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State of Charge Estimation of Li-ion battery for BMS Application: A comparative study

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***Abstract*--Electric vehicle adoption is being promoted as a major counteract to mitigate vehicular pollution. This calls for improvement of technologies to enhance the reliability and safety of electric vehicles (EV). The battery pack of an EV being its major component needs to be monitored properly in every charge-discharge cycle as it is subjected to different drive profiles in terms of current flowing through them. Battery Management System (BMS) considers the dynamic parameters of the pack and performs various functionalities which are helpful for the safekeeping of vehicles as well as users. State of Charge (SoC) estimation is an important function that helps BMS to monitor deterioration in charge available in cell. This paper implements the state of art techniques on an accurate Enhanced Self-Correcting model of Li-ion cell which considers dynamics and hysteresis profile observed in cell subjected to drive cycles. This paper describes three approaches i.e. EKF, SPKF and Bar delta algorithms for SoC estimation. Case studies and comparison of all the techniques are presented.**

Keywords— Polarization, Hysteresis, Diffusion, Covariances, Process Noise, Sensor Noise Gaussian Probabilistic Inference Solution

I. INTRODUCTION

With the current level of pollution all around the globe, there is a major concern of all the countries regarding the measures to bring it to a level which do not affect the sustainability of generations to come. The intellectual folks of the world have come to a consensus on which everyone should take appropriate actions to curb pollution. Vehicular pollution is the major contributor to pollution, there is a constant push toward the adoption of electric vehicles (EVs) and India is no exception to that. [1] The most widely used internal combustion engine, being a cheaper and more reliable alternative to EVs needs to be made more environment friendly. Hence attempts have been made by the automobile sector to include a battery pack or replace them with completely battery dependent EVs.

EVs are facing various challenges in terms of reliability and safety. There are various integrated embedded systems with battery packs which monitor the operating variables of vehicles subjected to different drive trains and driving profiles. Basically, these driving profiles are nothing but different load current profiles to which the battery pack is subjected. These current profiles are basically the current drawn by motors driving the EV which is supplied by the battery pack of the vehicle. [2] In each drive cycle there are points where the batteries are subjected to high currents which might subject the battery to be exploited to an extent, that might cause structural damage to the construction of electrodes of the cell. [3] Hence these dedicated embedded systems monitor the current, voltage and temperature of battery pack and thus make various decisions which improves the reliability and safety of EV.

There are two most widely used dedicated embedded systems used in EVs namely Battery Thermal Management System (BTMS) and Battery Management System (BMS). They apply various state of the art algorithms to estimate the parameters which in turn helps them to achieve their functionalities. [4] BTMS takes inputs of SoC, current and temperature from BMS which it uses to deliver operating commands to contactor circuits and protects the battery from being subjected to currents which may be hazardous with respect to vehicle or users.

So, BMS is an important system which has variety of functionalities ranging from estimating SoC, State of Health (SoH) and to maintain a log of the exploitation of battery pack. This can be used to claim the warranty to establish communication with various ancillary services which are performing important tasks required by the vehicle [5].

In this paper, four battery cells were taken as part of the battery module. The state-of-the-art algorithms for SoC estimation have been discussed. The algorithm takes Generic Random probabilistic approach into consideration to estimate the dynamically changing states of Li-ion battery when subjected to various charge discharge cycles [6-7]. The state space equations are formed with the help of mathematical model obtained from implementation of Enhanced Self-correcting model which replicates the dynamics of battery to a better extent. This model is an extension of Thevenin equivalent model which has RC branch. The details will be explained in a subsequent section. Based on the state space equations obtained from this model, the nonlinear form of Kalman Filter estimation technique is adopted [8]. This gives an accurate estimation of SoC as it takes care of processing noise and sensor noise which represents the modelling inaccuracies. The organization of the paper is as follows. Section II describes BMS and Battery modeling. Section III presents SoC estimation techniques. The implementation of KF based approaches for SoC estimation is explained in section IV. Section V presents the results and discussion, and section VI provides the conclusion.

