PREDICTION OF LI-ION BATTERY DISCHARGE CHARACTERISTICS AT DIFFERENT TEMPERATURES AND DISCHARGE RATES BASED ON A HYBRID SOC ESTIMATION APPROACH

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Abstract

State of charge (SOC) is an important battery parameter which provides a good indication of the useful capacity that can be derived out of a battery system at any given point of time. Li-ion has become state of the art technology for commercial and aerospace applications due to the various advantages that they offer. For spacecrafts requiring long lifetime, SOC estimation is crucial for on-orbit as well as offline data analysis. On-orbit estimation of SOC should be carefully addressed, as this provides information on survivability of battery and also serves as input to Battery Management System (BMS). In addition, detailed offline data analysis of battery electrical characteristics, which indicate the SOC-Voltage relationship is important to assess the performance of the battery under various mission scenarios at both Beginning of life (BOL) and End of Life (EOL) of a spacecraft system. In this work, a hybrid SOC estimation method, incorporating coulomb counting and Unscented Kalman Filter (UKF) is used, to predict the BOL discharge behaviour of an 18650 commercial Li-ion cell at different temperatures and discharge rates. The experimental results are encouraging and the approach gives a prediction error of less than 10%. The study will serve as basis for life assessment of Li-ion cells and batteries used for GEO and LEO missions.

Key Words: *Li-ion, State of Charge, Unscented Kalman Filter etc…*

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Nomenclature

$C(t)$	Current Capacity at time‘t’
C_{nom}	Nominal Capacity
C_T	Capacity at temperature ‘T’at constant discharge current of C/10 A
C_{Id}	Capacity at discharge current I_d at constant temperature of 20°C
$z(t)$	State of Charge (SOC) at time’t’
$\mathbf{z_k}$	Discrete state vector at time instant ‘k’
$\mathbf{y_k}$	Discrete observation vector at time instant ‘k’
R	Battery internal resistance
Q_k	Process Noise
R_k	Measurement noise/Observation noise
x_{k-1}	Initial State
P_{k-1}^x	Initial Covariance
N	Number of Sigma points
$w_0^{(m)}$	Weight for mean for first sigma point
$w_i^{(m)}$	Weight for mean for i = 1, 2,..., 2 N sigma points
$w_i^{(c)}$	Weight for co-variance for i = 1, 2,..., 2 N sigma points
x_k^-	Estimated State
P_k^{x-}	Estimated Co-variance
y_k^-	Measurement Estimate

α, β, λ	Unscented Kalman Filter parameters
K	Kalman Gain
Ah_{out}	Discharge Capacity

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1. INTRODUCTION

Several kinds of batteries are currently being used in industry namely Silver-Zinc, lead-acid, Ni-MH, Ni-Cd and Li-ion. Li-ion technologies have replaced many of the earlier battery systems due to its higher working voltage, higher energy density, compactness, and lesser self-discharge rates. They have been widely used in many fields like aviation, mobile communications, in laptops and of late have been the work-horse for spacecraft and launch vehicle technologies. Li-ion batteries can effectively reduce system mass in spacecrafts and can improve the payload capability of satellites.

State of charge estimations have gained much importance for batteries and have become a fundamental challenge for battery use. It helps to assess how much capacity can still be derived out of a battery, under specified operational conditions. SOC estimation can be used to characterize a cell during development stage and also to assess battery life in various applications like automobile, electric vehicles and aerospace. An extension of this which leads to life prediction of battery or a cell is indeed a necessity for spacecraft system which needs to cater for 12 - 15 years. This has to be analyzed at design stage itself to decide upon a particular battery system for a mission. A well defined battery model forms the basis of SOC estimation. Once a battery model has been formulated, there are various approaches adopted in literature for SOC estimation. Accurate estimation of the SOC remains very complex because of parametric uncertainties and limitations in battery models [1].

