INTERNATIONAL JOURNAL of RENEWABLE ENERGY RESEARCH
G. G. Ravali and K. N. Raju, Vol.13, No.2, June, 2023

Enhanced Lithium-Ion Battery Model for estimation of Degraded Capacity and SoC Using Sigma Point Kalman Filter

G. Geetha Ravali*, K. Narasimha Raju**‡

*Department of Electrical and Electronics Engineering, Research Scholar, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India

**Department of Electrical and Electronics Engineering, Professor, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India

(183060021@kluniversity.in, narasimharaju_eee@kluniversity.in)

‡Corresponding Author; Department of Electrical and Electronics Engineering, Professor, Koneru Lakshmaiah Education Foundation, Vaddeswaram, AP, India, Tel:+91 9666693394, narasimharaju_eee@kluniversity.in

Received: 17.11.2022 Accepted:08.02.2023

Abstract-For an effective battery management system (BMS), accurate estimation of the state of charge (SoC) is essential, which signifies the residual charge in the battery. In addition, SoC estimation relies on aspects such as appropriate battery modelling, battery age, ambient temperature, and many unknown parameters. Thus, the research focuses on developing an accurate battery cell model which includes these non-linearities and ageing effects. Existing mathematical models emphasize reflecting non-linearities such as diffusion and hysteresis effect, but they fail to incorporate the capacity fading effect model. Since the total capacity of the battery degrades concerning ageing. Including the capacity fading model in the battery cell model is critical. This work is on developing a mathematical model for the capacity fading effect. The capacity degradation model has been developed based on the temperature rate dependency and the number of cycles utilized for SoC estimation. The proposed model has been employed and given as input for the state estimation technique to obtain accurate SoC. Capacity loss for the sample battery cell is modelled up to 1000 cycles.Further, the effectiveness of the proposed model is validated and simulated using the SPKF algorithm in MATLAB/Octave environment. Throughout the evaluation procedure, SPKF achieved an estimation error of less than 1%. The proposed capacity fading model and estimation approach based on SPKF may thus provide high robustness and accurate SoC estimation.

KeywordsLi-ion battery, SoC estimation, battery model, Capacity fading, Degradation, Kalman Filter.

1. Introduction

Nowadays, the global automotive industry is undergoing a substantial electrification transformation as governments increasingly pay attention to energy and environmental challenges. Lithium-ion battery-powered battery electric vehicles (BEVs) are increasingly becoming dominant in the automotive sector [1]. The power battery system, as the primary energy source in BEVs, directly impacts the vehicle's overall performance [2]. However, as the time frame advances, lithium-ion batteries experience significant ageing, resulting in a reduction in energy and power output [3]. It will also result in an inaccurate assessment of battery conditions, such as SoC and capacity, which reflect imprecise energy and power limits. Significant roadblocks to BEV adoption and widespread use. Proper battery control and management are required to ensure that the battery pack's performance is maintained and that its life is extended. To manage a rechargeable battery pack, a BMS is an electrical system that monitors its states and characteristics [4]. These include cell voltage, current, temperature, state of charge (SoC), state of health (SoH), state of power (SoP), and other battery states. The BMS monitors these states, capable of making decisions on when to charge and turn off the battery based on the usage to avoid dangerous operating conditions of overcharging/discharging. SoC estimate is a critical component of a BMS that impactsvarious other functions. Other computations, such as SoH, cell balance, and power calculations, use the SoC value as an input. SoC is used to calculate the remaining battery's capacity, which has a significant relationship with its performance.

Furthermore, effectively maintaining batteries and identifying their power distribution strategy in EVs requires an accurate computation of the battery's SoC. Due to the battery's sophisticated electrochemical process and different effect considerations for practical applications such as battery ageing, ambient temperature, and charging/discharging current rate, measuring the SoC directly is difficult. As a result, estimating the SOC on board requires a reliable and time-saving technique [5].

Because the battery cell is complicated and associated with an electrochemically closed approach, evaluation of inherent reactions of electrochemical nature and its state parameters doesn't happen straightforward. A comparable battery model has to develop for output state estimation. Depending on how extensive the research work is directed on the intrinsic configuration of the battery cell, the method associated with modelling has been categorized into (1) White box model based on the battery laws and mechanisms; (2) Black-box model which emphasizes bulky dataset and white model's framework and calculation is far more complicated, whereas the black model is simply a data-driven technique, with output values acquired by various samples and training methods being significantly varied. (3) Grey box model is attributed to large datasets and vague knowledge of detailed system laws; the most common models of the Li-ion battery are the equivalent circuit model (ECM), Impedance model (IM), and electrochemical-based equivalent circuit model (EECM) [6]. As a result, they are challenging to implement in real-world vehicle operations. Overall, ECM configuration is straightforward and the most practical method for vehicular deployment. Regardless, the issue has yet to be remedied [7]. Because of the system's complex non-linearity and time-variability, modelling a battery that considers all conceivable parameters may be impossible. In consequence, a prognostic battery model is constructed by analyzing essential variables from a particular experiment cycle, such as voltage (V), current (I), battery temperature (T), and operation time (t). This method can provide precise battery health information, but it has drawbacks when utilized online. Furthermore, the ambient environment (pressure, temperature etc.) may contain too many external uncertainties that alter the battery's intrinsic characteristics of electrochemical.