II. BATTERY MANAGEMENT SYSTEM AND BATTERY MODELLING

A. Battery Management System

It is a dedicated embedded system attached with battery module which monitors, analyses and controls the quantities related to charge and discharge of battery. The architecture of BMS comprises of primary processors and secondary processors, that communicate among themselves using serial communication and CAN bus topology for others. The core BMS functionalities involve ensuring safe operations, maintaining various battery usage data, and running self-diagnostic tests which includes self-test, system monitoring and running integrity check on various components of electric vehicles. It also performs various control activities such as contactor control as well as thermal control. It basically passes on data to BTMS to perform temperature related control actions. It also has SDRAM and EEPROM for data storage. BMS has various applications of prediction and estimation of SoC and SoH which ensures the proper monitoring of the dynamic state of battery module being subjected to various drive cycles. There are basically three topologies available in BMS market, namely Centralized topology, Distributed topology, and Modular topology. The basic design blocks of BMS are given in Fig. 1.

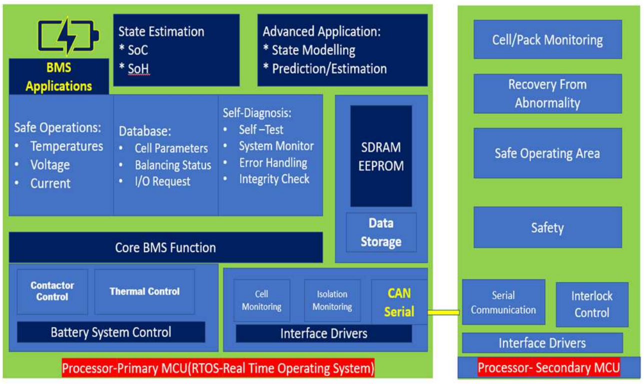

Fig. 1. Basic design blocks of Battery Management System

B. *Battery Modelling*

There are variety of battery technology developed until now and each cell has its own merits and demerits to be considered while deciding for adopting a particular type of cell technology. One of the basic measures for comparison of cell technology is based on their gravimetric and volumetric density. This considers the charge holding capacity and compares available cell technologies based on their size as well.

The higher accuracy of model representing the physical battery leads to higher accuracy of estimation of model-based algorithms. A precise battery model contributes to the battery's behavioral description and analysis, as well as the premise of battery management and state estimation. So, many attempts have been made in academia and literature explaining the various approaches to sort out the issue of model accuracy. These are the most acceptable approaches and are discussed in subsequent sections.

1) Thermal modelling

It combines the battery phrases of heat transfer, heat generation and dissipation to analyze any temperature distributions of battery cells, modules, and stack in the time and space domains. This model helps in optimizing the design and safety while applied in the BTMS. Cells heat transfer process is a typical unsteady, time-varied subject with an internal heat source.

2) Electrical Circuit modelling (ECM)

The ECM approach is a widely accepted model. It generally has electrical parameters which describe the complex non-linear charging as well as discharging phenomenon occurring inside cell. It is a good tradeoff between the characterization of the external dynamic behavior of the battery and the insight into internal and microscopic behavior.

3) Multi-physics modelling

This type of modelling is the most complicated, but it presents almost a replica of an actual cell model in many aspects. This can be classified into three categories namely Thermo-electrical coupling, coupling demonstrating thermo-electrical aging characteristic and the last one involving thermos electrical as well as mechanical characteristics. These modelling are complex to be implemented in BMS chip because of constraint of storage as well as processor in embedded system.

4) Enhanced Self-Correcting Model

Here, enhanced refers to a model that includes description of hysteresis. This model is improvement on basic ECM which has one open circuit voltage (OCV), one series resistance and a parallel RC branch the model is called enhanced as it includes a block to represent hysteresis effect that is observed while subjecting the cell to subsequent charge and discharge cycles and is called self-correcting because the model's OCV settles to values which is subtracted from the original OCV and thus explaining the phenomenon happening physically. This model is more accurate than any ECM.