Tremendous research has been carried out in this area and different approaches and models have been developed for SOC estimation. A few of them have been extended for life prediction. It is left to the user community to study the advantages and disadvantages of each of these approaches and make use of them based on the application for which they are put to use. In the beginning, electrochemical and electric circuit based models combined with voltage or resistance measurements (EIS based) were used for studies. Later, adaptive approaches like Kalman filter (KF), Artificial Neural networks (ANN) etc gained momentum due to better accuracy and simpler modeling compared to electro-chemical systems. Hybrid models like Coulomb Counting and Kalman filter, allow a globally optimal estimation performance, by combining any of the above approaches. They try to make the best use of the advantages of multiple estimating methods thus improving the prediction or estimation accuracy. Many adaptive and hybrid approaches can be applied even without complete knowledge of electrochemical reactions and hence have attracted many researchers in this field.

In [2], an electrochemistry-based model of lithium-ion batteries is developed for reliable End of Discharge (EOD) voltage prediction. Modeling based on designed experiments which provide insights about the impact of discharge rates and battery types as well as their interactions on battery performance metrics is described in [3]. An artificial neural network based battery model along with UKF is used in [4] to estimate the SOC, based on the measured current and voltage. [5] proposes a particle filtering approach for the estimation of the battery state-of-charge. A generic data-driven, model-free approach that integrates an artificial neural network with a dual extended Kalman filter (DEKF) algorithm for lithium-ion battery health management has been dealt in [6]. In [7], Datong Liu et al. proposed a complex Relevance Vector Machine (RVM) – Particle Filter (PF) approach in which Time interval between equal discharge voltage differences (TIEDVD) is used as health indicator. Since accuracy of prediction is important for satellite applications we planned to use a hybrid approach with UKF which is well known for non-linear system estimations and predictions.

In this paper, a study of various approaches for estimation of SOC of batteries have been made and a preliminary work for prediction of the discharge characteristics of 18650 Li-ion commercial cells at various discharge rates and temperatures has been carried out. The method uses Unscented Kalman Filter (UKF) based on a simple battery model proposed in [8]. The approach is generic in nature and can be used for different Li-ion chemistries by changing the parametric constants of state and observation equations in UKF. The basic Coulomb Counting method is used as process model for SOC computation in UKF. Hence, the adaptive method used in this paper can be considered hybrid in nature. The predicted data has been compared with real time test data.

2. THE COULOMB COUNTING- UKF FRAMEWORK

2.1 Li-ion model

The behavior of a cell or battery can be treated as a nonlinear system which changes continuously. Hence its characteristics can be modeled by state equations. A battery model based on discharge current rates and temperature is proposed in [8], eq (2) and (3) as these are the two major parameters which affect the battery capacity performance and in turn the SOC at a particular time instant.

SOC is one of the most important parameters for cells and batteries. In general, the SOC, z (t) of a battery during discharge is defined as in eq (1). C (t) is the current capacity and C_{nom}, nominal capacity, is the capacity specified by the manufacturer under standard conditions of test.

$$z(t) = 1 - \frac{C(t)}{C_{nom}} \quad (1)$$

In this work, the most important parameters which affect the discharge capacity is taken into account namely temperature and discharge current or discharge rate. More capacity can be drawn from the cell as temperature increases and as the discharge rate increases, only lesser amount of the total capacity can be drawn from the cell/battery. The two effects are modeled by C_T and C_{Id}. C_T denotes the total amount of capacity that can be drawn from the cell or battery, when it is discharged at a constant discharge rate of C/10 at an arbitrary temperature '*T'*. C_{Id} is the total capacity that can be drawn from the battery when it is discharged at a room temperature of 20°C at I_d discharge rate (current). Usually a second-order polynomial is used to describe or model the temperature variations and a polynomial of order four is used for discharge rate variations [7]. *i.e*.: where $\boldsymbol{P} = [p_2, p_1, p_0]$ and $\boldsymbol{Q} = [q_4, q_3, q_2, q_1, q_0]$ are coefficients of the two polynomials.

