Estimation of State of Charge and Terminal Voltage of Li-ion Battery using Extended Kalman Filter

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Abstract—**In this paper, the 2RC electrical equivalent circuit of the Li-ion battery (LIB) is considered for deducing a state space model. The estimation of State of Charge (SoC) and terminal voltage of the battery is derived through Coulomb counting and Extended Kalman filter for constant current discharge under a Urban Dynamometer Driving Schedule (UDDS) cycle. The parameters required for the state space model are determined experimentally for different discharge currents of a single cell. The design of battery pack for different power requirements like two, three and four-wheeler electric vehicles (EVs) from these 18650 cells is deduced and the performance indices are estimated based on an UDDS cycle. The estimated SoC and terminal voltage are compared with those obtained through preliminary Coulomb counting and 2RC model.**

Index Terms—**Battery management systems, Kalman filters, Lithium batteries, Parameter estimation, State of Charge, State-space methods, Urban Dynamometer Driving Schedule.**

I. Introduction

The operating voltage for EVs is achieved by connecting LIB batteries in series. But due to its unequal internal resistance of LIBs, the voltage across them are also not the same as needed. Due to this, LIBs under perform or even fail if overcharged, completely discharged, or operated outside their safe operating temperature window. This mandates the control system (BMS) to balance the voltage while batteries are connected and indirectly predict the life of the battery and time of replacement. One of the essential and inevitable modules in any BMS is the SoC estimator. In order to control the whole vehicle adequately an accurate estimation of SoC plays a major role. There have been many researches [2-6] and development projects going on to improvise the accuracy of the SoC estimation for better reliability, increased lifetime, prevent failure of batteries and enhance their performance.

Besides, the SoC and voltage measurement from the cell's terminal is very important information to determine the available energy in the battery, which can be used to determine the available driving range of the EV. Direct measurement of SoC is not possible from a battery. A battery pack consists of many cells connected in series and parallel combination to satisfy the voltage and current requirement for its application. Each cell in the series stack has different potential and it is difficult to have unique compensation or elimination methods. As all other parameters are estimated based on the voltage measurement, it requires high precision.

The Ampere-Hour method/Coulomb Counting method [1] is related to battery input current throughout the operating range to calculate SoC. The main drawback of this method is high accumulated integration errors when error prevail in the previous current value. The main drawback of this method is high accumulated integration errors when previous current value is having some error. An efficient way of Battery modelling to simulate battery behaviour is using Equivalent Circuit Modelling (ECM) [2] which consists of Electrical components such as Voltage source, Resistors, Capacitors values of which are found using parameter identification method [3]. The design of ECM is easy and may vary depending on the desired output accuracy.Complex models [4] will also have a higher parameterization complexity as more parameters are needed to capture higher order of nonlinearities.

An ECM using Kalman Filter [4] is one of the methods for estimation of SoC. But it requires a battery model and very high computing resources with accurate linearization of parameters. By considering the nonlinear behaviour [5] of battery in real time, linearization should be done and then only KF can be applied. This method is called as Extended Kalman Filter (EKF) [6] which improves estimation accuracy and reduces interference of system noise.

In literature ,the State-space model of the battery is obtained from two RC electrical equivalent circuit model and it is tested for continuous constant charge and discharge currents. The same model is tested using the driving cycles for Electric two wheeler [7], Three wheeler, [8] and Four wheelers [9]. An Extended Kalman Filter (EKF) algorithm is incorporated into ECM to estimate the SoC of the battery. In this paper, simple test bench is introduced with laboratory devices using controllino micro controller, which acts a low frequency switch. The NI-ELVIS II board is used for data acquisition which has 14 voltage sensors. The paper also focus on detailing the vehicle dynamics of different EVs for estimating the SoC. The electrical equivalent circuit parameters of the battery is used to SoC estimation of the different types of EVs at UDDS cycle. The objective of the present work is to (a) to conduct battery modelling of LIB and its state-space representation. (b) estimation of performance parameter using different methods (c) to identify system parameters using Pulse discharge test (d) Section 5 discusses Vehicle dynamics and Driving cycle.