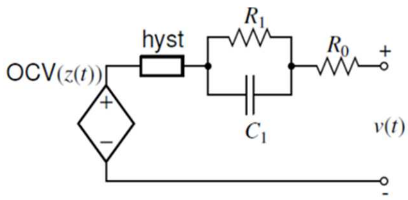

Fig. 2. Schematic of ESC of Li-ion cell

III. STATE OF CHARGE ESTIMATION

Physically, charging a Li-ion cell means moving Li ions from positive electrode to negative electrode via electrolytes and discharging involves reverse action. Hence, SoC can be related to average concentration of lithium in negative electrode, so we consider only negative electrode concentration of lithium for defining SoC. Which can be described as the average available concentration of lithium at negative electrode to the total concentration of possible lithium at negative electrode. In simpler way if it is represented in equation form where $\boldsymbol{\theta}_k$ is the concentration of lithium at k instant and $\boldsymbol{\theta}_{0\%}$ and $\boldsymbol{\theta}_{100\%}$ are the average concentrations at 0% and 100% SoC then Soc of a cell can be defined as:

$$z[k] = \frac{(Q_k - Q_{0\%})}{(Q_{100\%} - Q_{0\%})} \quad (1)$$

Where, z[k] is the soc of the cell at kth instant of time. There are Various methods for estimation of SoC like Voltage based State of Charge estimation, Current based

SoC estimation, Model based SoC estimation and Generic sequential probabilistic inference solution.

Generic sequential probabilistic inference solution is an approach which uses basics of probability theory to estimate the inaccuracies in measurements and process modeling. Here the motive is to seek an efficient recursive estimate of the present state of the dynamic system using information fed from the real system. Initial states and covariances are assumed and fed to the algorithm which has two parts namely priori estimate and posteriori estimate, former step is also called time update or prediction while the later step is defined as measurement update or correction step. Each step can be divided into three steps as represented in the following flow graph.

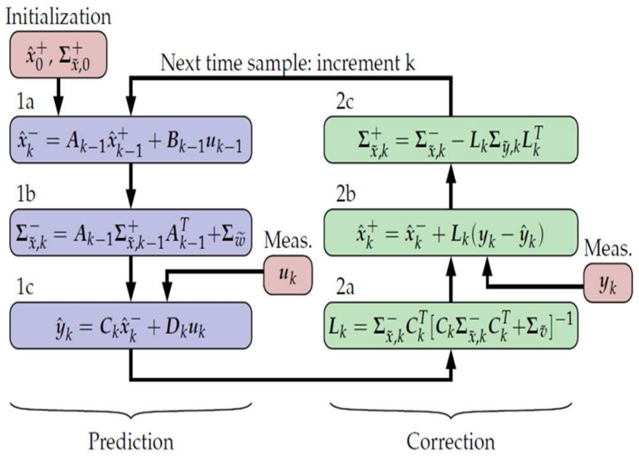

Fig. 3. Bar-Delta flow chart

In first step that is priori step or prediction step, the three sub-steps are:

a. State prediction time update.
b. Error covariance time update.
c. Predict system output.

In second step that is posteriori step or correction step there are three sub-steps:

a. Estimator gain matrix.
b. State estimate measurement update.
c. Error covariance measurement update.

These six steps are used as basis for calculation of states and covariance matrices in Kalman filter-based approaches. Normal Kalman filter-based approaches are used for linear systems where the system state matrices have linear dependence on time and using these steps the bound of error estimate as well as estimate of states are obtained. But as far as Li-ion battery characteristic is concerned it is highly non-linear in nature and thus general Kalman filter will not be applicable in such case as there are temperature and SoC dependence on various parameters. So, to get the accurate estimate of the states defined in earlier section nonlinear variants of Kalman filters are implemented in this research work and a comparative study of Extended Kalman filter (EKF) and Sigma point Kalman filter (SPKF) is done, and they proved to be giving promising results. Later, Bar-Delta filtering technique was implemented to obtain SoC estimate of battery pack.

IV. IMPLEMENTATION OF KALMAN FILTER BASED APPROACHES

Kalman filter (KF) based approach uses Generic sequential probabilistic inference solution-based algorithm. KF based approaches basically follow the closed feedback mechanism to reduce any error in terms of modelling or measurement inaccuracies and results in accurate results of state estimations up to certain extent. But the limitation of KF based approach is that it is only applicable to systems which have linearly varying states and thus is not applicable in our case where battery model chosen considers non-linearities involved in subsequent charge and discharge process of Li-ion battery cells. The two non-linear variants are Extended Kalman filter (EKF) and Sigma point Kalman filter (SPKF) and are discussed in further sections.