$$C_T = p_2 T^2 + p_1 T + p_0 \quad (2)$$

$$C_{Id} = q_4 \left({}^{I_d}/_{C_{nom}}\right)^4 + q_3 \left({}^{I_d}/_{C_{nom}}\right)^3 + q_2 \left({}^{I_d}/_{C_{nom}}\right)^2 + q_1\left({}^{I_d}/_{C_{nom}}\right) + q_0 \quad (3)$$

2.2 Methodology

The following sub-sections detail the basic equations and algorithmic steps that have been adopted in this hybrid method and how UKF has been applied to predict voltage characteristics of the Li-ion cell. The charge characteristics have not been dealt with in this paper and shall be presented later.

2.2.1 Coulomb Counting

The Coulomb counting method is a simple method which uses integration of discharging current over time to estimate SOC, z (t). z (t) at a particular instant is calculated from the discharging current, $I\ (t)$, and the previous SOC value, z $(t-1)$.

$$z\ (t) = z\ (t\ -\ 1) + \frac{I\ (t)}{C_{nom}} . \Delta t \quad (4)$$

This method has limitations while used as a stand-alone method for SOC estimation. Several external factors like temperature and discharge current affect the accuracy of this method. Hence, we have combined coulomb counting method with UKF, by using it as process model in UKF, to predict the discharge characteristics of the Li-ion cell.

2.2.2 Unscented Kalman Filter

UKF is generally used for non-linear systems as accuracy of KF for state prediction of a system when it has a non-linear behavior is fairly poor. The Extended Kalman Filter (EKF) which is an extension of Kalman filter is a bit complex as it requires Jacobian matrices to be computed and is generally not preferred for highly non-linear systems. UKF is another extension of the KF which is known to outperform the KF and EKF [9] in terms of accuracy and robustness for nonlinear estimation. It provides faster convergence. The UKF is based on a more deterministic sampling technique called Unscented Transformation (UT) [9] and is more suitable for SOC estimation as battery systems have a highly nonlinear behaviour. UKF eliminates linearization and approximates the probability distribution instead of function. Fig 1 provides the UKF steps with associated equations.

Process model: The process and observation models form the foundation of UKF. They describe SOC, z (t) in terms of measured or observed battery quantities like current; i (t), voltage; y (t), and temperature; T. SOC z (t) at time t is described in eq (5), where z(0) is the initial SOC, $\mathrm{i_d}(t)$ is the discharging current at time instant t, 'ε' is a coefficient of proportion, which is a function of temperature T and current i. Eq (5) can be discretized into eq (7) when the discrete KF is used. $'\Delta t'$ denotes the sampling interval at which the system is discretized. Equation (7) depicts the cell or battery process model.

$$z(t) = z(0) - \int_0^t (\varepsilon(i,T) i_d(t)/C_{nom}) dt \quad (5)$$

$$\varepsilon\ (i,T) = \frac{C_{nom}}{C_{Id}} . \frac{C_{nom}}{C_T} \quad (6)$$

Discretizing,

$$\begin{aligned} z_{k+1} &= g(z_k, i_k) \\ &= z_k - (\varepsilon(i_k, T_k)\Delta t/C_{nom})\ i_k \end{aligned} \quad (7)$$

Observation Model

The observation model defines the cell or battery voltage in terms of discharge current, temperature, and SOC. Several models exist in literature describing the behaviour of SOC vs. Voltage. The measurement model used here which has been described in [10], combines several mathematical models like Sheperd model, Unnewehr universal model and Nernst model. The combined model containing the non-linear parts is given in eq (8)

$$y_k = h(\boldsymbol{A}, i_k, z_k) = A_0 - Ri_k - \frac{A_1}{z_k} - A_2 z_k + A_3 \ln z_k + A_4 \ln(1 - z_k) \quad (8)$$

In eq (8), y_k is the battery or cell voltage; i_k is the discharge current, z_k is the SOC of the battery with z_k = 100% representing fully charged battery and z_k= 0% representing a fully discharged battery, R denotes the internal ohmic resistance of the battery, and A_1 and A_2 relates to the polarization resistance. A_0, A_3 and A_4 are empirical constants of the model. $\boldsymbol{A} = [A_0\ R\ A_1\ A_2\ A_3\ A_4]^T$ is the parameter vector.

