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State of Charge Estimation for Li-ION LFP Cell

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Abstract

SOC(State of Charge) estimation for Lithium ion cell with LFP(Lithium iron phosphate) chemistry using different methods. The aim of this study was to get practically accurate results of SOC while tackling the hyped flat curve characteristics of LFP chemistry li-ion cells. Hence the project is divided in two phases the first one focuses on the literature review & the second one on selecting the best method and then implementing & comparing it in real cell dataset to predict the SOC accurately. The study was conducted using smart control algorithms to predict SOC. Data was collected from Kaggle. The results of the study (first phase) showed that double RC model and EKF are the most common techniques which were successfully used for industry R&D. The findings of this study contribute to the existing knowledge by applying the ideas/techniques from different papers & concluding on the *best control algorithms to get accurate SOC for LFP cells*. The results also have practical implications for how the flatness of Vocv vs SOC curve of LFP affects the prediction. The comparison of the NMC chemistry to LFP then gives clarity on problems with flat curve & possible solutions using filtering techniques like EKF, UKF etc. *Overall, this project provides a comprehensive examination of characteristics of LFP and the results have the potential to be applied in industry and further could be used to make strategies for using LFP cells in battery pack.*

Keywords: LFP; Li-ION; EV

Introduction

EVs are future if there was any doubt in past regarding that, the data in (Fig. 1) makes it crystal clear. With increasing EVs in market there is increased focussed on research on the li-ion batteries (Fig.2) Compared with other materials, lithium-ion batteries have the advantages of a high energy density, high power density, long cycle life, strong environmental adaptability, and high cell voltage. However, State of the Art there are many kinds of lithium-ion batteries, each of which has its own advantages, such as, LCO has an important specific energy, LMO has a high specific power, NCA and NMC are the cheaper lithium-ion batteries and thermally stable, LFP which has a flat OCV high self-discharging rate & most thermally stable and LTO has a long lifespan and fast charge, but a low specific energy and higher cost. Commercial lithium-ion batteries and their characteristics are shown in (Fig.3). These batteries could be great candidates for use in EVs, as they provide the required performance. Since SOC is the realisation of remaining charge & gives user the idea of the time till the device will be usable. It is important to find correct SOC value. SOC changes only due to passage of current, either charging or discharging the cell due to external circuitry, or due to self-discharge within the cell. 0% SOC implies no charge to run further while 100% SOC implies completely charged. In EVs accurate indication of SOC could improve:

- Longevity - By Avoiding Overcharging, Over discharging & hence better cell life.
- Performance - By knowing the deterministic error bound one can use the remaining energy aggressively.
- Reliability - Consistent and dependable for any driving profile would further enhance the overall power-system reliability.

- Economic value - Smaller, denser & lighter packs would lead to cost effective batteries.

Hence it is *crucial* to estimate accurate SOC. And hence this research focusses on finding the best techniques available for estimating SOC for LFP cell chemistry.

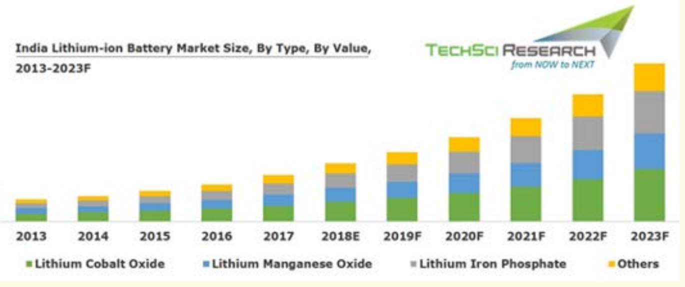


Figure 1: Indian Lithium-ion market growth.

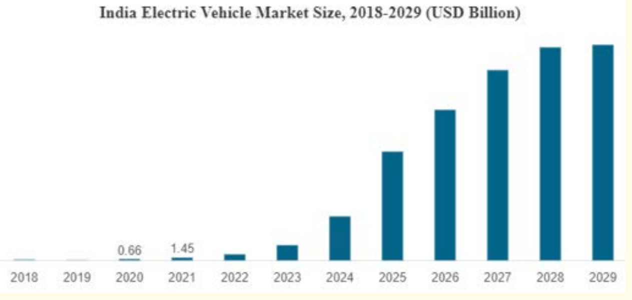


Figure 2: Indian EV Market growth.