A. Extended Kalman Filter implementation

EKF is basically a non-linear variant of KF which performs analytic linearization of the model. This performs well if system non-linearities are mild. EKF considers following form of state equations as mentioned above:

$$X_k = A_{k-1}\, x_{k-1} + B_{k-1}\, u_{k-1} + w_{k-1} \qquad (2)$$

$$Y_k = C_k x_k + D_k\, u_k + v_k \qquad (3)$$

Where w_{k-1} and v_k are terms representing the process noise and sensor noise. X_k is the state matrix and u_k is the input matrix, A_k, B_k, C_k, D_k are state coefficient matrices representing the non-linear relationships of states and inputs.

By using the derived state equations ESC model of Li-ion cell given as:

$$\begin{bmatrix} z[k+1] \\ i_R[k+1] \\ h[k+1] \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & A_{RC} & 0 \\ 0 & 0 & A_H[k] \end{bmatrix} \begin{bmatrix} z[k] \\ i_R[k] \\ h[k] \end{bmatrix} + \begin{bmatrix} -\eta[k]\Delta t/Q & 0 \\ B_{RC} & 0 \\ 0 & A_H[k]-1 \end{bmatrix} \begin{bmatrix} i[k] \\ sgn(i[k]) \end{bmatrix} \qquad (4)$$

Where,

$$A_{RC} = \exp\left(\frac{-\Delta t}{R_1 C_1}\right);\ B_{RC} = \left(1 - \exp\left(\frac{-\Delta t}{R_1 C_1}\right)\right) \qquad (5)$$

Output equation:

$$v[k] = OCV(z[k],T[k]) + M_0 S[K] + Mh[k] - \sum_j R_j i_{R_j}[k] - R_{0i}[k] \qquad (6)$$

B. Sigma point Kalman Filter implementation

For implementation of SPKF, the state and output equations will be same as that used in EKF. The difference lies in the linearization methodology used in both algorithms. In SPKF, from a large set of data points we choose a subset of data in such a way that the weighted mean and covariance matches exactly with the mean and covariance of input random variables of the non-linear system function. This subset of data is called input sigma points. These set of points are individually passed to non-linear equation such that output sigma points are obtained. And then the mean and covariance of original random variable is approximated from the mean and covariance of these output sigma points. The results produced by these techniques are often much better than that of EKF but at comparable computational burden. It gives reasonably accurate results even if the system has significant non-linearities.

To understand the choice of sigma points, the first number of sigma points is selected. If the input state vector is of L dimension, then p+1= 2L+1 sigma points are chosen such that $\bar{x}$ and $\Sigma\tilde{x}$ are the mean and covariance of random variable in form of state vectors. The 2L+1 sigma points are such that:

$$X = \{\bar{x}, \bar{x} + r * \sqrt{\Sigma_{\tilde{x}}\bar{x}} - r\sqrt{\Sigma_{\tilde{x}}}\} \tag{7}$$

TABLE I. Parameters of SPKF

Method	r	$a_0^{(m)}$	$a_k^{(m)}$	$a_0^{(c)}$	$a_K^{(c)}$
SPKF	$\sqrt{L+\lambda}$	$\frac{\lambda}{L+\lambda}$	$\frac{1}{2(L+\lambda)}$	$\frac{\lambda}{L+\lambda} + (1-\alpha^2+\beta)$	$\frac{1}{2(L+\lambda)}$

$\lambda = \alpha^2 (L + k) - L$; $0.01 \le \alpha \le 1$; k is either 0 or 3-L; and for Gaussian RV $\beta = 2$

Now, propagating these sigma points to non-linear state equations we get output sigma points as:

$$\bar{x} = \sum_{i=0}^{p} a_i^{(m)} X_i \quad \text{and } \Sigma_{\bar{x}} = \Sigma a_i^{(c)}(x_i - \bar{x})(x_i - \bar{x})T \tag{8}$$

$$\bar{y} = \sum_{i=0}^{p} a_i^{(m)} Y_i \quad \text{and } \Sigma_{\bar{Y}} = \Sigma a_i^{(c)}(Y_i - \bar{y})(Y_i - \bar{y})T \tag{9}$$

Using the flow graph of Figure 3. and passing the covariance matrices to the six sub-steps involved in Generic gaussian-sequential-probabilistic inference solution, we obtain the required estimate of states and its corresponding covariances which define the error bounds of the estimate.

