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Battery Remaining Useful life Forecast Applied in Unmanned Aerial Vehicle.

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ABSTRACT

The batteries has been widely used as an energy storage system for unmanned aerial vehicles (UAVs). To avoid faults in these systems (UAVs), which are powered by batteries, there are several approaches to forecast the Remaining Useful Life (RUL) of the batteries. In this work, it's proposed the use of a model based on Extended Kalman Filter (EKF) to estimate the RUL in Lithium-Ion batteries. The database used was available at NASA's repository in 2015.

***Keywords* -** Lithium-Ion batteries, Extended Kalman Filter, RUL Estimation, UAVs

I. INTRODUCTION

Li-Ion (Lithium-Ion) batteries are recently used in UAVs (Unmanned Aerial Vehicles Non-) due to its high energy density and its long life cycle when compared to other types of batteries [1]. Every battery has a remaining useful life, in which she will degrade over time and use. Often the equipment that typically more failures in UAVs are batteries.

For predict UAVs failures, there are techniques which aim to observation and evaluation of the degradation of components over time systems [2]. These forecasts are given from techniques: PHM (Prognostic and Health Monitoring). The PHM techniques acquire information on the health of the equipment, based on monitoring sensors, in which the collected result information of the nearby points of failure [3]. As the battery is the study of equipment in this work, it is one of the equipment that fail, it can be analyzed later after its monitoring, which will be obtained as driving may occur fault, through RUL (Remaining Useful Life) .

This paper deals with a proposed methodology to estimate the RUL of Li-Ion batteries. This battery as previously seen after, is used in UAVs, and it also is a equipment that might fail. The proposed methodology would be the battery being discharged behavior, where voltages was collected at its terminals by the end of the discharge profile. These data are obtained by a database that NASA released in 2015. To make estimates was used Extended Kalman Filter (EKF) which is an approach that works with non-linear behavior.

The remaining sections of this paper are divided as follows. Section 2 is a brief description of Li-Ion batteries. The next section will look at the database that will be used at this work. Section 4 presents the model based on Extended Kalman Filter.

The following section reports the results of the predictions and the conclusions.

II. LITHIUM-ION BATTERIES

Batteries are energy storage devices that convert chemical energy into electrical energy and vice versa. Batteries are formed of a pair of electrodes (anode and cathode) immersed in a [4] electrolyte. Figure 1 shows the operation of the Li-Ion battery.

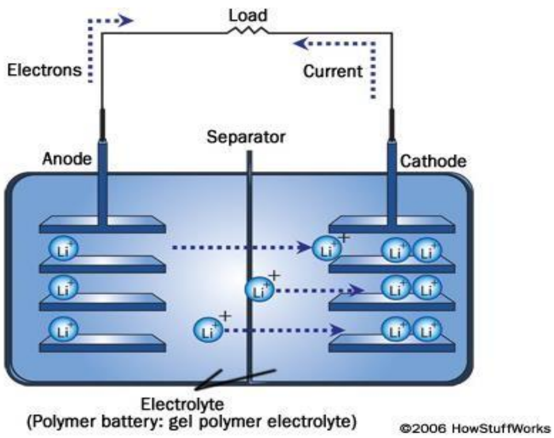

Fig 1. Battery Behavior lithium-Ion

One of the most important parameters in the analysis of the remaining battery life is the current required by the load. In general, the battery is specified as a function of current that can be supplied and duration. However, changes in battery discharge current gives rise to significant variations both in voltage at the battery terminals as the total amount of energy supplied by it [5]. It can be seen from Figure 2 that, for large values of the discharge current, the total amount of energy supplied by the battery (represented in the figure by the area under each curve) is lower.

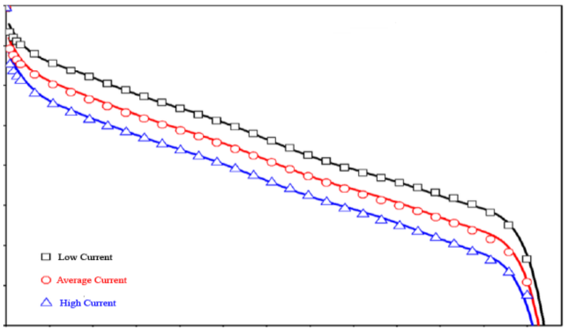

Fig. 2. Effect of Current in Battery Discharge Curve.

III. DATA BASE

This initial study is to carry out the forecast charging status using a NASA repository of Li-Ion, where these types of batteries are widely used in UAVs. Prognosis repository data was provided by NASA Ames Research Center in [6]. The data are divided into four Li-Ion batteries identified by RW13, RW14, RW15 and RW16, but the RW13 and RW14 batteries were used in this study.