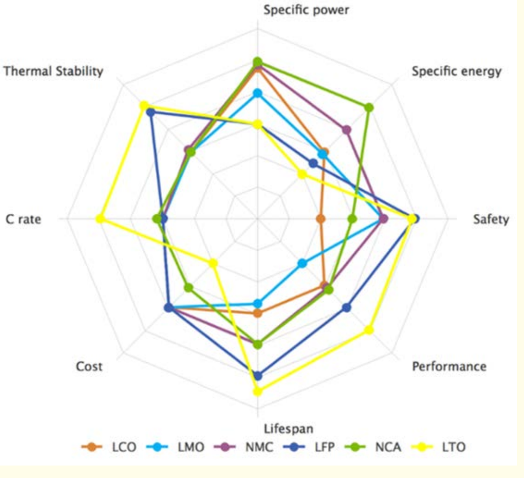


Figure 3: Spider chart for LIBs.

Literature Review

SOC

What exactly is SOC?

Electrochemically, the cell state-of-charge (SOC) is related to average concentration of lithium in the negative-electrode solid particles. When the cell is charging Lithium ions moves from positive to negative electrode and vice versa for discharging. More practically SOC could be seen as the 0% to 100% charge in your phones.

To derive a formula, say $\theta = \frac{Cs, avg}{Cs, max}$ where C is the concentration of Li ions then SOC denoted by z is defined as:

$$z = \frac{(\theta - \theta_{0\%})}{(\theta_{100\%} - \theta_{0\%})} \qquad (1)$$

$\theta_{0\%}$ & $\theta_{100\%}$ are concentrations at $V_{cell} = V_{min}$ & V_{max} respectively. To calculate SOC on field this technique could not be used hence we exploit the relationship of SOC and V_{ocv} to find the SOC.

Methods to Estimate SOC

SOC cannot be measured absolutely by some physical tool on field, hence we use the available inputs i.e. current, voltage & temperature to estimate the SOC. There are certain ways to estimate SOC:

Coulomb Counting or Ampere Hour

This technique basically takes the current measurement & integrate it to calculate the change in charge. The state-of-charge of the cell is the ratio of the residual capacity to the total capacity of the cell as looked in 7.1.1. Hence using the $i = \frac{\Delta q}{\Delta t}$ we get

$$z(t) = z(0) - \frac{1}{Q}\int_0^t \eta\, i(\tau)d\tau \qquad (2)$$

$$z(k+1) = z(k) - \frac{1}{Q}\eta\, i(k)\Delta t \qquad (3)$$

i is Cell current is positive on discharge, negative on charge, η is cell coulombic efficiency, Q is the cell total capacity in ampere seconds (coulombs).

Advantages of this technique comes when enough rest is provided (to let the RC dynamics die down) then we get accurate results. Easy to implement & low power consumption cost.

Disadvantages is that unknown initial SOC, capacity fading, self-discharge rate, and current sensor errors are the error sources which drifts the prediction away from original value over time. Since small errors tend to build up overtime and give wrong estimates hence a reset is frequently required, the initial capacity and SOC value of the battery, and the current sensor drift can be corrected and adjusted regularly through a resetting cycle. State of Health (SOH) overtime reduces and has to be updated in the equation or else inaccurate SOC estimation could be registered.

Voltage Look up

This method uses the stable battery electromotive force in the open circuit state (*Vocv*) and SOC relationship to estimate the SOC value. Here we exploit the relationship of voltage and SOC, which is experimentally known beforehand. Voltage is then measured and as per that whatever is the expected SOC is shown. The relationship depends on type and chemistry of battery, for example, a lead-acid battery has a linear SOC and OCV relationship, while a lithium-ion battery does not have this relationship. LFP batteries have a very flat SOC-OCV relationship.

Advantage is that once relationship is established then it could work for the whole life of batteries with accurate SOC predictions.

Disadvantage is that massive experiments at different temperature and cycle lives needs to be done for reliable relationship. Secondly *Vocv* cannot be directly measured if there is no sufficient rest (to let the RC dynamics die down)

Model Based technique

Model-based state estimators implement algorithms that use sensor measurements to infer the internal hidden state of a dynamic system. A mathematical model of the system is assumed known. Same input propagated through true system and model. Measured and predicted outputs compared; error used to update model's estimate of the true state. Output error due to: state, measurement, model errors. Update must be done carefully to account for all of these.

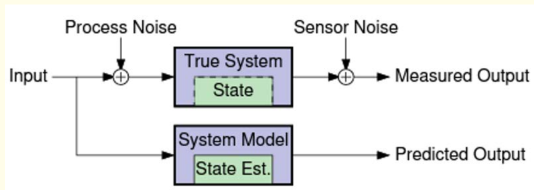


Figure 4: Credits to Dr. Gregory L. Plett.