II. State-Space Model of Li-ion Battery

Among various models like electro-chemical, single-particle, state space, etc. to predict the behavior of any system state space model is advantageous as it is applicable to any time invariant, nonlinear and multiple input multiple output systems with any initial conditions.

A. Continuous time model of LIB:

In this study, the LIB is modelled as an electrical equivalent circuit containing a series resistor and two RC parallel networks as shown in Fig. 1. The elements R_s, R_1, C_1, R_2 and C_2 in the two RC model represent the electro-chemical behavior of the battery. R_s represents the internal resistance of the active material. C_1 represents the

polarization capacitance which is due to the dissociation and association of Li-ions and electrons in the Li metal during discharging and charging respectively. C_2 represents diffusion capacitance which is due to the ion movement through the electrolyte during charging and discharging of the battery. R_1 and R_2 are the internal resistance of the capacitances C_1 and C_2 respectively.
Through the model it is clear that there are three electrical

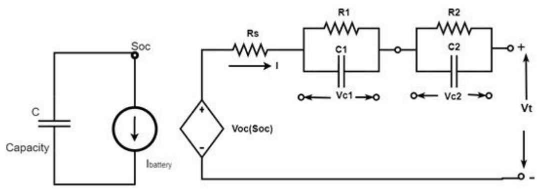

Fig. 1. Two RC electrical equivalent circuit model approximating the behavior of LIB.

states for the LIB. The voltage across the three capacitors act as the state variables. and are assumed as:

$$X = \begin{bmatrix} V \\ V_{C_1} \\ V_{C_2} \end{bmatrix} \tag{1}$$

The accuracy in the response of LIB depends on the number of RC parallel branches available in the model. The capacity of the cell C and the ideal current source I_b represents stored charges conveying the state of charge (SoC) of the battery. Let V be the voltage across this capacitor C which is a measure of SoC and is represented as:

$$\frac{dV}{dt} = \frac{1}{C_m}\int_{-\infty}^{\infty} I_b dt = V + \frac{\eta}{C_m}\int_0^t I_b dt \tag{2}$$

where, V is the initial voltage available in the battery and η is the Coulombic efficiency and Cm is the nominal capacity of the battery
The voltage across the first RC branch is represented as:

$$V_{C_1} = \frac{1}{C_1}\int_{-\infty}^{\infty} I_{C_1} dt = \frac{dV_{C_1}}{dt} = \frac{I_{C_1}}{C_1} \tag{3}$$

The third state variable obtained as:

$$V_{C_2} = \frac{1}{C_2}\int_{-\infty}^{\infty} I_{C_2} dt = \frac{dV_{C_2}}{dt} = \frac{I_{C_2}}{C_2} \tag{4}$$

The current through C_1 is calculated as:

$$I_{C_1} = I - I_{R_1} \Rightarrow I_{C_1} = I - \frac{V_{C_1}}{R_1} \tag{5}$$

The current through C_2 is calculated as:

$$I_{C_2} = I - I_{R_2} \Rightarrow I_{C_2} = I - \frac{V_{C_2}}{R_2} \tag{6}$$

Substituting (5) and (6) in (3) and (4) respectively,

$$\frac{dV_{C_1}}{dt} = \frac{I}{C_1} - \frac{V_{C_1}}{R_1 C_1} \tag{7}$$

$$\frac{dV_{C_2}}{dt} = \frac{I}{C_2} - \frac{V_{C_2}}{R_2 C_2} \tag{8}$$

From (2), (7) and (8) the state equation of the LIB is:

$$\begin{pmatrix} \dot{V} \\ \dot{V_{C_1}} \\ \dot{V_{C_2}} \end{pmatrix} = \begin{pmatrix} 1 & 0 & 0 \\ 0 & \frac{-1}{R_1 C_1} & 0 \\ 0 & 0 & \frac{-1}{R_2 C_2} \end{pmatrix} \begin{pmatrix} V \\ V_{C_1} \\ V_{C_2} \end{pmatrix} + \begin{pmatrix} \frac{\eta}{C} \\ \frac{1}{C_1} \\ \frac{1}{C_2} \end{pmatrix} I \tag{9}$$