Data-driven based SOC estimating algorithms have a lot of interest since they have a lot of computational capacity and can handle any complex non-linear function for the reasons stated above. Due to technical improvements, fast computer processors, big data availability, and high-capacity storage devices, more research and development is going into estimation techniques of type data-driven based SoC assessment. Model-based SoC estimate algorithms can be robust and precise since they rely on a comprehensive understanding of the system rather than dependency on datasets. A model-based approach is required for many problems in engineering and physics. However, developing the perfect model of any system raises both practical and theoretical concerns [8]. The main issue in LIB SoC estimation is to enhance the algorithm's accuracy, productivity, and robustness despite retaining the algorithm's minimal computational complexity so that low-cost BMS hardware can be implemented [9]. The main goal of the research is to develop an efficient SoC method that strikes a balance between accuracy and compactional complexity. Due to uncalibrated sensors of current and voltage, an initial SoC, an inaccurate battery model, and a capacity fading model can cause SoC errors [10].

Nonetheless, in the preceding literature reviews, battery cell SoC and capacity have been calculated individually. Nevertheless, there isn't much research evaluating a battery pack's SoC and capacity combined. As a result, a low-SoC-error-cause technique must be established.

This work proposes a combined Li-ion battery model that addresses hysteresis, operating temperature, and ageing procedure concerns. Eventually, the simulation results from MATLAB/Octave environment are utilized to validate and verify the proposed method's efficacy. The following are the article's primary contributions, taking into account the points mentioned earlier:

1) To develop an improved Li-ion battery model considering the impacts of hysteresis, operating temperature, self-discharge, and ageing.

2) To introduce an advanced and simple method for estimating the battery's degraded capacity, further assisting in accurate SoC estimation.

The rest of the article has been structured as stated: The related works on battery modelling and state estimation are discussed in Section II. The structure of the battery model chosen for this study is described in Section III. The robustness of the model based SoC estimators is investigated in Section IV. It indicates that when model uncertainties are considered, such SoC estimators are fundamentally problematic in terms of robustness. Section IV discusses capacity and SoC estimation analysis, including the degradation mechanism. Section V identifies and demonstrates the properties of the proposed algorithm convergence. Section VI is followed by results and analysis of SoC estimation. Section VII concludes with the significance of the proposed SoC estimator, which combines the system model with SoC and capacity estimation.

2. Related Works

Through tests and theoretical/numerical investigations, a lot of effort has gone into studying capacity fading [11]. Xiong, Rui and Yongzhi Zhang [12] presented the Li-ion battery prognostics based on a real battery management systems in EV application. The experimentation categorized the capacity loss into three groups: primary and secondary active material losses, rate capability loss, and total capacity loss. However, they did not create a model to describe the capacity loss caused by diverse processes quantitatively. Safari and Morcrette [13] projected a multimodal associated physics-based ageing model for Li-ion batteries to anticipate a capacity decrease. Also, hypothesized about the direction in which capacity fading is being driven by anode SEI growth leading to the Li-ion depletion or utilization in the course of

SEI growth stood as the principal driver for the cycling degradation process [14] [15] [16].

Due to the coupling relationship, joint capacity estimation along with additional battery states includes sequential estimation over SoC and battery capacity. Due to their reasonable precision and robustness, some joint algorithms are drawing attention to these estimation quantities. With the assistance of specific advanced estimation techniques which incorporate the concept of filtering, the battery states and model parameters are subjected to joint estimation. The advanced techniques are PI observer , H^{∞} filter [17], Luenberger observer, particle filter (PF), Kalman filter (KF), Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF), Cubature Kalman filter (CKF); all these conceptually work under the prerequisite condition of accurate ECM model. Wei, Zhongbao, Jiyun Meng and Jinhao [18] has been implemented simplief model-based for the SoC estimation with battery model of 2nd order resistance-capacitance (RC) ECM considering the non-linearities. Meanwhile, the evolutionary algorithm recognizes capacity as an important element in the model (GA). Chen, Cheng, Rui Xiong, and Weixiang Shen [17] proposes a multiscale dual H-infinity filter for real-time estimation of SoC and capacity under various timeframes correlating to gently varying power capability and fast varying battery conditions. [19] provides a combined methodology for predicting SoC and capacity that combines KF with the recursive least square (RLS) method, through the adaptative update of model parameters employing the novel vector grouping under RLS to account for the model parameter fluctuation rates. The goal is to improve estimation precision. Rezaei and Habibifar [20] provides a consecutively associated model of battery pack dependent on second-order RC ECM Li-ion. Single-cell capacity, SoC, and model parameters in battery packs are then precisely estimated using a multiscale extended KF algorithm.