Impedance and internal resistance method

The lithium-ion battery impedance and internal resistance can be used to describe the intrinsic electric characteristic under any current excitation, if temperature, SOC, and SOH are fixed. But it is very difficult to measure online electrical impedance spectroscopy (EIS), because sinusoidal alternating current (AC) may be required, the SOC and impedance relationship is not stable, and the cost is expensive [8]. To obtain the internal resistance, it needs direct current (DC) and the value of the voltage and current at a small-time interval. However, internal resistance changes slowly and is hard to observe for SOC estimation. In general, SOC estimation based on the impedance and internal resistance method is not suitable for use in EVs [3].

Electrochemical method

Estimating the amount of Li or the average Li concentration in the positive or negative electrodes is critical for SOC estimation based on the electrochemical model with partial differential equations. The SOC can be directly calculated from Li amount identification in the negative or positive electrodes of the electrochemical model. Nevertheless, the solution of partial differential equations is always too complex for online applications [3]. Generally speaking, the electrochemical model can theoretically obtain the most accurate SOC estimation. But this model is only suitable for off-line design and performance analysis for lithium-ion batteries. Nevertheless, due to the complexity of the electrochemical model and the dozens of parameters of the battery model, this method is too difficult to use for online SOC estimation [3].

Out of all above technique for current research we go with *Model based* (7.1.2.3).

Battery Modelling

Model	Temperature Effect	Capacity Fading	Accuracy	Complexity
Electrochemical model	Yes	Yes; support for Arrhenius tempt dependence & cycle aging added by Rong and Pedram[2]	Very High	High
Empirical Model (Peukert's law)	Yes; needs recalibration for each temperature	No	Medium	Low
Abstract (Electrical equivalent circuit)	Yes; needs recalibration for each temperature	No	Medium	Low
Weibull fit (Syracuse and Clark)[3]	Yes	No	Medium	Low
Stochastic (Chiassereni & rao)[4]	No	No	High	Medium

Table 1: Battery Models.

The Abstract based model i.e. *Electrical Equivalent* model is used because of it's most usability and less complexity hence could be implemented easily. Types of Electrical Equivalent models Single RC & Double RC (more accurate while relatively complex).

For the research project double RC model will be used to handle the dynamics.

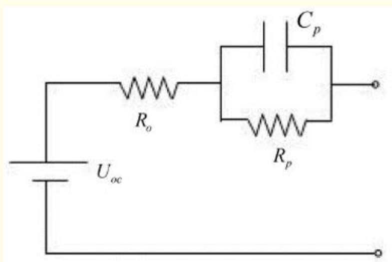


Figure 5: Single Dynamics model.

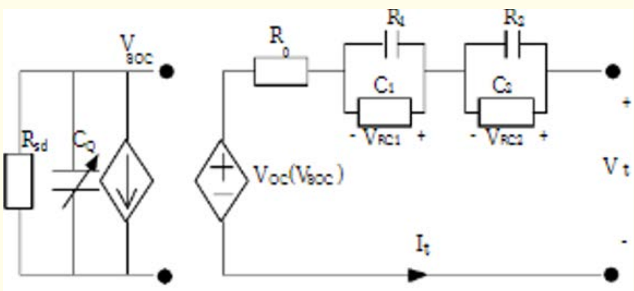


Figure 6: Double Dynamics model.

Simulation for different RC networks

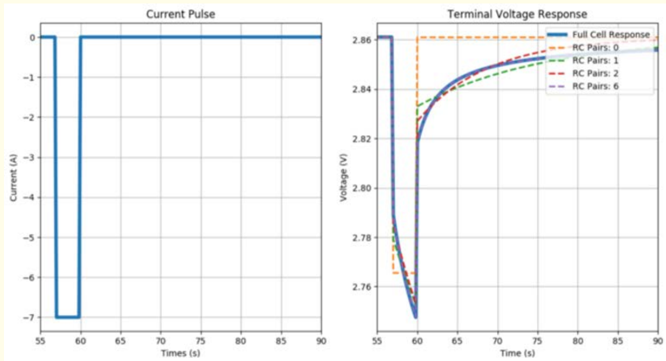


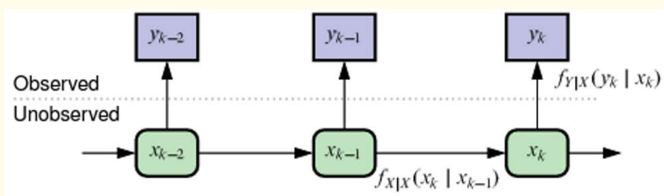
Figure 7: Successively higher order RC parameter approximations vs. measured voltage response.

Filtering Techniques

Filtering allows us to handle noises in the inputs to the system i.e. current and voltage. Below are certain methods used for estimating SOC for Li-ion cells.