Also, the terminal voltage of LIB is obtained through KVL and from all the available states as follows:

$$V_t = V_{OC} \pm (IR_s + V_{C_1} + V_{C_2}) \tag{10}$$

+ sign indicates charging mode and – sign indicates discharging mode.where, V_{oc} is the open circuit or no-load voltage (OCV) of the battery. The output equation is given by:

$$y = \begin{pmatrix} \frac{dV_{oc}}{dV} & -1 & -1 \end{pmatrix} \begin{pmatrix} V \\ V_{C_1} \\ V_{C_2} \end{pmatrix} - R_S I \tag{11}$$

B. Discrete time model of LIB:

The difference equation corresponding to (2) can be written as:

$$V_k = V_{k-1} - \frac{\eta I_{k-1}}{C_m} \tag{12}$$

Using backward Euler expansion (3) becomes:

$$\frac{V_{C_{1k}} - V_{C_{1(k-1)}}}{T_s} = \frac{I_{k-1}}{C_1} - \frac{V_{C_{1k-1)}}}{R_1 C_1} \tag{13}$$

where, T_s is the sampling time.
The K^{th} instant value of voltage across the first RC branch is obtained by relating the delayed value of states in terms of exponential function.

$$V_{C_{1k}} = V_{C_{1(k-1)}} e^{\frac{-T_s}{R_1 C_1}} + I_{k-1} R_1 (1 - e^{\frac{-T_S}{R_1 C_1}}) \tag{14}$$

Similarly, K^{th} instant value of the third state variable also can be written as:

$$V_{C_{2k}} = V_{C_{2(k-1)}} e^{\frac{-T_s}{R_2 C_2}} + I_{k-1} R_2 (1 - e^{\frac{-T_S}{R_2 C_2}}) \tag{15}$$

From (12), (14) and (15), the discrete state equation is as mentioned below:

$$\dot{x}k = \begin{bmatrix} V_k \\ V_{C_{1k}} \\ V_{C_{2k}} \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & e^{\frac{-T_s}{R_1 C_1}} & 0 \\ 0 & 0 & e^{\frac{-T_s}{R_2 C_2}} \end{bmatrix} \begin{bmatrix} V_{k-1} \\ V_{C_{1(k-1)}} \\ V_{C_{2(k-1)}} \end{bmatrix} + \begin{bmatrix} \frac{-\eta}{C} \\ R_1(1 - e^{\frac{-T_s}{R_1 C_1}}) \\ R_2(1 - e^{\frac{-T_s}{R_2 C_2}}) \end{bmatrix} I_{k-1} \tag{16}$$

The terminal voltage is the measured output and the output equation in discrete time is represented as:

$$y = \begin{bmatrix} \frac{dV_{oc}}{d(V)} & -1 & -1 \end{bmatrix} \begin{bmatrix} V_{k-1} \\ V_{C_{1(k-1)}} \\ V_{C_{2(k-1)}} \end{bmatrix} - R_s I_{k-1} \tag{17}$$

where T_s indicates the sampling time (say 1s) and C_m indicates the battery rated capacity.
The initial conditions that are used during discharging of LIB is $\begin{bmatrix} 1 & 0 & 0 \end{bmatrix}^T$ because for fully charged battery SOC is 100% and the voltage across $R_1 C_1$ and $R_2 C_2$ are zero.

III. Estimation Methods For Performance Parameters

The performance of the battery is deteriorated with increase in number of charging and discharging cycles. The SoC of a battery plays a major role in predicting the performance of the battery. In this section of the paper various methods to determine SoC such as Ampere hour method (Coulomb counting method), Kalman filter method and extended Kalman Filter method are discussed.

A. Ampere-hour method:

This technique is established on the fact that the battery's SoC is related to the input current. Thus, if the Initial SoC is known then by adding or subtracting the current requirement to the battery the remaining SoC level can be calculated as illustrated through (3). Even though, it is a better method still there are some issues associated with it and are listed as follows:
a) The sole dependency on the current measurement results in a high accumulated error due to the integral action.
b) This method may have to be re-calibrated as the battery ages.
c) All the current supplied to the battery is not completely utilized and there is some amount of losses in the battery.
These issues can be addressed by implementing a highly accurate current sensor (expensive) and setting a predefined re-calibration point with a correcting factor (losses) for charge and discharge. The other performance defining parameters of the battery are calculated using the 2RC model along with the primitive Ampere hour method.