According to [7] the batteries were loaded with voltage up to 4.2 V and discharged until reaching the voltage of 3.2 V, using a random sequence current 0.5 to 5 A. During unloading every one minute is chosen at random a new load set point. Table 1 shows the probability of choosing the load set point during battery discharge.

Table 1. Probabilities of selecting each potential load setpoint

Load Setpoint	Probabiliy
0.5A	7.2%
1.0A	14.8%
1.5A	19.3%
2.0A	21.6%
2.5A	14.6%
3.0A	10.0%
3.5A	6.5%
4.0A	4.0%
4.5A	1.5%
5.0A	0.5%

Figures 3 and 4 represent the discharge profile curves batteries RW13 and RW4 respectively.

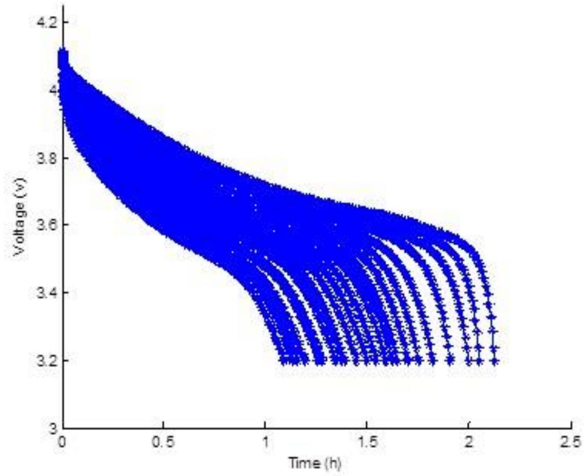

Fig. 3. Discharge of Battery [RW13].

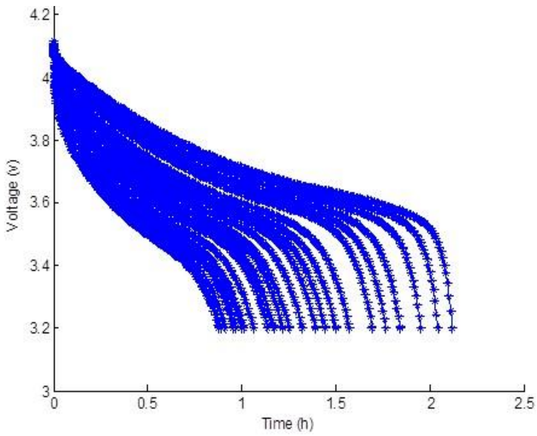

Fig. 4. Discharge of Battery [RW14].

Figures 5 and 6 show the ability of RW13 and RW14 batteries respectively over the days, starting in the month of July 2014 and ending in April 2015.

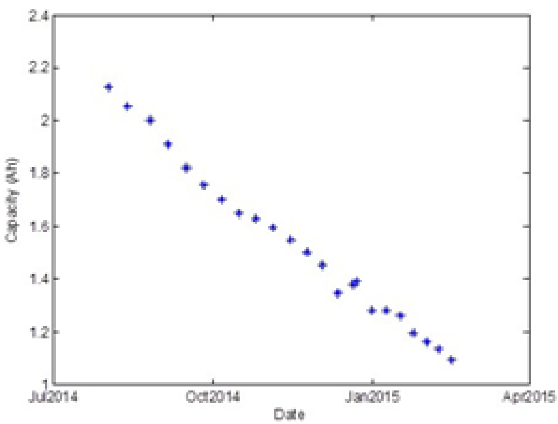

Fig. 5. Degradation of Measured Capacity of Battery [RW13].

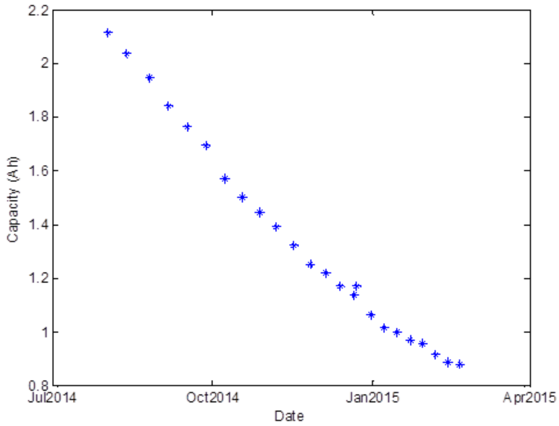

Fig. 6. Degradation of Measured Capacity of Battery[RW14]

IV. PREDICTION

The load prediction was performed using an Extended Kalman Filter (EKF). 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 equation (1).

$$d[k+1] = r \cdot d[k] + w_1[k] \qquad (1)$$

$$m[k] = d[k] + v[k]$$

Where the degradation of the system at time is given by *d[k]*, r is the rate at which degradation is modified, m is the voltage measurement obtained in the tests and w1 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 check by Figures 3 and 4 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 in equation (2).

$$d[k+1] = r[k] \cdot d[k] + w_1[k]$$

$$r[k+1] = r[k] + w_2[k] \qquad (2)$$

$$m[k] = d[k] + v[k]$$

In this model, r is estimated along the iterations using a random walk model (w2 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 [8]. In this strategy, w2 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 (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 the first two equations (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 the intervals of 3 and 3.5 V.