Sequential Probabilistic inference

Estimate the present state k of a dynamic system using all measurements Yk={$y0$ $y1$, $y2$……. yk}. The observations allow us to "peek" at what is happening in the true system. Based on observations and our model, we estimate the state (SOC would be a state in our case). However, process-noise and sensor-noise randomness makes it difficult to compute the state exactly. So, we assume a probabilistic noise term in our model. Basically, implementing Kalman Filter with different variations, linear nonlinear etc.



Kalman Filtering

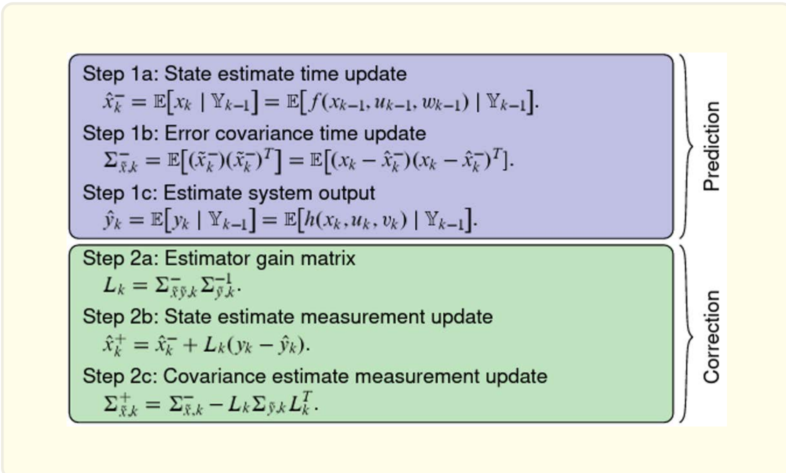
The linear Kalman filter assume linear Kalman filter assumes that the system being modeled can be represented in the "state-space" forms that the system being modeled can be represented in the "state-space" form:

$$x_k = A_{k-1}x_{k-1} + B_{k-1}U_{k-1} + w_{k-1} \quad (4)$$

$$Y_k = C_k x_k + D_k U_k + v_k \quad (5)$$

We assume that w_k and v_k are mutually uncorrelated white Gaussian random processes, with zero mean and covariance matrices. To be perfectly clear, the output of this process has two parts:

1. The state estimates: At the end of every iteration, we have computed our best guess of the present state value, which is $\hat{x}_{k+}$.
2. The covariance estimates: The covariance matrix $\Sigma\hat{x}_{k+}$ gives the uncertainty of $\hat{x}_{k+}$ and can be used to compute error bounds.



Kalman Filter Variations & other advanced filters

We now generalize to the nonlinear case, with system dynamics described as

$$x_k = f(x_{k-1},\ u_{k-1}, w_{k-1}) \quad (6)$$
$$y_k = h(x_k,\ u_k, v_k) \quad (7)$$

where u_k is a known (deterministic/measured) input signal, w_k is a process-noise random input, and v_k is a sensor-noise random input. There are three basic generalizations to KF to estimate the state of a nonlinear system:

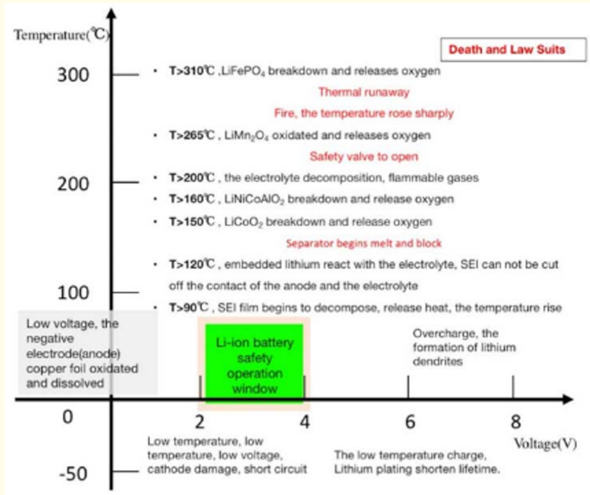
Extended Kalman filter (EKF): Analytic linearization of the model at each point in time. Problematic, but still popular.

Sigma-point (Unscented) Kalman filter (SPKF/UKF): Statistical/empirical linearization of the model at each point in time. Much better than EKF, at same computational complexity.

Particle filters: The most precise, but often thousands of times more computations required than either EKF/SPKF. Does not assume Gaussian distributions but approximates distributions via histograms and uses Monte-Carlo integration techniques to find probabilities, expectations, and uncertainties.

Temperature Consideration
Why would Temperature going to affect SOC?