C. Bar-Delta approach for battery pack SoC estimation

The above discussed two algorithms that is EKF and SPKF are not well suited for SoC calculations for battery packs due to several drawbacks such as Computational burden and as different individual cells may have different level of charging or discharging. So, to overcome these issues a new approach named Bar-Delta approach for SoC estimation is given. In this filtering technique:

One algorithm is used to determine the composite average behavior of all cells in the battery pack and another algorithm to determine the individual differences between specific cells and that composite average behavior.

Bar filter equation: In the following block the pack average state is evaluated:

Fig. 4. Simple representation of Bar filter.

To demonstrate how average states are calculated we have the following equations.

$$Z_k^{(i)} = Z_{k-1}^{(i)} - i_{k-1}\,\Delta t/Q(i) \tag{10}$$

$$\frac{1}{N_s}\sum_{i=1}^{N_s} Z_k^{(i)} = \frac{1}{N_s}\sum_{i=1}^{N_s} Z_{k-1}^{(i)} - \frac{i_{k-1}\Delta t}{N_s}\sum_{i=1}^{N_s}\frac{1}{Q^{(i)}} = \frac{1}{N_s}\sum_{i=1}^{N_s} Z_{k-1}^{(i)} - \frac{i_{k-1}\Delta t}{N_s}\sum_{i=1}^{N_s}\frac{1}{Q_{inv}^{(i)}} \tag{11}$$

$$\bar{z}_k = \bar{z}_{k-1} - i_{k-1}\,\Delta t\bar{Q}_{inv} \tag{12}$$

Delta filter equation: Following block diagram describes the Delta filtering procedure:

Here we estimate using the state equations where delta-x is the difference between state vector of cell i and the pack-average state vector:

$$\Delta Z_k^{(i)} = Z_k^{(i)} - \bar{Z}_k = \Delta Z_{k-1}^{(i)} - (i_{k-1} - i_{k-1}^{b})\Delta t\Delta Q_{inv,k-1}^{(i)} \tag{13}$$

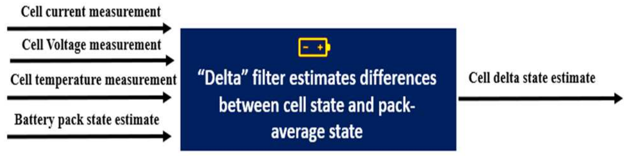

Fig. 5. simple representation of Delta filter

$\Delta Q_{inv}^{(i)}$ it was observed to be changing slowly and hence $\Delta Z_k^{(i)}$ in turn does not change quickly. In Delta filter implementation only $\Delta Z_k^{(i)}$ is considered as the only state variable. Implementation of SPKF on a single state variable is much faster than implementing it on all set of variables. The output equation is:

$$Y_k^{(i)} = \mathrm{OCV}(Z_k^{(i)} + \Delta Z_k^{(i)}) + \mathrm{M}\,\bar{h}_k - \textstyle\sum_J R_j i_{j,k} - (\bar{R}_{0,k} + \Delta R_{0,K}^{(i)})(i_k - i_k^{b}) + V_k \tag{14}$$

So, using these implementation techniques the bar-delta filter is implemented, and results obtained are quite convincing and impressive. The results of these implementations and their conclusions are made in the next section.

V. RESULTS AND DISCUSSIONS

The implementations explained so far were carried out using MATLAB 2021a script files and the results obtained are presented below with detailed discussion.