On the other hand, deterioration of Li-ion rechargeable battery remains sequential as well as often entails cycles of a certain range (100-1000), with the subsequent development of degradation being tightly tied to the earlier information of degradation or fading all over operations conducted under the charge/discharge cycle [21]. Furthermore, specific beneficial qualities are derived through patterns linked with charging and discharging that appear with individual age-related fluctuation development. Certain variables tend to be viewed progressively with time-series signals, with the quantity of current being related to historical values over time. The traditional approach of data-driven like Fuzzy logic (FL), support vector machine (SVM), Neural network (NN) and genetic algorithm (GA), on the other hand, are ineffective at learning long-term dependencies, making superior in achieving accurate estimation for extended-time capacity forecast problematic.

According to some researchers [22], a deeper depth of discharge (DoD) promotes capacity fading, which correlates with the established logarithmic distribution of conversion efficiency as a factor of the battery's DoD. The Department of Defense, according to other researchers, does not seek to accelerate capacity weakening [23]. A higher starting outcome of SoC stemmed from a faster rate of capacity fading during the cycling process, although opposite results were recorded for storage cells. Furthermore, a high SoC has been proven for a considerable effect on fading effect not influenced by calendar loss. When it comes to temperature, there are no contradicting findings. According to experimental observations [24], extreme temperature rate as a weight component that might be described using the Arrhenius equation, a temperature dependency with relation to chemical reaction. Overcharge/discharge, and superior C-rates have all been studied towards the acceleration of capacity fading [25]. Real-world EV operation conditions will be used to mimic capacity fading. Because this represents the capacity that has been irreversibly degraded in the cell, merely accurate capacity fading has been measured. With a reduced current, capacity fading owing to rate capability loss can be rectified [26]. If the cell impedance increase is known, rate capability losses can be calculated numerically. Consequently, primary cycle losses have been recognized, with calendar losses remaining unaccounted for. When compared to cycling losses, Li-ion cells have relatively low calendar losses, only a few percentage points per year, and hence have no impact on capacity fading.

It is critical to precisely calculate the model parameters before using the battery model in a vehicle system. These characteristics are frequently determined through time-consuming and resource-intensive, prior domain knowledge, and error-prone, cumbersome experiments [27]. Conducting such costly and time-consuming experiments to evaluate the performance characteristics of various types of batteries is not feasible. Furthermore, capacity losses are not considered in the existing battery models. As a result, a mathematical model for Li-Ion batteries has been suggested that accounts for capacity losses and further estimation is carried out. Thus, accurate modelling and estimation be capable of accelerating the vehicle performance to a greater extent and improving the driving range of the EV.

3. Li-ion Battery Modelling

In this section, first, we will discuss the Li-ion battery model subjected to different non-linearities and then address the capacity degradation model.

3.1 *Enhanced Battery Model*

To attain an accurate estimation of SoC and battery pack capacity, the core criterion is modelling of battery accurately which describes all non-linear characteristics such as diffusion, hysteresis, and capacity fading effect [27] [28]. The enhanced self-correcting battery model (ECM) has been broadly utilized in real-time applications for exemplifying the dynamic characteristics of the battery and serves as the source for the design and control of the battery. Figure 1 depicts the schematic arrangement of the enhanced self-correcting battery model. Compared with other electrochemistry models, this ECM has the finest advantages of high precision and low computational complexity. The model which is developed is now being utilized in the grouping of state estimation algorithms and adaptive filters.