According to Panchal's research, the decomposition of LiFePO4 battery positive electrode and negative electrode materials is high [2]. When the temperature becomes higher, the positive material will start decomposing (LiCoO2 will start decomposing at temperature of about 150 °C, LiNi0.8Co0.15Al0.05O2 at about 160 °C, LiNixCoyMnzO2 at about 210 °C, LiMn2O4 at about 265 °C, and LiFePO4 at about 310 °C) and produce oxygen. When the temperature is above 200 °C, the battery electrolyte will decompose and produce combustible gas [7]. Therefore, the heat management system is also very important in the battery system of electric vehicles. It is necessary to study the battery heat model and design a proper heating and cooling system for the batteries.



Literature Survey for temperature-based models

S. Panchal [11] has studied EV battery system for four drive cycle in actual conditions at various ambient temperatures. When the temperature rises, chemical reactions in the battery will intensify, the utilization ratio of active substances will increase, the lithium-ion transfer capacity will be strengthened, the actual available electricity will increase, but when the temperature is too high, the reaction will be restrained, the performance will be reduced, and serious explosion will occur. Otherwise, when the temperature is lower, the utilization ratio of active substances will be increased. Additionally, actual electricity consumption will be reduced. With the increase of lithium battery cycle times, the internal chemicals will age and deteriorate, resulting in increased internal resistance and decreased capacity, hence temperature affects, check above paper to see how it affects for LFP. Methods to understand *state of the art* techniques to consider temperature into the model are:

Variable R, C parameters

In this [4] paper, R and C parameters were varied with temperature to get accurate SOC values. In satellite application, the temperature varies at different orbital time and it has a significant effect on battery parameters and SOC, hence a reliable and accurate model is proposed.

Why variable R, C method?

From Fig.7, it is observed that the internal dynamic response of the battery varies at different temperatures. As such, online identification and updating of battery parameters are necessary to improve the battery model accuracy if it is expected to operate at different temperatures.

How variable R, c method?

Check Fig. 8 V_{oc} represents the battery OCV and it is a function of battery SOC and temperature (T). Here I_b is the battery current and V_t is the battery terminal voltage. *Ro* represents the instantaneous voltage drop to model the resistance from electrolyte and RC networks are used to represent the relaxation effects of the battery during the charging and discharging process. Li-ion (NCR18650) was used while doing the study in above paper.

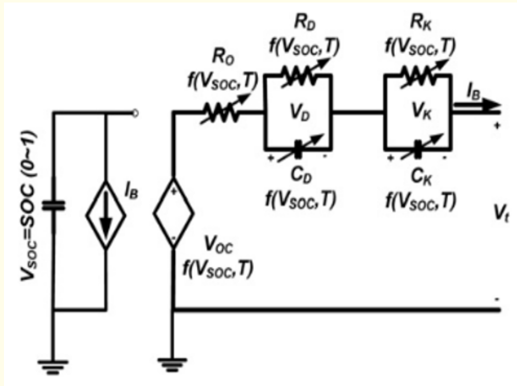


Figure 8: Temperature dependent double polarization model.

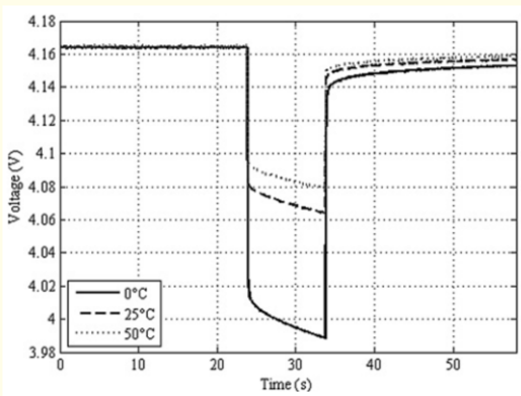


Figure 9: Experimental battery response at different temperature.

Observations

Below two figs shows the values of Ro, Td and Tk at 0, 25 and 50°C. These estimated values during the experiment are plotted against SOC to have a clearer understanding how the battery parameters changes across different SOC level and at different temperature. It can be observed that the parameters of battery vary across different temperature and SOC. From Fig.9a, Ro is higher in cold temperature and lower in hot temperature as expected. However, these updated parameters might not reflect the actual battery parameters values. Still, it is able to represent the Vt used for the SOC estimation in the above paper. The experimental results demonstrate that the proposed DUKFST outperforms the UKFST and EKF with the lowest RMSE and the lowest maximum errors. The improvement is particularly significant at 0 and 50°C. For the computational analysis, this improvement in performance comes from the increased computational requirement compared with UKFST and EKF.

Fitting method
How & why Fitting method?

The OCV-SOC characteristic curves at different temperatures were studied by modeling, exponential, polynomial, sum of sin functions, and Gaussian model fitting method with pulse test data.