B. Kalman Filter

The Coulomb counting method is not suitable to find SoC for a dynamic application like electric vehicles where the discharge current is dependent on various parameters associated with the cruising of the vehicle. Hence, there is need to estimate all the states of the battery so as to predict the SoC accurately under dynamically varying loads [6]. Kalman filter is widely used in many engineering applications for predicting the system's states. Along with the SoC, the terminal voltage and temperature are also predicted. Let the generalized state space and output equations of the system are as described below:

$$x_{k+1} = A_k x_k + B_k u_k + Q \tag{18}$$

$$y_k = C_k x_k + D_k u_k + R \tag{19}$$

Where x_k denotes the n-dimensional system state vector; y_k denotes the m-dimensional output vector of observations; u_k denotes the one-dimensional input vector.
A_k (nxn) is system matrix; $B_k(nx1)$ is input matrix; C_k (mxn) is output matrix; D_k (mx1) is feedforward matrix; Q and R are indicated Gaussian white noise.
The procedure for state estimation using Kalman filter is as follows:
(1) Initialize the state variables x_k and error covarianceP_k.
(2) Predict the state vector x_k and error covariance matrix

$$x_k = A_{k-1}x_{k-1} + B_{k-1}u_{k-1} \tag{20}$$

$$P_k = AP_{k-1}A^T + Q_{k-1} \tag{21}$$

(3) Calculation of Kalman gain.

$$k = P_k C_k^T [C_k P_k C_k^T + R]^{-1} \tag{22}$$

(4) Update the values of state vector x_k and error covariance of P_k as

$$x_{kupd} = x_k + K[y_k - C_k x_k - D_k u_k] \tag{23}$$

$$P_{kupd} = (P_k - KC_k P_k) \tag{24}$$

High values of P_k indicates high levels of uncertainty in the error covariance whereas low values indicate low levels of uncertainty [2]. The Kalman gain is used to update the state vector and the error covariance. This process is repeated till the KF yields an optimal solution to the linear quadratic regulator (LQR) by minimizing the mean-square error of the state. The KF estimator is applicable to linear systems and requires exact knowledge about the covariance of system and measurement noise. The estimator is valid only for white and Gaussian noise. Any significant deviation from these assumptions will drive the system to instability.

C. Extended Kalman Filter

In reality, most of the practical systems are highly nonlinear. LIBs are highly nonlinear as visible from the discharge behavior and the model, need to be linearized first to implement KF. This is called the extended Kalman filter (EKF). Let the nonlinear discrete system be represented as:

$$x_{k+1} = g(x_k, u_k) + Q \tag{25}$$

$$y_k = h(x_k, u_k) + R \tag{26}$$

where g denotes the state transfer function of the nonlinear system; h indicates the measuring function of nonlinear systems. The remaining parameters are similar to KF. The EKF has proven to yield good results when the consist consists of low order nonlinearities.

IV. Identification of System Parameters using Pulse discharge test:

As per the state space model in (16) the system matrix contains the following unknowns: (1) the capacity C, (2) time constants R_1C_1, R_2C_2 and $R_{th}C_{th}$ which decides the response of the LIB. The experimental set up as shown in Fig. 2 is used for determining these parameters of 3.6 V, 3 Ah, NMC-LIB. A constant pulse current of 3 A excitation is given to the cell for 20 s and withdrawn for 20 s while the cell is under no load condition. The pulse discharge test is conducted when the cell is fully charged. The cell is charged for 20 s where the open circuit voltage is found to be 2.24 V (V_{oc}) and allowed to self-discharge for the succeeding 20 s and the cell attains an OCV of2.13 V. The system matrix parameters are calculated from the voltage response observed via pulse discharge test via curve fitting technique.