Any measurement has errors associated with it. The current or voltage errors are absorbed by including noise terms to the process and observation models. The models after incorporating process (Q_k) and measurement noises (R_k) are as given below, eq (9) & (10).

$$\begin{aligned} z_{k+1} &= g(z_k, i_k) + Q_k \\ &= z_k - (\varepsilon(i_k, T_k)\Delta t/C_{nom})\ i_k + Q_k \end{aligned} \quad (9)$$

$$y_k = h(\boldsymbol{A}, i_k, z_k) + R_k$$

$$= A_0 - Ri_k - \frac{A_1}{z_k} - A_2 z_k + A_3 \ln z_k + A_4 \ln(1 - z_k) + R_k \qquad (10)$$

Initialize state and covariance, for $k = 1, 2, \ldots \infty$

$$x_{k-1} = [z_{k-1}\ 0\ \ 0]^T$$

$$P_{k-1}^x = \begin{bmatrix} P_{k-1} & 0 & 0 \\ 0 & Q_k & 0 \\ 0 & 0 & R_k \end{bmatrix}$$

Calculate sigma points & weights for mean and covariance

$$\textbf{Weighted sigma points}: \boldsymbol{S} = \{w_i, X_i, i = 0,1 \ldots 2N\}$$

$$\textbf{Sigma Points}: X_0 = \hat{x}_{k-1}$$

$$X_i = \hat{x}_{k-1} + \left(\sqrt{(N+\lambda)P_{k-1}}\right), i = 1,2,\ldots,N$$

$$X_i = \hat{x}_{k-1} - \left(\sqrt{(N+\lambda)P_{k-1}}\right), i = L+1,\ldots,2N$$

$$\textbf{Weights}: w_0^{(m)} = \frac{\lambda}{(N+\lambda)}$$

$$w_0^{(c)} = \frac{\lambda}{(N+\lambda)} + (1 - \alpha^2 + \beta)$$

$$w_i^{(m)} = w_i^{(c)} = \frac{1}{2(N+\lambda)}, i = 1,2 \ldots.,2N$$

Time Update

- Propagate sigma points through state model
  $$X_{k/(k-1)} = h(X_{K-1}, u_k)$$
- Estimate State
  $$x_k^- = \sum_{i=0}^{2N} w_i^{(m)} X_{i,k/(k-1)}$$
- Estimate covariance of estimated state
  $$P_k^{x^-} = \sum_{i=0}^{2N} w_i^{(c)} \left(X_{i,k/(k-1)} - x_k^-\right)\left(X_{i,k/(k-1)} - x_k^-\right)^T$$

Measurement Update

- Measurement Update
  $$Y_{k/(k-1)} = g(X_{K-1}, u_k)$$
- Measurement estimate
  $$y_k^- = \sum_{i=0}^{2N} w_i^{(m)} Y_{i,k/(k-1)}$$
- Estimate covariance of estimated measurement
  $$P_k^{y^-} = \sum_{i=0}^{2N} w_i^{(c)} \left(Y_{i,k/(k-1)} - y_k^-\right)\left(Y_{i,k/(k-1)} - y_k^-\right)^T$$
- Compute cross covariance
  $$P_k^{xy} = \sum_{i=0}^{2N} w_i^{(c)} \left(X_{i,k/(k-1)} - x_k^-\right)\left(Y_{i,k/(k-1)} - y_k^-\right)^T$$
- Compute Kalman gain
  $$K_k = P_k^{xy} \left(P_k^{y^-}\right)^{-1}$$
- Update state and covariance of update state
  $$\hat{x}_k = x_k^- + K_k(y_k - y_k^-)$$
  $$P_k^x = P_k^{x-} - K_k P_k^{y^-} K_k^T$$

