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State of Charge Estimation of Lithium Ion Battery in Kalman Filter from Real Data

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***Abstract*: Battery is an important energy component in the Hybrid electrical vehicles. Wrong estimation of SOC brings the battery Overcharge or discharge. Other methods are not correct and hence high deviation occurs between the estimated and real SOC .The real time SOC is important to know the remaining battery capacity state. To estimate SOC of the battery it is necessary to design BMS. This paper discusses the SOC of battery and Kalman filter methods for SOC estimation using real time data.**

***Index Terms*: SOC,** *Battry*

I. INTRODUCTION

Lithium ion batteries are widely used in many applications due to its advantages long life cycle, high energy density and low self-discharge rate. SOC is important for performance and safety of the battery. SOC is the ratio of total current flowing through the battery and overall capacity of the battery.

The conventional methods for estimation of SOC are Coulomb counting and direct measurement of voltage and they are having some errors. In this paper new SOC estimation method using Kalman Filter is presented with verified experimental results.

II. CONVNTIONAL MTHODS FOR STIMATION OF SOC

This method involves measuring the current flowing into or out of the battery, which is integrated over time to evaluate the remaining charge in the battery. That is SOC derived as,

$$SOC(t) = \frac{\int Ib(t)*100}{FCC} \quad (1)$$

$Ibatt$ is the battery current and t is time and to satisfy this equation following are conditions,

1) No current sensor error
2) Less initial error
3) zero battery degradation error
4) No self-discharge

The Direct Measurement of Voltage

This method depends on voltage sensor measurement, temperature and charge/discharge rates. This method uses a lookup technique. When Current is larger than the battery capacity at that time voltage of the battery is inaccurate indicator of SOC.Hence this method is used for small application where current flow is sufficiently small.

Hence above methods are not find the correct SOC, as per them none of combine high accuracy, high robustness and high stability. The purpose of this paper is to get better SOC estimation method

III. BATTRY MODLLING

Battery model for HEV/EV described in this section. There are two main parts of battery modeling: open circuit voltage and over potential .Number of battery models have been presented to describe battery operations they are electrochemical and equivalent circuit models. Resistors and capacitors used in equivalent circuit to model the battery dynamic operations.Thevenin resistive used in equivalent circuit models.Thevenin model and (Rth) model, as shown in Figure 1.

To represent the dynamic and transient response of the battery during charging/discharging Thevenins model and RC network is used.RC network added in series to Thevenins model for accurate battery dynamic response at the charge/discharge stage.

The charge transfer resistance is R0, interfacial transfer between the electrolyte and the electrodes is (Rp, Cp) , The internal voltage source open circuit voltage and cannot measured when a load is connected to the battery.The dynamics of the equivalent circuit whose Terminal voltage and current are defined by Vp and Ibatt is described by equation,

$$\text{Ibatt} = \text{Cp}\frac{dVp}{dt} + \frac{Vp}{Rp} \quad (2)$$

$$(t)=(SOC)+Vp+R0Ibatt \quad (3)$$

The State-of-Charge (SOC) is defined by for number of cell parallel and series is given by equation 4-5.

$$SOC(t) = SOC0 - \int \frac{IBatt*100}{CellAh*3600*CellnP} dt \qquad (4)$$

$$VBatt = [Voc + \frac{IBatt*\ CellmS*CellRo}{Cellnp} + \frac{CellRp*\ IBatt}{(CellRp*CellCp)S+1}] \quad (5)$$

Plant dynamic is the basic of estimator design. The dynamics of equations are of two forms: Process equation and measurement equation. The process equation represents the function of plane input, system noise and state variables. Measurement equation represents the function of measurement noise and state variable. White noise used in this model having zero mean value. The estimation equations are

$$X = f\dot{(}x, u, v)$$

$$Y = h(x, u, w) \qquad (6)$$

Equation (6) described functions can be linear of nonlinear depending upon the plant behavior and v are system and measurement noise.Equation (6) can be described as:

$$X = Ax \dot{+} Bu + v$$

$$Y = Cx \dot{+} Du + w \qquad (7)$$

The linear model is quite easy to analyse.Equation (7) is linear model equation. The state space model for battery is given as:

$$\begin{bmatrix} S \\ Vp \end{bmatrix} = \begin{bmatrix} 0 & 0 \\ 0 & -\frac{1}{cellRp*cellnp} \end{bmatrix} \begin{bmatrix} SOC \\ Vp \end{bmatrix} + \begin{bmatrix} \frac{100}{cellnp*3600*cellAh} & 0 \\ \frac{cellms}{cellnp*cellcp} & 0 \end{bmatrix} \begin{bmatrix} IBatt \\ Vocv \end{bmatrix} \quad (8)$$

$$V = [0\ 1] \begin{bmatrix} SOC \\ Vp \end{bmatrix} + [\ \frac{cellR0*cellMS}{cellnp} \quad 1] \begin{bmatrix} IBatt \\ Vocv \end{bmatrix} \qquad (9)$$