A. Identification of R_s:

Let V_0 be the steady state voltage available at the terminals of the battery during the 20s constant current charging. During the next 20s the battery is allowed to self-discharge as shown in Fig. 3. The linear drooping behavior of the terminal voltage from V_0 to V_1 indicates the measure of internal resistance of the active material Rs which is calculated as:

$$R_s = \frac{\Delta V_0}{\Delta I} = \frac{|V_0 - V_1|}{I} \tag{27}$$

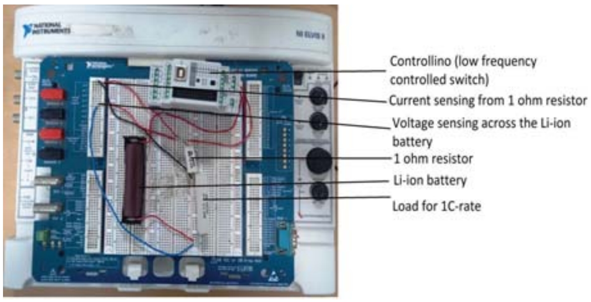

Fig. 2. Experimental set up for parameter estimation of the battery using pulse discharge test.

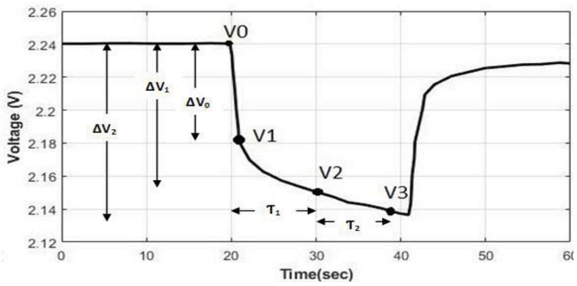

Fig. 3. Discharge curve for the estimation of LIB parameters

B. Identification of R_1 and C_1:

The polarization capacitance introduces a faster response compared to the diffusion capacitance. Hence, from the self-discharge pattern the quadratic fit to the curve is identified as the transition from V_1 to V_2 and the polarization resistance can be calculated as:

$$R_1 = \frac{\Delta V_1}{\Delta I} = \frac{|V_1 - V_2|}{I} \tag{28}$$

As the polarization time constant is available from the discharge pattern, corresponding capacitance C_1 can be calculated using:

$$C_1 = \frac{\tau_1}{R_1} \tag{29}$$

C. Identification of R_2 and C_2:

The cubic fit for the discharge curve as shown in fig:3 (transition from V_2 to V_3) is used to calculate the diffusion resistance of the cell and is obtained as:

$$R_2 = \frac{\Delta V_2}{\Delta I} = \frac{|V_2 - V_3|}{I} \tag{30}$$

From the diffusion time constant obtained from the discharge curve, corresponding capacitance C_2 is calculated.

$$C_1 = \frac{\tau_2}{R_2} \tag{31}$$

SoC calculated using Coulomb counting during ON period of the cell is tabulated against OCV. This SoC vs OCV is used for mapping the OCV of the battery during the self-discharge period and for representing the parameters as a function of SoC. The data so collected is at room temperature and is tabulated along with SoC and OCV as in Table. I.

Table I
THE PARAMETERS OF THE EQUIVALENT CIRCUIT DEDUCED EXPERIMENTALLY THROUGH DISCHARGE TEST.

SoC	OCV	$R_s(\Omega)$	$R_1(\Omega)$	$R_2(\Omega)$	C_1(F)	C_2(F)
1	3.57	0.0742	0.00576	0.00307	901.36	1787.5
0.95	3.506	0.0731	0.00538	0.00307	1468.4	3876.2
0.9	3.488	0.07538	0.00538	0.00346	1411.53	1438.3
0.85	3.467	0.07346	0.00692	0.005	1010.4	2260
0.8	3.438	0.07307	0.00884	0.004615	1018.09	2166.2
0.75	3.382	0.07912	0.01038	0.00384	866.31	2734.3
0.7	3.286	0.07038	0.00923	0.00846	985.91	186
0.65	3.208	0.06884	0.01192	0.0076	637.5	1560.4
0.6	3.153	0.0684	0.0126	0.0076	638.2	1313.3
0.55	3.077	0.0665	0.0134	0.01192	520.05	1866.
0.5	2.998	0.06692	0.014615	0.01384	478.9	895.95
0.45	2.85	0.0681	0.02153	0.01807	311.19	664.36
0.4	2.59	0.0634	0.0292	0.0238	239.7	507.43
0.35	2.292	0.0034	0.0215	0.0169	279.069	609.4
0.3	2.135	0.1553	0.025	0.0165	236	671.5
0.25	1.1971	.1726	0.02538	0.01269	240.34	795
0.2	1.818	0.17	0.0265	0.0203	116.84	691.8