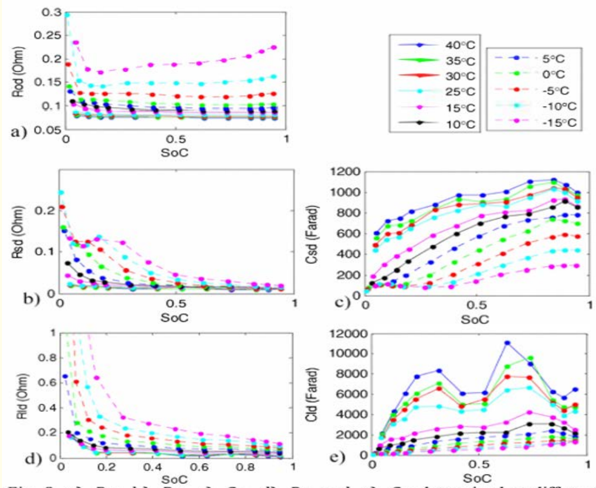
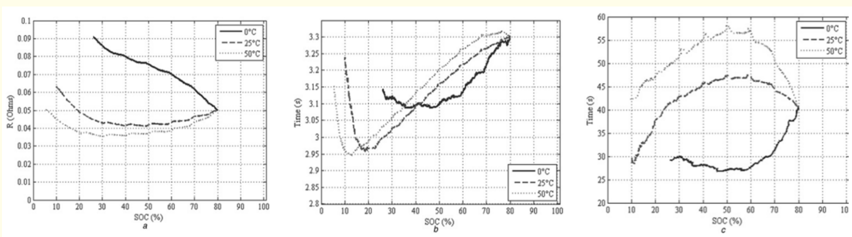


Fig. 9. a) R_{od}, b) R_{sd}, c) C_{sd}, d) R_{ld} and e) C_{ld} determined at different temperatures between 40°C and -15°C for discharge.



The parameters of fitting OCV-SOC curves by exponential model (n = 2), polynomial model (n = 3~7), sum of sin functions model (n = 3), and Gaussian model (n = 4) at temperatures of 45 °C, 25 °C, 0 °C, and −20°C are obtained, and the errors are analyzed.

The studies done shows that the operating temperature of the battery influences the OCV-SOC characteristic significantly. Therefore, these factors need to be considered in order to increase the accuracy of the model and improve the accuracy of battery state estimation.

Experimentations & results - Check this [9]

Capacity batteries under the influence of different temperatures. The result shows the OCV-SOC characteristic curve is greatly influenced by the temperature change. The polynomial fitting of the model is clear and simple so that it is widely applied in engineering. In the battery modeling, exponential, polynomial, sum of sin functions model, and Gaussian model are compared. In these models, accurate fitting of OCV-SOC curves in *low SOC interval is a key and difficult point* in battery state estimation, which has a great influence on the accuracy of battery state estimation.

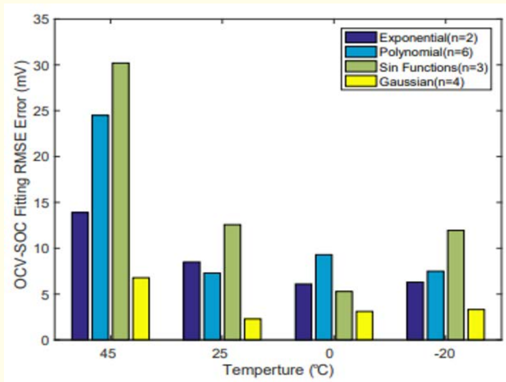


Figure 10: Comparing 4 types of fitting techniques.

Look up table method(SOC-OCV-T Look up table method for LFP as per this [7]***)***

How looking up table method?

OCV-SOC test was conducted from 0 °C to 50 °C at an interval of 10 °C. The test procedure at each temperature is the same as follows:

Firstly, the cell was fully charged using a constant current of 1C-rate (1C-rate means that a full discharge of the battery takes approximately 1 h) until the voltage reached to the cut-off voltage of 3.6 V and the current was 0.01 C.

Secondly, the cell was fully discharged at a constant rate of C/20 until the voltage reached 2.0 V, which corresponds to 0% SOC.

Finally, the cell was fully charged at a constant rate of C/20 to 3.6 V, which corresponds to 100% SOC. The terminal voltage of the cell is considered as a close approximation to the real equilibrium potential. As shown in Fig. 11, the equilibrium potential during the charging process is higher than that during discharging process. It accounts for a hysteresis phenomenon of the OCV during the charging/discharging. In our paper, the OCV curve was defined as the average value of the charge and discharge equilibrium potentials. The effect of the hysteresis was ignored.

What model was used?

For Li-ion, the internal resistance (R_{int}) model is generic & straight forward to characterize a battery's dynamics with one estimated parameter.

Why simpler model was used?

