to predict the RUL of Li-Po (Lithium-Polymer) batteries. The approach uses an extended Kalman filter and an exponential model for the degradation evolution. The proposed methodology uses time series of battery terminal voltages, assuming that the discharge occurs under a constant current condition. Different discharge current levels were considered. The results showed that the proposed methodology provides good results, despite its simplicity.

Key words: Extended Kalman filter, Li-Po battery, RUL estimation, UAV.

1. Introduction

The use of batteries in UAVs (unmanned aerial vehicles) provides certain advantages over the use of propellant combustion. Among these advantages, it is possible to mention the weight reduction, noise reduction, emission reduction and improved power control capability [1, 2]. However, for these vehicles it is important to monitor the remaining battery power. This information can be used to aid decision-making about which missions can be attributed to the UAV before the next recharge.

This paper proposes a methodology to estimate the RUL of Li-Po (Lithium-Polymer) batteries. This type

of battery appears as an alternative Li-Ion batteries having higher energy density [3, 4].

The method uses data sets containing the voltage at the battery terminals. The data sets were obtained during a test campaign on the bench. For the prediction step, an approach based on an EKF (extended Kalman filter) has been used.

The paper is organized as follows: Section 2 is shown as data collection and a brief description of the trial bench was made; Section 3 presents the prediction model, which was performed using an EKF; Section 4 describes the results of the predictions made; the conclusions of the paper are presented in Section 5.

2. Data Base

In this paper, we chose the UAV model Gyro-200 ED-X8 manufactured by Gyrofly. The aircraft has 8

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rotors it is a platform for experimental purposes, for research applied and universities. Fig. 1 shows the Gyro-200ED-X8.

The Gyro-200 ED-X8 offers an open communication that allows access to the aircraft telemetry, read all embedded sensors and a microcontroller with hardware that allows the user to embark on your own code. This UAV is equipped with a Li-Po type 2 A/h voltage of 14.8 V [5].

In this initial study, it chose to carry the load prediction for battery constant current consumption. This case simulates a UAV operation with constant height and position (HOLD), performing the monitoring of an area. For this purpose it was built a test rig where the battery is discharged following a configurable constant current reference.

The use of different currents simulates different levels of “payload” on the UAV. This electronic charge is divided into two stages, one digital and another analog stage.

The digital stage consists of a 16F877A microcontroller, which controls the discharge current, the catch voltage and current values and radio communication with the computer. The analog step comprises a closed loop of an operational amplifier and a MOSFET that performs discharge of the battery. Fig. 2 show parts of the test bench.

The solution connects to a computer through a radio frequency link that lets you control the download and store the voltage and current data of the battery where a supervisory software on the computer is used as a man-machine interface. This software is used to set the discharge current watching in real time the measured values of the battery and generate the file with the discharge data for later analysis. Thus it has been produced solution that allows adjustment of the discharge current of 2.5 A until discharges with set intervals of 0.15 A. Fig. 6 shows the software interface.

For the generation of data were used three batteries. For each battery, were performed discharge test using the current values 1.0 A, 1.5 A and 2.0 A. The batteries

Fig. 1 UAV Gyro-200 ED-X8.

Fig. 2 Electronic load connected to the battery.

Fig. 3 Curves resulting from tests on bench.

were discharged until they reach voltage 12.5 V. The voltage data were recorded at a sampling rate of one sample per minute. Fig. 3 shows the data obtained in the tests.

3. Model Prediction

The load prediction was performed using an EKF [6]. The use of filtering techniques to forecast involves two steps: estimation of degradation and forecast moment of failure.

During the degradation estimation step is used a model to describe the degradation of the equipment. In

this study, we used the model described by Eq. (1).

$$\begin{aligned} d[k+1] &= r \cdot d[k] + w_1[k] \\ m[k] &= d[k] + v[k] \end{aligned} \quad (1)$$

where, the degradation of the system at time t is given by $d[k]$, r is the rate at which degradation is modified, m is the voltage measurement obtained in the tests and w_1 and v are white noise Gaussian process and measured, respectively.

The chosen model assumes that degradation has an exponential behavior determined by the r parameter.

It can be checked by Fig. 7 that the data series have exponential behavior but with different decay rates. This fact is quite visible to different discharge currents, but is also present in series with the same discharge current. Thus, it is necessary to estimate r in each data series. Incorporating this estimate to the model we have this final model.

$$\begin{aligned} d[k+1] &= r[k] \cdot d[k] + w_1[k] \\ r[k+1] &= r[k] + w_2[k] \\ m[k] &= d[k] + v[k] \end{aligned} \quad (2)$$

In this model, r is estimated along the iterations using a random walk model (w_2 is a Gaussian white noise). Whereas the estimated value of r should not vary over a range of data, it was decided to adopt the strategy described in Ref. [7]. In this strategy, w_2 variance is adjusted according to the variance of the

estimate of r given by the Kalman filter. This procedure is designed to start the estimation with a high variance, enabling to search a larger space and narrow the search space as the filter is converging.

The estimation step of degradation is therefore estimate d from the measurement of m using the model described in Eq. (2) and an EKF. This step is performed to the moment where you want to make a prediction.

During the forecast stage the estimates of d and r are used together with the model (2) to simulate the evolution of the degradation over future iterations.

Cast lots up points belonging to estimated distribution of d and r then verified the evolution of each point using Eqs. (1) and (2). A prediction of failure time is determined by the violation of the failure threshold for the measurement of degradation. The predicted distribution of the failure time is constructed from the predictions of multiple points drawn from r distributions. For this paper, the fault threshold was established as 12.5 V.

4. Results

Figs. 4 and 6 show the results of predictions carried out in 1 to 10 min prior to battery failure. The confidence intervals include 99% of the predictions made.

Fig. 4 Prediction results for 1.0 A current.

Fig. 5 Prediction results for current 1.5 A.

Fig. 6 Prediction results for current 2.0 A.

Although the use of a simple model of progression of degradation was observed a good performance of the forecasting system, the failure of real moment are within the confidence intervals scheduled up to five minutes in advance for most datasets.

As can be seen, the quality of the predictions decays as the discharge current increases. This can be explained by the fact that higher currents imply faster decay resulting in a series of data with fewer points. The presence of a few points impacts on estimates of the EKF.

5. Conclusions

This paper presents a methodology to estimate the remaining useful life of a Li-Po battery used in UAVs. The proposed method used an EKF with an exponential model of evolution of the degradation.

The used model generated good results, despite the simplicity of the approach. As further work has been identified the need of using a higher sampling rate, this change impacts the quality of the estimate, given that generate series with larger numbers of points.

Other future studies must involve the use of other

degradation progression models and the load forecast when the battery discharge current changes during operation.

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