The curve fitting technique is used to establish the relationship of these parameters w.r.t SoC. Seventh order polynomial of SoC is chosen to represent the equivalent circuit parameters as shown below using Table I data. Higher order polynomials will give a smoother and accurate relation between them which are given from (32) to (37)

$$\begin{aligned} V_{OC} = \; & 57SoC^7 - 5146SoC^6 + 8623SoC^5 - 7594SoC^4 \\ & + 3726SoC^3 - 1034SoC^2 + 149.5SoC - 7.069 \end{aligned} \tag{32}$$

$$\begin{aligned} R_S = \; & 573.2SoC^7 - 2511SoC^6 + 4559SoC^5 - 4422SoC^4 + \\ & 2548SoC^3 - 776SoC^2 + 127.2SoC^1 - 8.752 \end{aligned} \tag{33}$$

$$\begin{aligned} R_1 = \; & -22.96SoC^7 + 107.5SoC^6 - 207.1SoC^5 + 211SoC^4 - \\ & 122SoC^3 + 39SoC^2 - 6.691SoC^1 + 0.011 \end{aligned} \tag{34}$$

$$\begin{aligned} C_1 = \; & -25E4SoC^7 + 82E5SoC^6 - 12E5SoC^5 + 107E5SoC^4 - \\ & 54E5SoC^3 + 13E5SoC^2 - 17E5SoC + 9615 \end{aligned} \tag{35}$$

$$\begin{aligned} R_2 = \; & -41.7SoC^7 + 191.8SoC^6 - 366.3SoC^5 + 211SoC^4 - \\ & 219.6SoC^3 + 73SoC^2 - 12.71SoC^1 - 5.63 \end{aligned} \tag{36}$$

$$\begin{aligned} C_2 = \; & -21804556SoC^7 - 107000SoC^6 - \\ & 9184559SoC^5 + 5709742SoC^4 - \\ & 1629743SoC^3 - 115823SoC^2 + 31034SoC^1 - 3722 \end{aligned} \tag{37}$$

V. VEHICLE DYNAMICS AND DRIVING CYCLE

The demand for Electric Vehicle is increasing day by day with the number of new inventions in energy storage devices. Optimum utilization of energy from the energy storage devices need to be arrived at based on the road, vehicle and driving conditions. Driving cycle is a set of data relating the vehicle speed w.r.t time. In this study a well known UDDS is used to validate the estimator. Data for various types of vehicles is collected and parameter identification methods are applied.

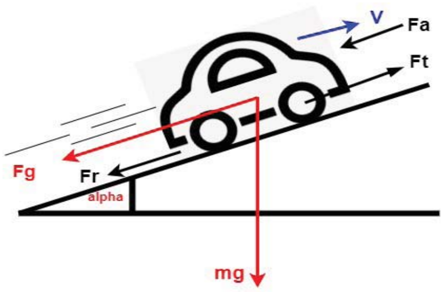

Fig. 4. Free body diagram of 4W Electric Vehicle

Table II
VEHICLE DYNAMIC EQUATIONS

Force balace equation (N)	$m_v.\dot{v}(t) = F_t(t) - (F_a(t) + F_r(t) + F_g(t))$
Traction Force (N)	$F_t(t) = ma + F_a + F_r + F_g$
Rolling Resistance Force (N)	$F_r(t) = c_r.m_v.g.cos(\alpha)$
Gravity Force (N)	$F_g(t) = m_v.g.sin(\alpha)$
Aerodynamic drag Force (N)	$F_a(t) = \frac{1}{2}.\rho_a.C_{aero}.v(t)^2$
Traction Power (W)	$P_t(t) = P_{el}(t).\eta_m = F_t(t).v(t)$

A very important keynote to be considered is that the braking force which is not mentioned in this model, which extremely solves data acquiring at the cost of some accuracy determining useful parameters. The parameters which are used for calculation of the required power from the battery bank for different EVs are given in Table. III can be identified from the data set [1].