Fig – 1: Unscented Kalman Filter Steps with Equations

Model Parameters Determination

The polynomial coefficient vectors ***P*** and ***Q*** in the process model can be determined using the least-squares method by using the end-of-discharge capacity values (Ah_{out}) at different temperatures and discharge rates obtained from offline tests. As seen earlier, ***P*** and ***Q*** are model parameters which capture variations in cell/battery characteristics with respect to temperature and discharging rates. The parameter vector ***A*** in the measurement model is obtained by least square fit of typical SOC - Voltage discharge characteristics. Typically, this is done once for particular cell chemistry and their values can be estimated offline.

Input parameters
Discharge current rate, I_d
Temperature, T
Nominal capacity, C_{nom}

Least square solution: End of discharge capacity (Ah_{out}) data at different temperatures and discharge rates
Compute coefficients of ***P*** and ***Q***: eq 2- 3
Compute C_T , C_{Id} and ε using eq 2- 4

Compute SOC, $z = f(\varepsilon, C_{nom}, I_d)$: eq (7)

Compute K coefficients of parameter vector ***A*** by curve fitting of discharge curve at T=20°C, I_d= C/10 rate: eq (8)

Compute Voltage, $y = f(z, R)$: eq (8)

Apply UKF to predict SOC at different temperatures and discharge rates

Output
State of Charge (SOC), **z**
Discharge Voltage (V), **y**

Fig - 2: Flowchart of the Proposed Approach

2.3 Proposed Approach

Initially, offline computation of the parameter vectors ***P***, ***Q*** and ***A*** is performed as indicated in the previous section. The state vector '**z**' and measurement vector '**y**' are computed using eq (7) and (8) at 20°C with a discharge current of C/10. The parameters like discharge rate, $I_{d(pred)}$ and temperature, $T_{(pred)}$ at which the discharge characteristics need to be predicted are provided as inputs to the UKF algorithm. The parameter 'ε' is calculated accordingly. Using the **z** and **y** computed from the previous step, UKF predicts the discharge behaviour at each discretized time step for the specified temperature, $T_{(pred)}$ and discharge current, $I_{d(pred)}$. Flow chart indicating the steps followed for the approach is shown in Fig 2.

3. EXPERIMENTAL RESULTS AND DISCUSSION

18650 Li-ion commercial cells were used for all experimental studies. The algorithm was implemented using MATLAB R2013a. The nominal capacity of the cells chosen for the study was 2.6Ah. As shown in Fig 2, ***P*** and ***Q*** parameters of the Li-ion cell model were found from End of Discharge (final Ahout) values at 20°C, 30°C and 10°C obtained from typical test data of 18650 commercial cells, by solving the matrix equations through least squares method. The discharge characteristics of the cells from 4.2V (100% SOC) to 3V(< 10% SOC) for a C/10A discharge current at a temperature of 20°C was taken as the basis for determining the parameters, of the parameter vector ***A***, eq (8). They were determined by curve fitting of the SOC - Voltage discharge characteristics at 20°C, C/10 rate.

The model was validated by computing the SOC values and cell voltages at discretized time intervals for 20°C, C/10 rate and by comparing with the real time test data available. The discharge characteristics at different discharge currents (namely C/2 and C rates) and temperatures (namely 30°C and 10°C) were predicted by applying the UKF equations, with the discharge rate, Id (pred) and temperature, T(pred) as the only input parameters. It was observed that the UKF parameter α controls the stability and smoothness of the discharge curve and β controls the extent of fall. In general, $0 \leq \alpha \leq 1$, $\beta \geq 0$, $\lambda = (\alpha^2-1)$ N. Appropriate tuning of the parameters should be done for practical systems as the characteristics of noise is often unknown.