IV. KALMAN FILTR

To get optimal convergence Kalman filter came in to picture. The concepts of Kalman filter first come in to reality during cold war between Soviet Union and American Treaty organization. R.E Kalman first develop the Kalman filter for navigation of the Apollo project to the moon. This proves to be quite reliable and effective in estimation of the trajectory of manned spacecraft for travelling to moon and return to earth with astronauts Let us assume a system having two states $x1(t)$ and $x2(t)$. The measurement of the system can be represented as the summation of these states i.e

.

$$y(t) = x(t) + x2(t) \qquad (10)$$

Intervals t0, t1, t. Now three situations are being described which are known as filtering smoothing and prediction**.** The term E [xˆ - x || 2 | z] is known as the variance of the error and is related to the error covariance matrix.i.e. E [(xˆ - x) (xˆ - x) T] . The variance of the error for estimator can be calculated from the trace of the "error covariance matrix". This can be represented as:

$$E[||X^{\wedge} - X||^2] = \text{trace E}[(X^{\wedge} - X)(X^{\wedge} - X)T] \qquad (11)$$

Kalman filter mainly works in the principle of minimum variance of error can work with both time invariant as well as time variant system. This is treated as the best linear filter among all the linear filters. The "minimum variance of unbiased error estimator(MVUE) can be represented as the linear function of all the measurements by considering all the states and measurements are Gaussian distribution. So MVUE is also known as the "linear minimum variance (LMV)" estimaton. Let us consider a state space model represented by the following equation,

$$X_{k+1} = FkXk + G_K U_K + W_K \qquad (12)$$

Where X_k is known as state vector W_k is known as combination of modeling error and the system noise which is assumed to be white noise with zero mean. U k is the input to the plant. F k , G k are considered as the system matrix and the input matrix respectively. The measurement equation of the above plant can be illustrated as:

$$Y_k = H_K X_K + v_k \qquad (13)$$

Where Y k is the measurement vector of the above plant with some inaccuracy which can be represented as v k which is also considered to be a white noise with zero mean. Here H k is the output matrix of the plant. The above described system can be represented as the block diagram in the Fig. 3.4 below,

Kalman filter follows a recursive process which is used to update the prior state i.e. X_k which was estimated by processing the information of new measurement Y_{k+1} and the new updated estimated state X_{k+1}. The estimated state will be optimal state at instant k+1. The main function of the filter is the formation of innovation matrix (Z_k) which can be from the difference between actual measurement and the predicted measurement on the basis of prior measurement.

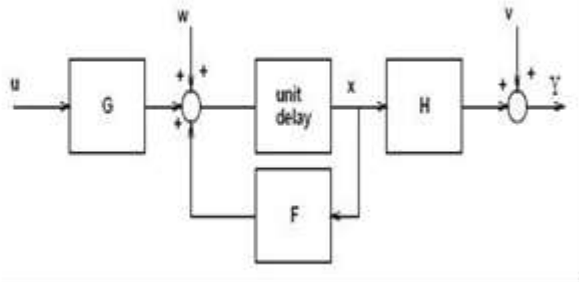

Fig.2. State space model for Kalman filter

Notation Used:

X (k 1 | k) means X(k 1) given measurement upto instant k
t - Present time.
to – Observation time.
X – State.

From the above equation we can conclude that Gain, Estimated covariance, Predicted covariance are independent of the innovation, estimation and prediction. From the above discussion we conclude that “the estimated covariance” of the estimated state has no relation with the measurement of the system up to the specific instant. So the covariance of the state and process noise are assumed to be known prior. These covariance of the noise have impact on the convergence rate of the algorithm i.e. it provides the optimal solution of the states at minimum time consumption.