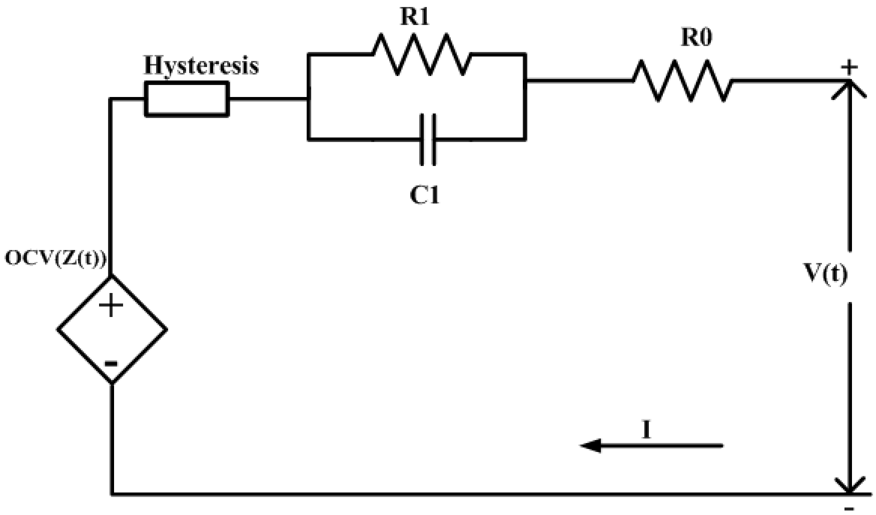

Fig. 1. Enhanced Self-correcting Battery Model

The model considers the parameters meant for ohmic resistance, open-circuit voltage (OCV) as a function of SoC, diffusion, and hysteresis effect. With the help of an equivalent circuit, the discrete form of equations can be approximated as:

The state equation below defines all the dynamic properties,

$$x[K+1] = A[K]x[K] + B[K]u[K] \tag{1}$$

$$\begin{bmatrix} z[K+1] \\ i_{R1}[K+1] \\ h[K+1] \end{bmatrix} = \begin{bmatrix} 1 & 0 & 0 \\ 0 & A_{RC} & 0 \\ 0 & 0 & A_H[K] \end{bmatrix} \begin{bmatrix} z[K] \\ i_{R1}[K] \\ h[K] \end{bmatrix} + \begin{bmatrix} -\eta[K]\Delta t/Q & 0 \\ B_{RC} & 0 \\ 0 & A_H[K]-1 \end{bmatrix} \begin{bmatrix} i[K] \\ sgn(i[K]) \end{bmatrix} \tag{2}$$

Where Z represents the state of charge (SOC),

$$\mathrm{Z}[k+1] = \mathrm{Z}[k] - \frac{\Delta t}{\mathrm{Q}} i[k] \tag{3}$$

In discrete time, the current is assumed constant throughout the sampling interval of is the initial state of charge, is the instantaneous current discharged from the battery, indicates the coulombic efficiency, and available capacity is denoted with.

The output equation below computes battery terminal voltage,

$$V[K] = f(x[K], u[K]) \tag{4}$$

$$V[k] = OCV(z[K], T[K]) + M_0 S[K] + Mh[k] - R_1 i_{R1}[K] - R_0 i[K]$$
(5)

Here, i represents battery current, i_{R1} represents the current flowing through R1, Q represents rated capacity, η denotes coulombic efficiency, A_{RC}, B_{RC}, A_H, M_0, M are the arbitrary constants, and sgn forces stability for both dis/charge scenarios.

3.2 Degraded Capacity Model

From the SoC formula given in Equation (3), the quantity Q denotes the total capacity, which is not a static quantity: as the cell ages, it gradually decreases [29]. Due to aging, total capacity will degrade which deteriorates the battery performance. In Li-ion cells, the main cause of battery ageing is the loss of useable lithium ions, together with the formation, origination and thickening of the solid electrolyte interface (SEI) film caused by undesirable side reactions that occur regularly during the chemical process [13] [14]. The factors affecting these sources of ageing are SoC, temperature, C-rate, and depth of discharge (DOD subjecting to ageing enhancement. Also, there exist various physics-based degradation mechanisms such as surface cracking, pore-clogging, active material dissolution, diffusion into SEI, Lithium plating, and electron tunnelling when considered give more accuracy. Besides, it requires domain knowledge of spectrum analysis and single particle battery model (P2D), instead of the traditional electrochemical model that was developed. The above degradation mechanism occurs due to these degradation procedures like calendar ageing (resting cell for a long time), cycle ageing (constantly charging and discharging), and drive cycle (constantly repeating with a certain current profile) [30].

With reasonable accuracy and reduced model complexity, the aging effect can be incorporated using the temperature and power-law relation [31] [32]. The loss of lithium ions is usually caused by the formation and thickening of the SEI film. It is widely accepted that the film thickness is proportional to the square root of time, i.e. $t^{1/2}$, and so is the capacity loss, especially for the calendar life. Here consider the main aging mechanism is the lithium ion loss, the capacity loss would be considered to follow a power law relation with the cycle times. And it is widely accepted that, for most chemical process, the influence of temperature on the reaction rate follows the Arrhenius law. Thus, the influence of temperature on capacity loss could also be modeled by this Arrhenius law.

The mathematical model for capacity loss is developed by using a combination of the Arrhenius equation and power-law relation. As per theArrhenius equation, at the corresponding temperature for every charge/discharge cycle, the capacity loss is given by the following Equation (6),

$$Q_{loss} = A \times \exp\left(\frac{-E_a}{RT}\right) \qquad (6)$$

Where, Q_{loss} is the relative capacity loss, A is the pre-exponential factor, T is absolute temperature, E_a is the activation energy, and R is the gas constant. If N denotes the number of charge/discharge cycles to be considered, the capacity loss can be determined using a power-law relationship with N times the power of the adjustable factor (z).

$$Q_{loss} = A \times \exp\left(\frac{-E_a}{RT}\right) \times N^z \qquad (7)$$

Q_{loss} is the relative capacity loss at the N^{th} cycle, N is the number of cycles, and z is the power law factor. Therefore, with the developed battery and capacity degradation model, the BMS could produce an accurate battery capacity estimation and gain the precise SoC and SoH of the battery. For the battery cycling under an unchanged working conditions, the model parameters A, Ea/R and z are directly obtained by curve fitting.