Table III
PARAMETERS USED FOR DEDUCING POWER REQUIREMENT FOR 2W, 3W AND 4W APPLICATIONS

Physical parameters	2W [1]	3W [8]	4W [9]
Mass of Vehicle m_v (kg)	400	550	1350
Rolling Resistance coefficient C_R	0.05	0.015	0.02
Aerodynamic coefficient C_{aero}	1.5	2.09	0.42
Power rain efficiency η	0.99	0.97	0.98
Battery pack Voltage (V)	60	100	144
Pack current (A)	53	90	83
No.of cells in series N_S	16	27	40
No.of cells in parallel Np	18	30	28
Single cell specification NMC	3.6V,3Ah		

The following are the steps involved in validating the EKF for SoC and terminal voltage estimation under dynamic road conditions:
1. Decide the voltage (V) of the battery pack for EV depending on its power requirement P(t).
2. From this power, Battery pack current is calculated: I_{bpack}= P(t)/V.
3. To know the individual cell current, identify how many batteries are connected in parallel to make it equal to I_{bpack}.

VI. RESULTS AND DISCUSSION

A. *Estimation of SoC and Terminal Voltage of LIB under constant current discharge mode:*

A LG Li-ion battery of 3.6 V, 3Ah is considered for this simulation study. The 2RC model battery parameters are identified experimentally as discussed in Section 3, at 0.5C, 1C and 2C-rates and fed into the Extended Kalman filter. The SoC and terminal voltage of the cell are estimated and is compared with the true values based on Coulomb counting method. The error is found to be very minimal less than 3%. Fig. 5 and Fig. 6 show the estimated values of terminal voltage and SoC for various C-rates against the true value obtained theoretically.

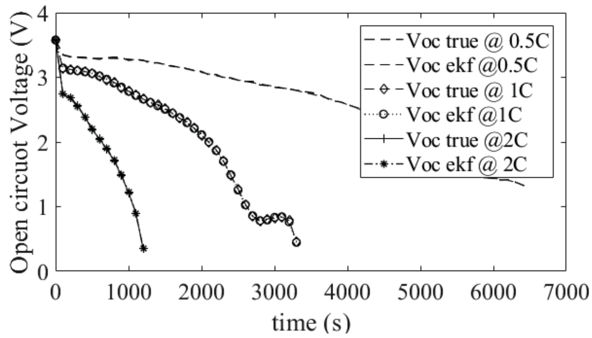

Fig. 5. Comparison of terminal voltage of LG Li-ion battery at different C-rates

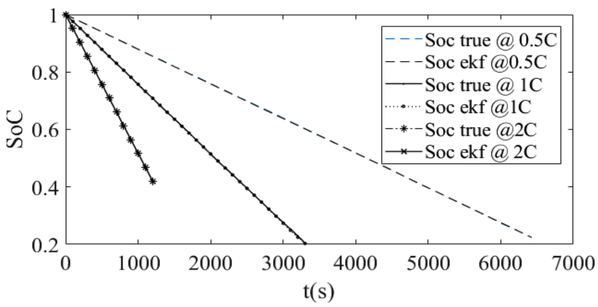

Fig. 6. Comparison of SoC of LG Li-ion battery at different C-rates

B. *Estimation of SoC and Terminal Voltage of LIB under Indian UDDS discharge mode:*

In this section, the battery is operated with urban dynamometer driving cycle via simulation. The data which is required for simulating UDDS shown in Fig. 7 is referred from [10] . In this study the discharge rate of the battery pack is assumed as 1C. As per the current requirement depending on the vehicle dynamics EKF estimates the performance parameters and is compared against the true values for various EV applications like 2-wheeler, 3-wheeler and 4-wheeler.