A. Extended Kalman Filter results

EKF algorithm was implemented for dynamic battery data after being subjected to current profiles under Urban dynamometer drive schedule (UDDS). After implementing MATLAB code for EKF algorithm and using cell test data, the results were satisfactory. The model used in EKF implementation was ESC model which is accurate enough to the extent that error in model prediction is 10.24 mV. Root means square SoC estimation error is 1.525% for one Li-ion cell. Time taken for implementation = 11.5748 sec. This signifies the computational burden on the microprocessor. This algorithm can be implemented easily with a BMS chip. EKF performed well compared to coulomb counting which had an RMS error of 2.5 % which caused a significant deviation in SoC vs OCV predictions and thus causing miscalculations.

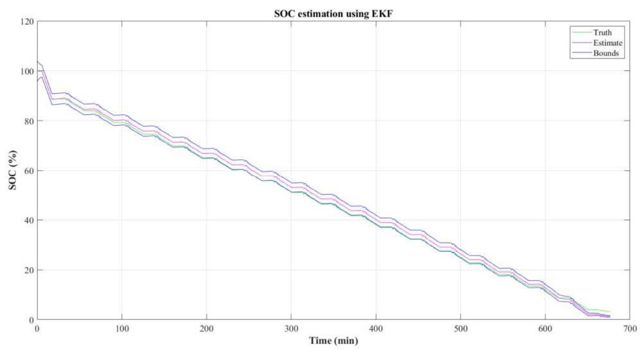

Fig. 6. SoC estimation results for EKF

The plot in Fig. 6. shows the degradation of SoC as time is elapsed when subjected to UDDS drive cycle. It has three plots; one shows true values of SoC estimate obtained from battery test data and other plot is that of the estimated SoC value obtained from EKF algorithm. The third plot indicates the bounds of errors obtained from the covariance matrix which shows the allowable limit and the error bound also lets us know the accuracy of estimate in terms of duration of time for which estimate is out of bound.

Fig. 7. shows the SoC estimation error which is basically obtained by subtracting true SoC obtained of the test data from the estimated SoC obtained from EKF implementations. It demonstrates the portion of plot which is out of the bounds of allowable error. From implementation it was observed that 35.92% of the time elapsed for implementation error was outside of the bounds defined by the covariance obtained from EKF estimations. This is also a parameter on which there is a need to make significant improvement which will improve the accuracy and consistency of our estimation algorithm.

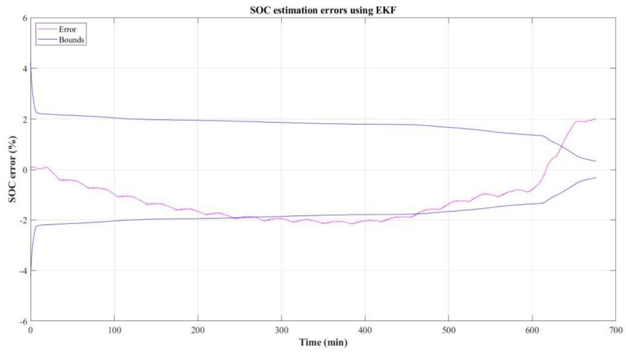

Fig. 7. SoC estimation error for EKF

B. *Sigma Point Kalman Filter results*

SPKF algorithm was implemented for dynamic battery data after being subjected to current profiles under UDDS. The model used in SPKF implementation was ESC model which is accurate enough to the extent that error in model prediction is 10.24 mV. Root mean square SoC estimation error is 0.837% for one Li-ion cell. Time taken for implementation is 8.74 sec. This algorithm can be implemented easily with a BMS chip. SPKF performed well compared to earlier implemented EKF which had an RMS error of about 1.5 %.