The ohmic resistance was taken as a sweep parameter for the study and the discharge behaviour at different resistance values were obtained. It was observed that the real time and predicted data matched at the resistance values which were very close to the measured ohmic resistance of the cells used. The typical experimental results are depicted in Figs. 3-6. Fig 7 shows the Ahout or discharge capacity, C (t) at different temperatures. C (t) is related to the SOC, z(t) as indicated in eq (1). The Mean Squared Errors (MSE) for SOC estimation was found to be of the order 10^{-3} to 10^{-4} for all cases. The MSE and the error percentage computed at higher temperature are a bit more than in other cases. This is because of higher error between the end-of-discharge (EOD) values of predicted and real time data. The SOC prediction errors are all within 2% except at 30°C (higher temperatures) which is about 5-6%. However, the error is <10% which is fairly reasonable for life prediction. This can further be fine tuned by tuning the α, β parameters in the UKF algorithm. The algorithm has been extended to simulate discharge characteristics of spacecraft battery (series – parallel connected Li-ion cells).

The discharge characteristics during mission simulation ground test at variable discharge rates for spacecraft battery and the predicted behaviour using proposed approach is provided in Fig 8. It is observed that the prediction fairly matches the mission simulation test data. Also faster response of the algorithm to track changes in discharge rates is evident from the results. The voltage behaviour at EOD slightly deviates from the test data in all cases. This can be improved by incorporating the internal resistance variations with SOC. Here, a constant ohmic resistance has been used for the entire discharge duration.

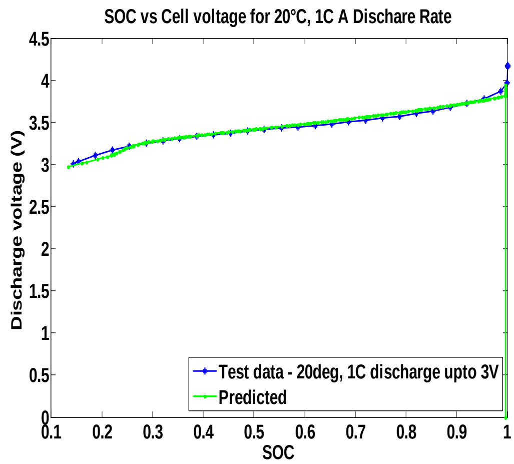

Fig - 3: Comparison of Test data and Predicted 20°C, 1C Cell discharge characteristics

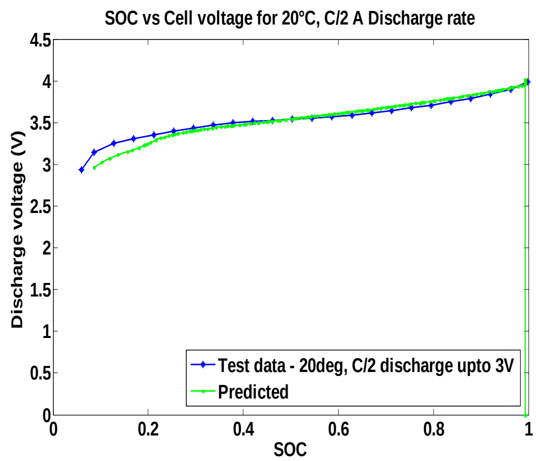

Fig - 4: Comparison of Test data and Predicted 20°C, C/2 Cell Discharge characteristics

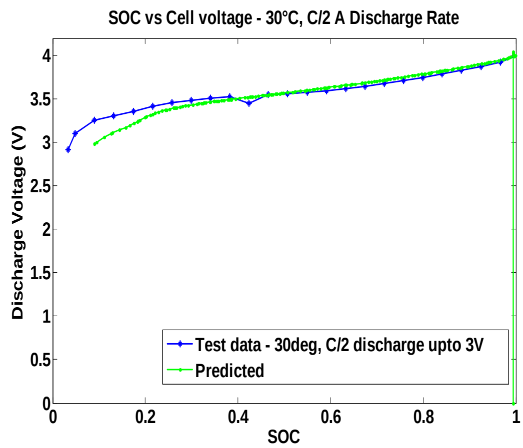

Fig - 5: Comparison of Test data and Predicted 30°C, C/2 Cell Discharge characteristics