C. *Battery pack voltage discharging of EV at UDDS:*

The required voltage,power, current for electric two wheeler, three wheeler and four wheeler are given in Table IV. Table IV also have the series and parallel connected cells for operating electric two wheeler, three wheeler and four wheeler. Fig. 8 to Fig. 10 represents the discharge voltage of battery pack of electric two wheeler, three wheeler and four wheeler respectively.

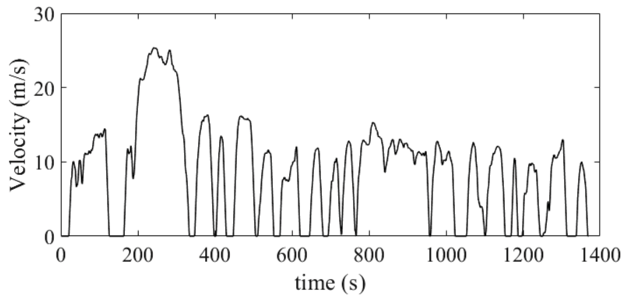

Fig. 7. Urban Dynamometer schedule Drive cycle

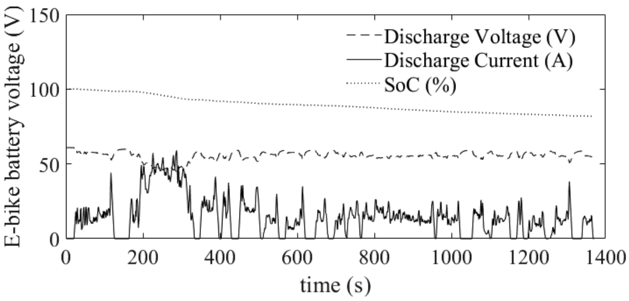

Fig. 8. SoC of E-bike battery bank during UDDS

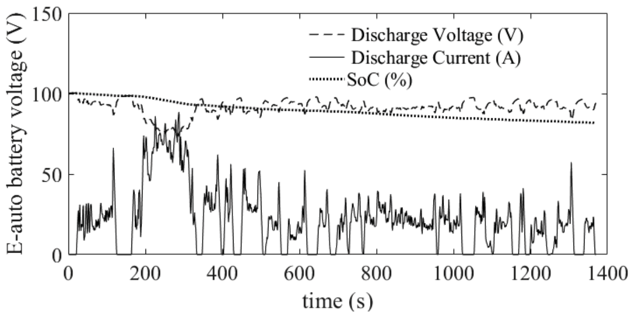

Fig. 9. SoC of E-auto battery bank during UDDS

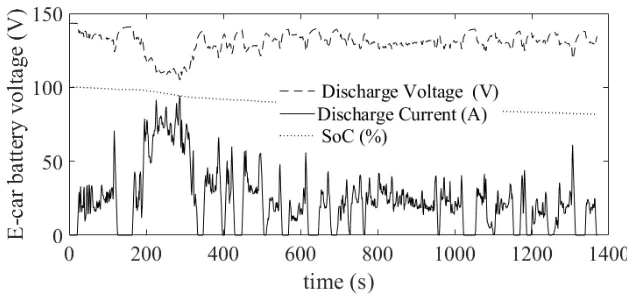

Fig. 10. SoC of E-car battery bank during UDDS

VII. Conclusions:

The importance of Li-ion battery electrical equivalent circuit parameters is mentioned in this paper. The experimental set up is established using controllino for determining Li-ion battery (LG HG2 3.6V,3.0 Ah) parameters. The behavior of the two RC model is analyzed and is used to estimate the SoC and terminal voltage of the Li-ion battery for different types of EVs using EKF.

The same methodology is also used for individual cells of the battery pack during running condition of the vehicle which will sort out the problems of failure of the cells in the battery pack of EVs. so the paper also detailed on the open circuit voltage estimation of the individual cell which is shown in the earlier part of the section VI. The battery pack is designed for various electric vehicle applications like two-wheeler, three-wheeler and four wheeler and the estimator is validated for a UDDS cycle.

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