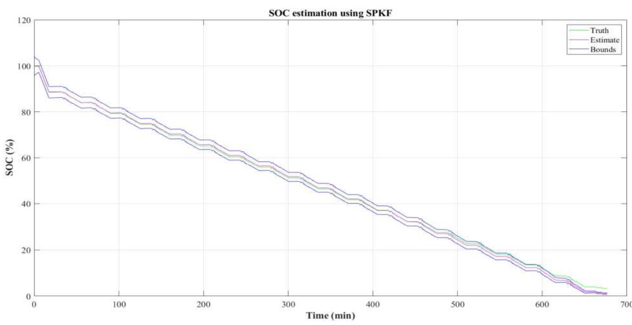

Fig. 8. SoC estimation results for SPKF

Fig. 8. shows the plots of SPKF implementation for SoC estimation. The plot shows the degradation of SoC as time is elapsed when subjected to UDDS drive cycle. It has 3 plots, one showing true values of SoC estimate obtained from battery test data other plot is that of the estimated SoC value obtained from EKF algorithm. The third plot indicates the bounds of errors obtained from the covariance matrix which shows the allowable limit in estimate and the error bound also lets us know the accuracy of estimate in terms of duration of time for which estimate is out of bound.

Fig. 9. shows the SoC estimation error which is basically obtained by subtracting true SoC obtained of the test data from the estimated SoC obtained from SPKF implementations. The plot described is between % SoC error and time, from implementation it was observed that 10.53 % of the time elapsed for implementation error was outside of the bounds defined by the covariance obtained from SPKF estimations. This shows that SPKF brought a significant improvement in terms of accuracy of estimate and hence proved to be a better algorithm.

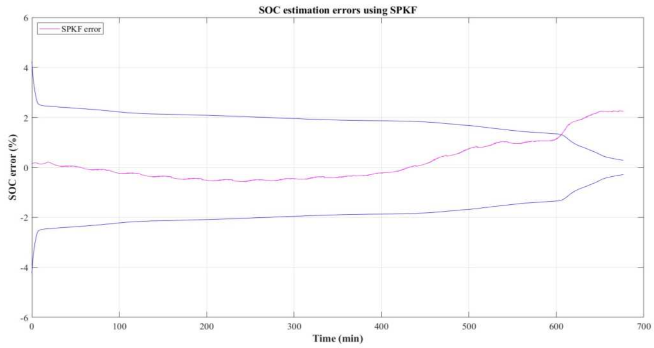

Fig. 9. SoC estimation error results for SPKF

C. *Bar-Delta results*

Bar-Delta filtering technique is used for estimation of states of Li-ion cells in a pack and it uses SPKF to implement estimation after Bar-Delta transformation. The algorithm was implemented for dynamic battery data which was collected at 5 °C and after being subjected to current profiles under UDDS. After implementation the Bar- Delta filtering algorithm based on SPKF implementations and observing the results obtained it is evident that model used in Bar-Delta implementation was ESC model which is accurate enough to the extent that error in model prediction is 10.24 mV. Here 4 battery cells were taken as part of battery module to give a feeling of estimation technique for multiple cell module. The root means square SoC estimation error for cells 1, 2, 3 & 4 are 1.494%, 0.498 %, 0.499 % & 1.495 % respectively. The time taken for implementation of this algorithm and obtaining SoC estimate is 7.903 sec. This algorithm can be implemented easily in BMS chip.

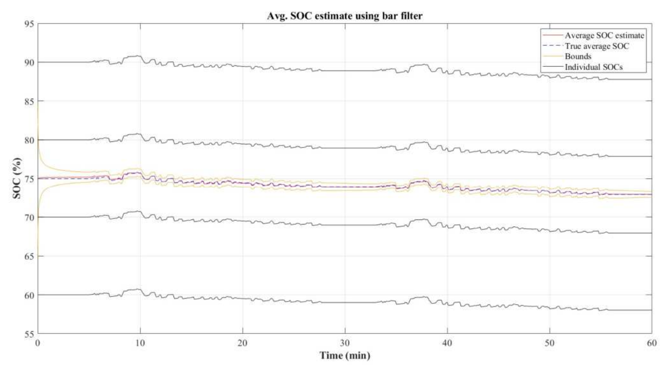

Fig. 10. Average SoC estimate for Bar-Delta filtering

Fig. 10. shows the results obtained after implementation of Bar-Delta algorithm and assuming different initial SoC

for each cell. It shows average SoC of each individual SoCs estimated by Bar algorithm. The bounds are obtained from the covariance of SPKF algorithm. It shows that the estimated average SoC of four cells are having same pattern as observed from the plot of the SoC obtained from the test data at corresponding point of time.