Table 1&2 listed below shows the battery specifications and parameter values of the mathematical model for the determination of capacity loss.

Table 1. Specifications of the battery cell

Parameter	**Content**
Type	LiNMC
Nominal Capacity	24Ah
Nominal Voltage	3.6 V
Upper/Lower cut off voltage	4.2/2.5 V

Table 2. Parameter values of capacity degradation model

A	$\boldsymbol{E_a}$**/R**	**z**
0.3687	1472	0.6405

From the open source platform available (http://mocha-java.uccs.edu/BMS1/CH02/ESCtoolbox.zip), the ESC tool box-dataset has been utilised for developing the SoC estimation process.

4. General concept of State Estimation Techniques

Since SoC is not a measuring quantity unlike voltage, current, and temperature measurements. It can only be estimated with the support of state estimation techniques. There exist various state estimation techniques for battery SoC estimation. In which, voltage-based/look-up table and current-based/coulomb counting approaches are the conventional techniques [33]. Whereas, model-based and data-driven are the advanced estimation techniques which predominantly drawn the researcher's attention in the past times. Model-based approaches, on the other hand, produce more accurate long-term results than current and voltage-based methods, which fail to deliver accurate estimation due to flaws such as open-loop computation, initial SoC variation, and uncertainty disruption in real-time applications [34,35,36]. In general, model-based state estimators combine voltage, and current measurements, using a cell model to do so, to produce better state estimates [37]. Thus, it is a widely accepted concept that considers battery model and filter. The applied filtering technique is the Kalman filter (KF) algorithm, which develops with state-space equations. Figure 2 below depicts the overall structure of implementing the model-based state estimation technique in addition to the battery model.

Consider the non-linear state-space model as follows,

$$x_k = f(x_{k-1}, u_{k-1}, w_{k-1}) \qquad (8)$$

$$y_k = h(x_k, u_k, v_k) \qquad (9)$$

Where, x_k is state equation, y_k is output equation, u_k is input signal, v_k denotes sensor-noise random input, w_k denotes process random noise. These model-based estimation techniques work on the concept of a 2-step estimation problem, i.e., state prediction, and measurement update.

The flowchart of the KF is demonstrated below in Figure 3. Initially, the estimator is given with an initial guess of state and covariance (uncertainty) at time zero and then following the 2-step problem. At every time step, the output of the estimator is state estimate and error covariance. Hence, this is a recursive process.

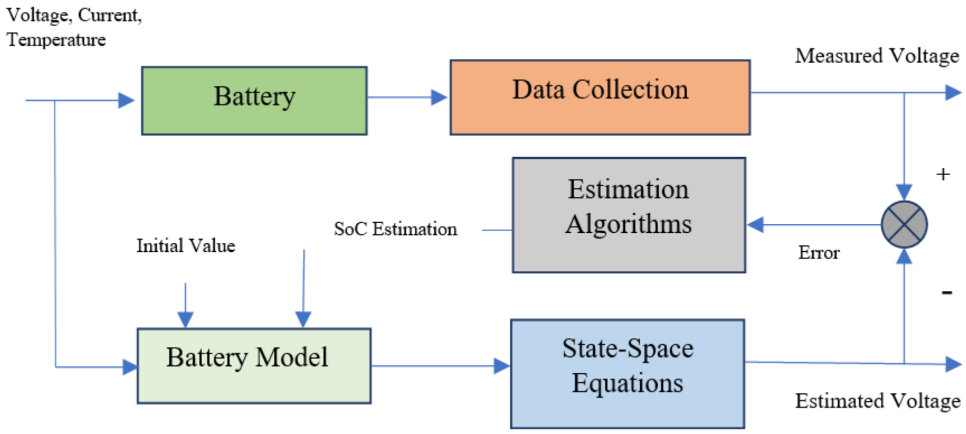

Fig. 2. Overview of model-based state estimation technique

Under certain conditions of probability that consider zero-mean Gaussian environment for inclusion of process noise and measurement/sensor noise, KF implements minimum mean square error, optimal state estimator, for a linear system. Because KF is largely concerned with stochastic systems, it is preferable to such estimating problems. But this technique fails for non-linear cases [38, 39-41]. Since battery cells are non-linear devices, models that describe battery cells ought to be non-linear. The correlation between the output terminal voltage and SoC in a rechargeable battery is non-linear, hence distribution might not consider the Gaussian environment. In such an instance, the KF perhaps incorrectly estimate the system's condition [42]. As a result, non-linear Kalman filters, namely the extended Kalman filter (EKF) and the Unscented/ Sigma point Kalman filter (UKF/SPKF) are being used to generalize the method. The non-linear system is linearized using piecewise linearization about each interval and then KF is applied [43, 44]. To come up with equations that are a linear approximation to the actual non-linear model, implementation of math function is required using derivatives, which in-depth required lot of approximations use to the digital process and thus increases the error rate, thus leading to huge loss in estimation accuracy [45, 46].