V. SIMULATION RESULTS

Figure 3-6 shows the estimation results. the Kalman filter based on local linearization and designed is used to estimate the SOC, and the result of the Coulomb integral method is selected as the reference to verify the accuracy of our SOC estimation, SOC estimation shown in Figure 4 and the terminal voltage and OCV estimation of the battery are shown in Figure 5,. With the assumption that the equivalent circuit parameters are unchanged during the battery discharge process, the OCV estimation result shown in Figure uses the equivalent circuit parameters from real data. During the battery discharge process every 400 s, segment data, which are similar to the discharge transient characteristics is used to identify the model parameters. Then the identified parameters are used to immediately update the filter system parameters. After the estimation results converged from the initial 50% value, the SOC estimation precision is better than 0.5%. If OCV dominates the estimation results, its action should be that it directly obtains the results by the using of SOC-OCV curve in a form similar to a look-up table. This will lead to the fact that the SOC estimation result has an obvious fluctuation with the OCV fluctuation. In addition, the results are not completely dominated by the Coulomb counting method. In figure 6 result for real data is exactly estimated using kalman filter is shown. From this it is observed that this method is better than coulomb counting method.

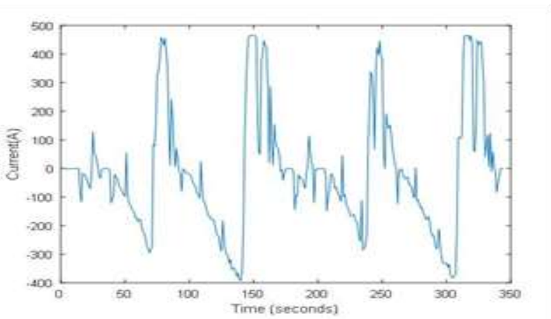

Fig. 3. Input Current $I_{batt.}$

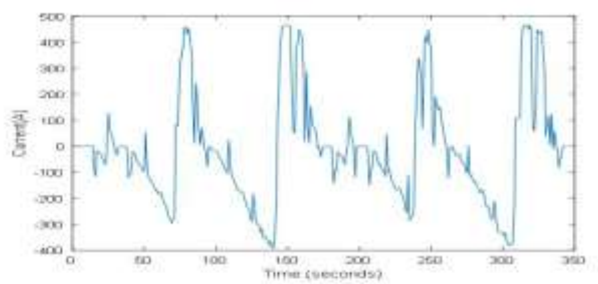

Fig. 4. SOC Estimation

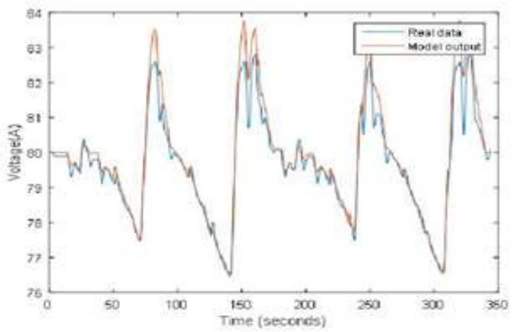

Fig.5. Model Voltage for Real Data

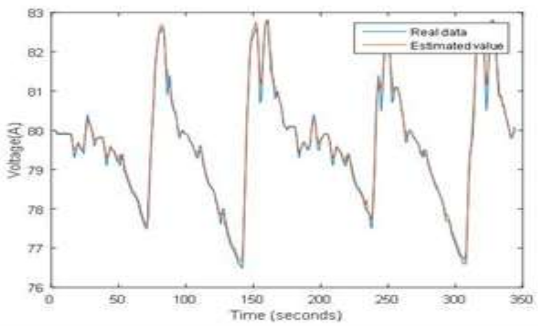

Fig.6. Voltage Estimation using kalman Filter from Real Data.

VI. CONCLUSION

An improved Thevenins model has been proposed which parameter identification performed by KF for lithium-ion battery module.From this estimation parameter we get the reduce noise in parameters. The maximum error of the improved Thevenin model is within 5.12%. from simulation results. The effectiveness of the proposed method was validated by performing a series of simulations under an HEV operating environment.

As future work, validations with experimental data must be carried out before practically implement proposed method. In particular, experiments on a degraded battery are important. Also To improve the accuracy, reliability, and robustness of the SOC estimation, the use of EKF or AEKF algorithm can take into consideration for the model.

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