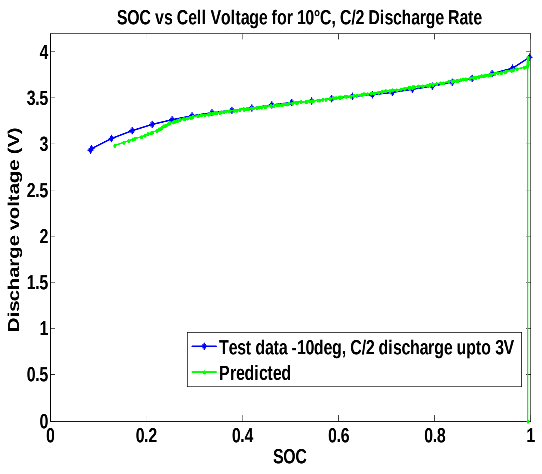

Fig - 6: Comparison of Test data and Predicted 10°C, C/2 Cell Discharge Characteristics

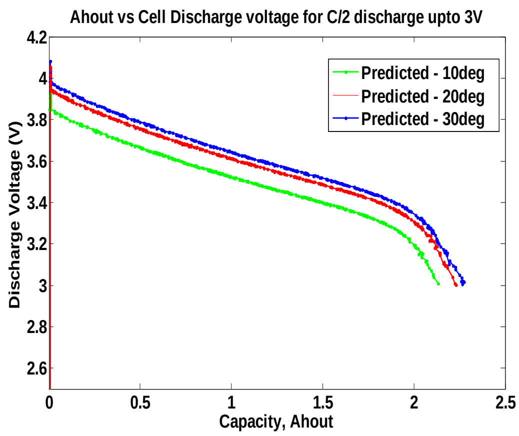

Fig - 7: Cell Discharge Capacity (Ah_{out}) at 10°C, 20°C and 30°C for C/2 Discharge Rate

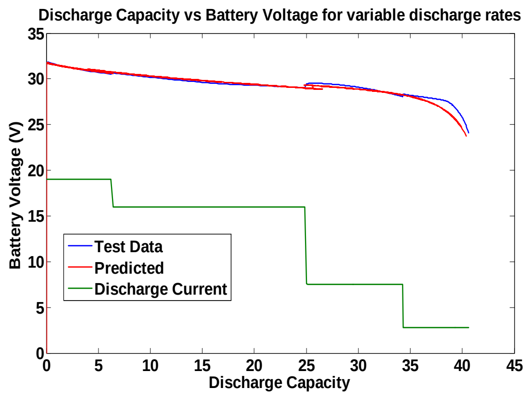

Fig - 8: Comparison of Mission Simulation Test and Predicted discharge behaviour for variable discharge rates – Spacecraft Battery

4. CONCLUSION

The hybrid approach which has been adopted in this paper is a simple and fairly accurate method which can form the baseline for life prediction studies for Li-ion cells/ batteries. Though it has been applied on an 18650 commercial Li-ion cell, the method is generic and can be applied to any Li-ion cell chemistry by changing the model parameters. Also the error percentage is considerably less and the prediction error is found to be < 10%.

Further studies by incorporating the resistance into the state vector to compensate for SOC and aging related changes in the characteristics of the cell is planned to be carried out. This will improve the errors at EOD. The experimental study can be extended for predicting the EOL (End-of-life) discharge characteristics of Li-ion cells and batteries which are used in 12-15 years satellite missions at various depth of discharge (DoDs) ratios. Incorporation of accurate noise estimations can improve the algorithmic performance further.

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BIOGRAPHIES

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