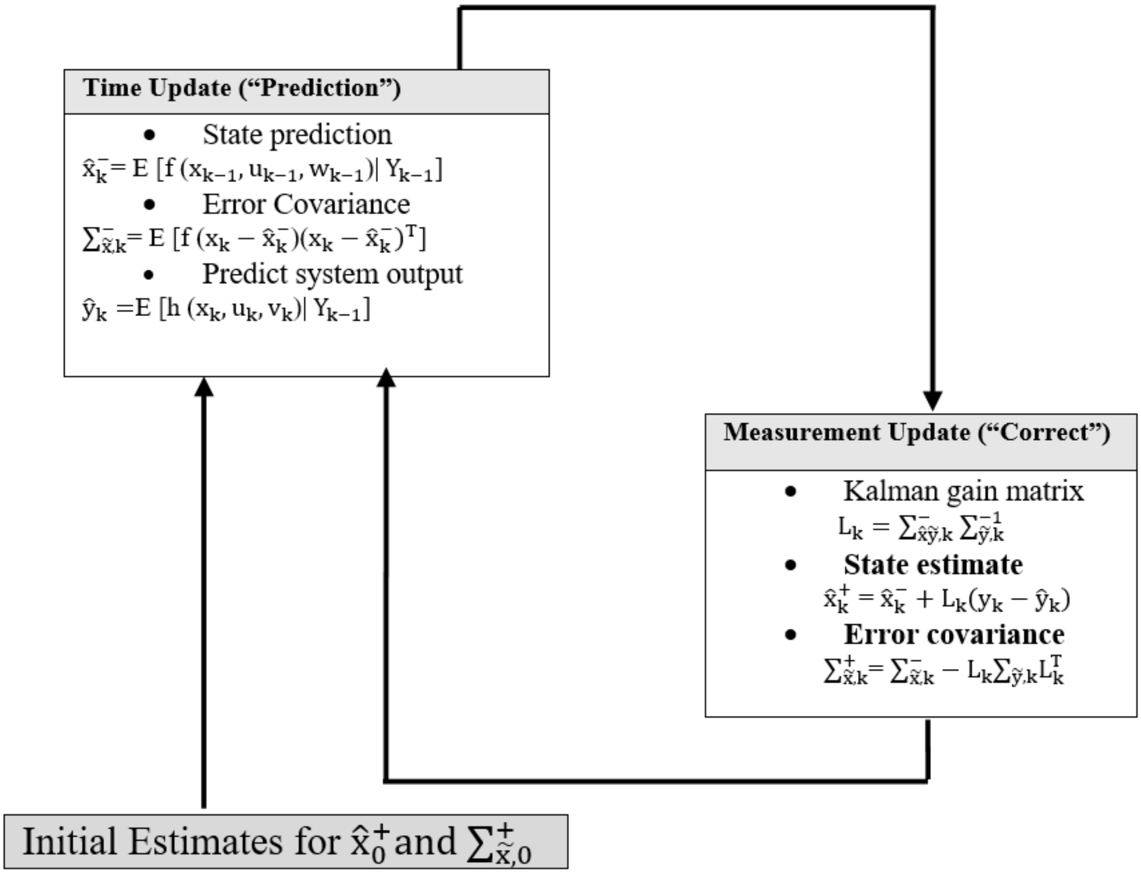

Fig.3. Implementtaion flowchart of KF, EKF algorithm

Table 3. Illustrates the comparison among various model-based methods for SoC estimation [38].

Method	Model	Assumptions	Complexity	Estimate accuracy	Response Time
LKF	Linear	• Linear function • Model error & measurement error (noises) must be Gaussian with zero mean	Low	Low	Low
EKF	Slightly Non-linear	• $E(fn(x)) = fn(E(x))$ • Taylor-series expansion to linearize system equations for covariances	Medium	High	High
UKF/SPKF	Highly Non-linear	• 2L+1 Sigma points	High	Very High	High

To overcome the drawbacks of EKF, the new estimation technique; SPKF or UKF is recommended since it is a derivative less non-linear Kalman filter. In Sigma point Kalman filtering technique, only one point. i.e., mean to approximate a new non-linear function for a non-linear function [47]. Therefore, a group of points including the mean is considered and then approximates around those multiple points in the source gaussian and finally transformed and approximated. Moreover, there is a trade-off relation between the number of points and approximated precision. A comparison of various model-based adaptive filtering methods has been studied and listed in Table 3.