Although a sophisticated model with more parameters would possibly show a well-fitting result, such as an equivalent circuit model with several amounts of parallel resistance-capacitance (RC) networks, it would also pose a risk of over-fitting and introducing more uncertainties for online estimation at the same time. Especially taking into account temperature factor, more complexity should be imposed on battery modeling. Therefore, we would prefer a simple model to a sophisticated model if the former had generalization ability and provided sufficiently good results.

Observations

Fig. 12 shows the measured and the estimated voltage response on the DST profile at 20 °C based on the proposed model. It can be found that the mean error of the new model is reduced with small variations as compared to the original model in Fig. 13.

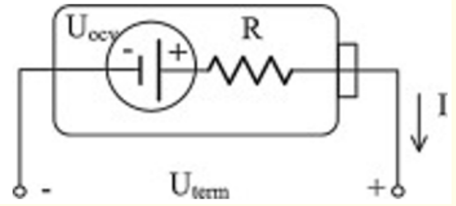


Figure 11: Zero dynamics model.

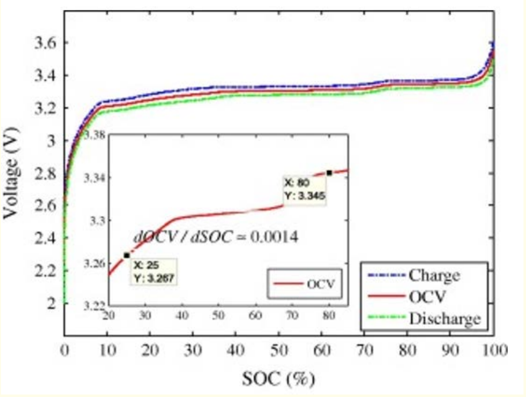


Figure 12: Voltage vs SOC.

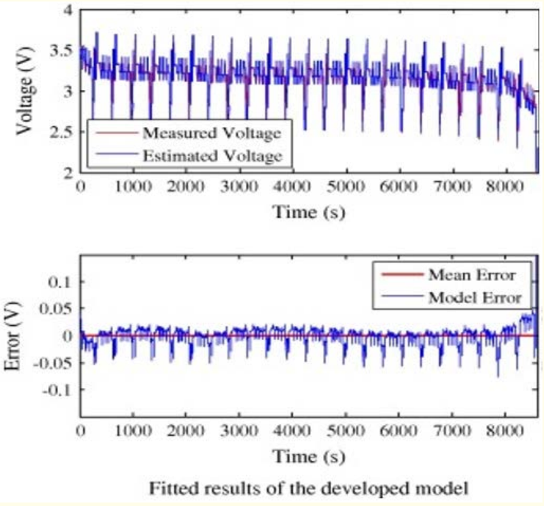


Figure 13: The measured and the estimated voltage response on the DST profile based on the proposed model at 20 °C.

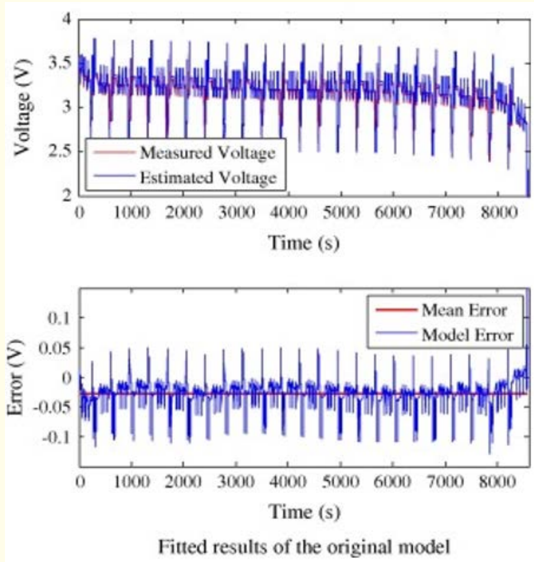


Figure 14: The measured and the estimated voltage response on the DST profile based on the original model at 20 °C.

The estimation covered the working range from 25% to 85% SOC. The results indicated that the estimation based on the developed battery model provided more accurate SOC values with smaller RMS estimated errors at different temperatures. The robustness of this method was verified under the conditions of three different initial SOC values. Thus, this approach could be successfully applied in BMSs for electric vehicles. Two issues about the developed method are worthwhile to be mentioned here for an optimized online application. One is that the OCV-SOC-temperature table can be refined to save memory space in the online system by normalizing the temperature dependence of the OCV-SOC. The other is that the estimation based on our developed model provided a sufficiently accurate result with RMS estimated errors of less than 5% within the major working range. If there were a higher requirement on the estimated accuracy at temperature lower than even 0 °C, the SOC estimation based on a more sophisticated model would possibly make more sense.