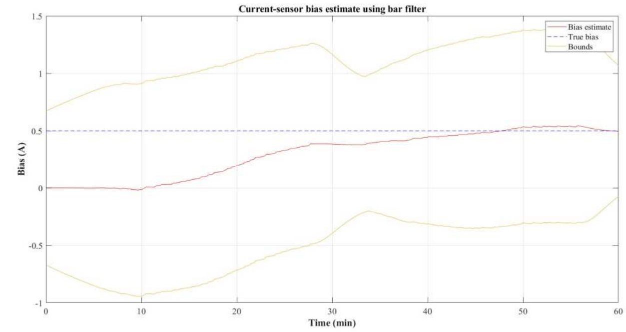

Fig. 11. Current Bias Estimate by Bar filter.

Fig. 11. shows the current bias estimate by Bar filter. During implementation current bias was taken as 0.5 A and while initialization it was taken as 0 A. This is evident from the plot that the algorithm is aptly able to estimate the current bias included. The estimate of current bias is well within the limits of bounds defined by the covariance of the state variable defined for DC current bias.

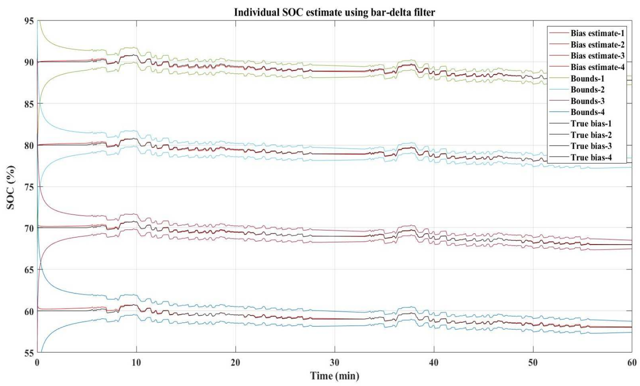

Fig. 12. Individual SoC estimate using Bar-Delta filtering

Fig. 12. demonstrates the individual SoC estimate of each cell with their corresponding initial SoC levels. It is very evident from the plot that the estimation made is accurate. If SPKF is applied for each cell separately, despite being a better algorithm the time taken and computational burden on microprocessor will be almost four times than the one applicable in Bar-Delta implementation.

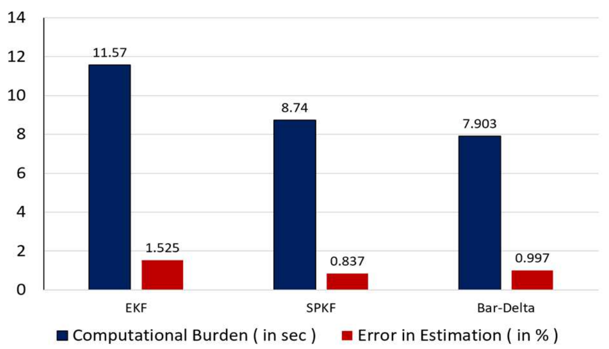

Fig. 13. Comparison of Computational Burden and Error in SoC Estimation

Fig. 13. shows a comparative study of all the three algorithms in terms of Computational Burden by time taken to get the estimation and percentage error in estimation i.e., represented by RMS SoC estimate error. The algorithm which has higher computational burden that will required embedded system with high storage and processing capability which will increase the cost of BMS Kit. Model accuracy for all the three algorithms are almost the same and can be easily implemented with a BMS chip.

VI. CONCLUSION

The nonlinear Kalman Filter techniques were studied and implemented for SoC estimation. EKF and SPKF were implemented with the help of MATLAB coding, and it was observed that SPKF performed better than EKF as it does not use any approximations, and hence this technique was chosen to be implemented for estimation of SoC for battery pack having more than one cell. The Bar-Delta filtering algorithm was implemented for SoC estimation of battery pack having four cells in series combination and the results obtained are discussed in detail and it proved to be an efficient as well as an accurate estimation technique for SOC. The objectives defined are clearly met in each implementation.

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