5. Implementation of Sigma Point Kalman Filter

SPKF [48] utilizes the sigma-point method to propagate the uncertainty of input RV to the output of the model's (possibly) non-linear state and output equations. As a result, the state estimation problem is approached using the sigma-point strategy of propagating data through a non-linear function. These sigma points must model all randomness together: Process noise, sensor noise, and state uncertainty. Applying this procedure to generic-probabilistic-inference solution yields SPKF steps. It is a convenient way to store all the sigma points in Matrices and vectors, and then compute the means and covariances from the sigma points. The framework of SPKF is described in Figure 4.

5.1 *Central Principle of Sigma-Point Methods*

Illustrating the statistics of a non-linear function,

1. Group of χ sigma points have been selected such as the weighted values of mean and covariance of sigma points precisely correlate with the prior RV mean $\bar{x}$ and covariance $\sum_{\tilde{x}}$ that is being developed (input given to function).
2. Propagating these points through the non-linear function, thus developing a group of transformed sigma points $\mathcal{Y}$.
3. Approximating the posterior mean $\bar{y}$ and covariance $\sum_y$ through statistical analysis under mean and covariance for transformed points of $\mathcal{Y}$.

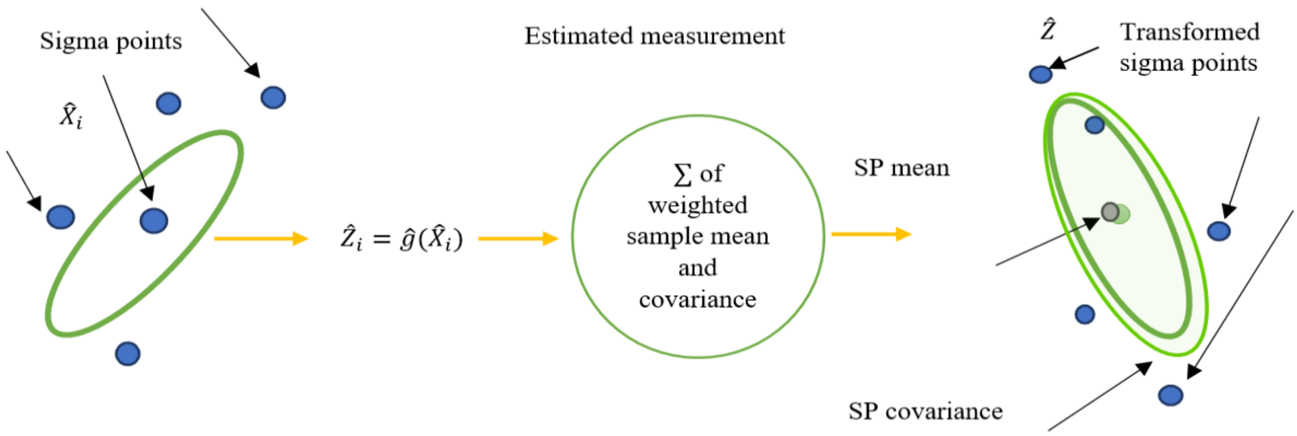

Fig. 4. Framework of sigma point kalman filter

5.2 Approximating the Uncertain variables to sigma points

For the input random variable $x \in \mathbb{R}^L$, and $x \sim (\mu, \sum)$; where μ or $\bar{x}$ is mean and $\sum$ is covariance, then p+1=2L+1 (L=Dimension of the system) sigma points are generated with the matrix set elements of

$$X_0 \text{ or } \bar{x} = \hat{X}(k|k) \tag{10}$$

For i=1……., n

$$X_i(k|k) = \bar{x} + \left(\gamma\sqrt{\textstyle\sum_{\tilde{x}}(k|k)}\right)_i \tag{11}$$

For i=1…….,2n

$$X_i(k|k) = \bar{x} - \left(\gamma\sqrt{\textstyle\sum_{\tilde{x}}(k|k)}\right)_{i-n} \tag{12}$$

Therefore, the sigma points as a group generated as follows,

$$\chi = \left\{\bar{x}, \bar{x} + \sqrt{\textstyle\sum_{\tilde{x}}(k|k)}, \bar{x} - \sqrt{\textstyle\sum_{\tilde{x}}(k|k)}\right\} \tag{13}$$

Values assigned for the weights have been listed in Table 4 for computing the weighted mean and covariance $(\alpha^{(m)}, \alpha^{(c)})$ can be employed based on two different methods that include Central Difference Kalman Filter (CDKF) and the Unscented Kalman Filter (UKF).