On-line estimation(Temperature based online estimation- Check this*[10]*)
What is On line estimation?

To achieve accurate state-of-charge (SoC) estimation for LiFePO4 batteries, the effects of temperature, hysteresis, and thermal evolution are elaborately modelled.

The hysteresis potential (V_h) is geometrically modeled with respect to (dis)charge history.

A battery thermal evolution model (TEM), involving the effects of heat generation and dissipation, is formulated and exploited to identify OCV and ECM parameters.

Two approaches are developed to extract ECM parameters: One uses the differential evolution (DE) algorithm to achieve off-line calibration; the other one realizes online regulation using both electrical and thermal behaviors.

Integrating temperature, hysteresis, and thermal effects with the ECM, 2 SoC estimation schemes are proposed:

One is based on the recursive least square with forgetting factor (RLSF) algorithm the other one resorts to the adaptive extended Kalman filter (AEKF).

Why this method?

Generally, the SoC can be inferred from predetermined open-circuit voltage (OCV)-SoC lookup tables with the online-identified OCV. However, the flat OCV plateau plus the hysteresis phenomenon.

Especially for LiFePO4 batteries (LFPBs), makes OCV-based methods of low precision. Battery internal resistance has also been exploited for the pursuit of SoC through feature recognition. However, the irregular relevance between SoC and internal resistance proves unsuitable for reliable SoC estimation either.

Conclusion

Benefiting from the online updated parameters, the adaptive EKF estimator behaves best for giving consistent SoC-tracking performance under different conditions.

Problem Statement

The problem for the LFP batteries is that it has a very *flat OCV-SOC* correlation curve. Current SOC estimation models are unable to take care of all of these complications. A more robust algorithm is needed to estimate the instantaneous total charge available for work inside an LFP cell. This project presents a novel, simplified implementation of the extended Kalman filter technique that overcomes the practical challenges involved in runtime evaluation of the SOC of commercial high-power LFP cells. Its formulation demands a lower level of resources compared to traditional EKF implementations.

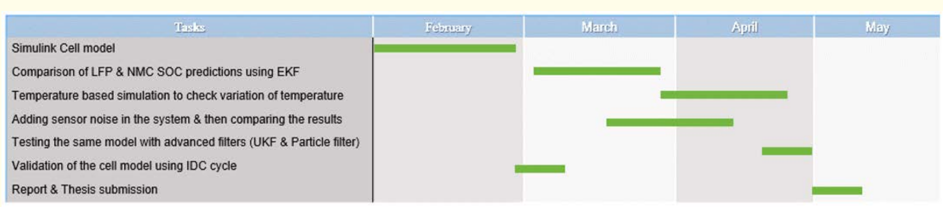
Objective of the Work

This project aims to a do a comprehensive examination of characteristics of LFP and find the results which have the potential to be applied in industry and further to be used to make strategies for using LFP cells in battery pack for EVs.

Methodology

The project is divided into 2 phases, one being Literature review and the second one being implementation of best technique out of all studied in phase one. The idea now is to collect cell voltage and current data, do a RC fitting & find the parameters at each SOC points. Then Implement EKF using Simulink Battery software to tackle the flat SOC challenge for LFP using different variations of filtering techniques.

Future Work & Timeline



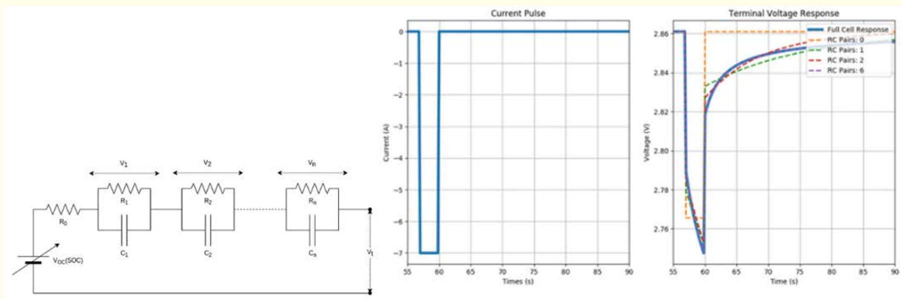
Cell Characterization

Cell characterization is a process through which one finds the R0, R1, R2…,C1, C2…, Vocv vs SOC charactecterstic curve for a particular cell chemistry.

Simulink Model

Modeling the cell using Equivalent Circuit modelling method

The equivalent cell model behaves very close to the real cell as we increase the RC units. Refer the figure below which shows how the increasing RC units from 0 to 6 makes an impact on the SOC predictions. To create a practical model we take 2RC as the one which balances the accuracy and complexity.



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