V. RESULTS

Figures 7 at 10 show the results of predictions carried out in 1 to 10 minutes prior to battery failure. The confidence intervals include 99% of the predictions made. 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 is 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 impact on estimates of the EKF.

VI. CONCLUSION

This paper presents a methodology to estimate the remaining useful life of a Li-ion battery used in UAVs. The proposed method used an Extended Kalman Filter (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.

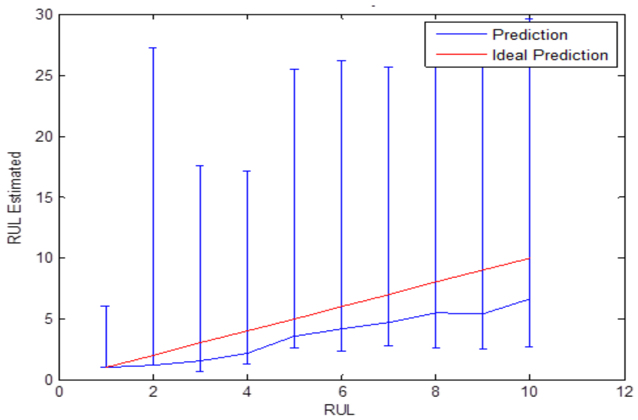

Fig. 7. Result of the first cycle of the NASA database RW13 Battery

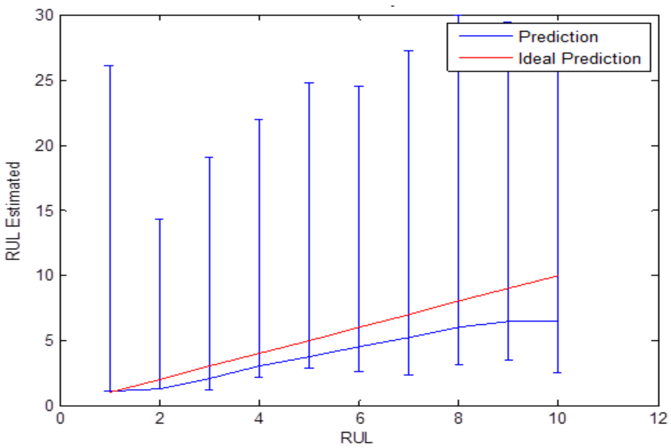

Fig. 8. Result of the last cycle of the NASA database RW13 Battery

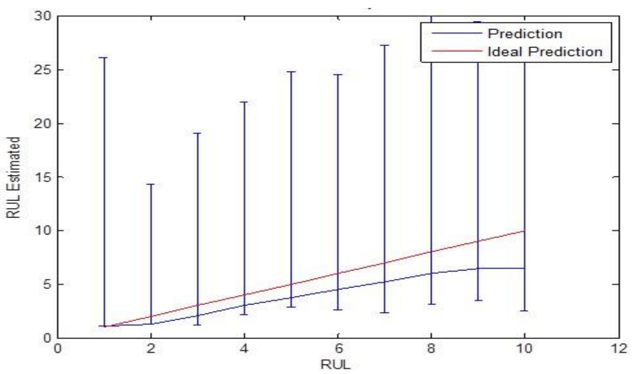

Fig. 9. Result of the first cycle of the NASA database RW14 Battery

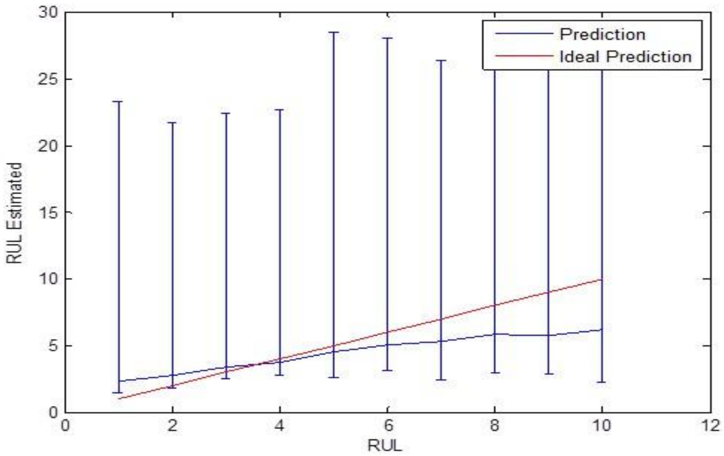

Fig. 10. Result of the last cycle of the NASA database RW14 Battery

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