Table 4. Weighing factors for different SPKF/UKF methods

Method	γ	$\alpha_0^{(m)}$	$\alpha_k^{(m)}$	$\alpha_0^{(c)}$	$\alpha_k^{(c)}$
SPKF/UKF	$\sqrt{L+\lambda}$	$\frac{\lambda}{L+\lambda}$	$\frac{1}{2(L+\lambda)}$	$\frac{\lambda}{L+\lambda} + (1-\alpha^2+\beta)$	$\frac{1}{2(L+\lambda)}$
CDKF	h	$\frac{h^2-L}{h^2}$	$\frac{1}{2h^2}$	$\frac{h^2-L}{h^2}$	$\frac{1}{2h^2}$

Where, $\lambda = \alpha^2(L+k) - L$, within the range of $(10^{-2} \le \alpha \le 1)$ and $k \in \{0,3,-L\}$.

For the random variable of Gaussian probability density function, the value chosen for tuning parameters; β=2, and h=$\sqrt{3}$.

Weighted mean, the covariance of χ equivalent to the actual with added weights of $\{\gamma, \alpha^{(m)}, \alpha^{(c)}\}$; $(\alpha^{(m)}, \alpha^{(c)}$ are real scalar quantities) is computed as

$$\bar{x} = \textstyle\sum_{i=0}^{n} \alpha_i^{(m)} \chi_i \text{ and} \tag{14}$$

$$\textstyle\sum_{\tilde{x}} = \sum_{i=0}^{n} \alpha_i^{(m)} (\chi_i - \bar{x})(\chi_i - \bar{x})^T \tag{15}$$

Following Figure 5 indicates the framework of the sigma point Kalman filter.

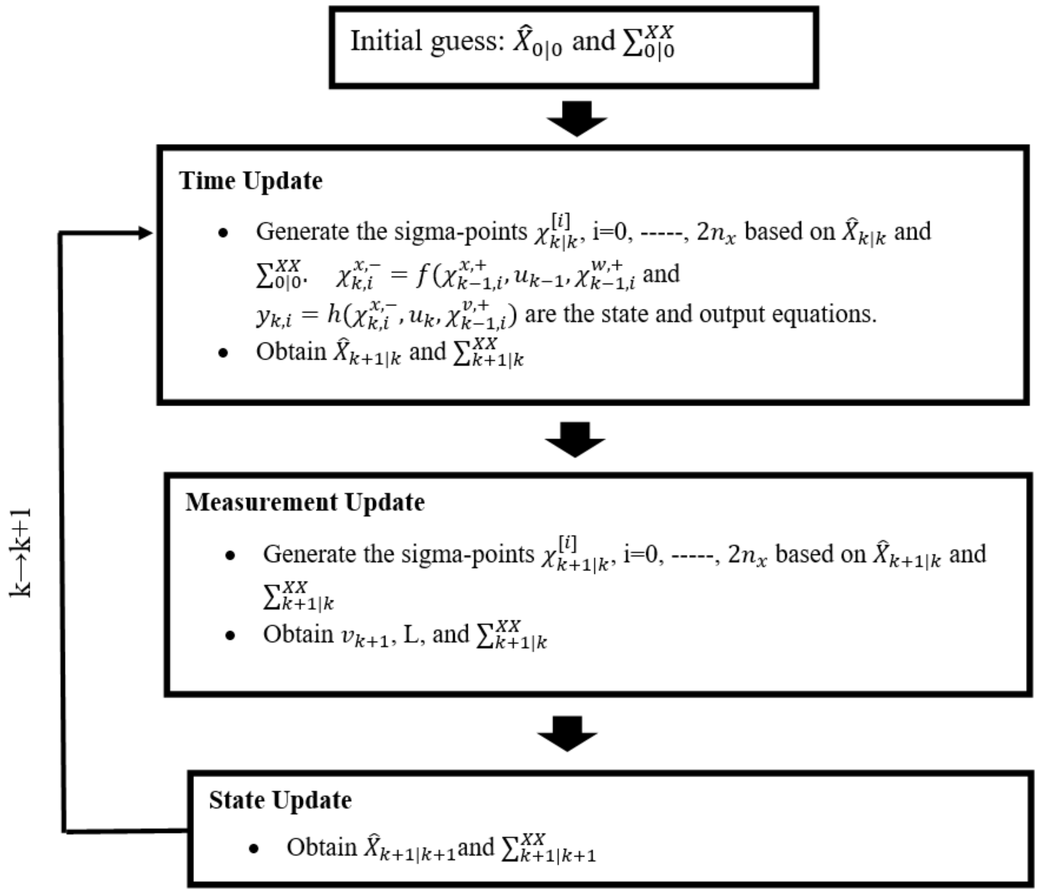

Fig. 5. Flow diagram of SPKF/UKF algorithm

So, certain points carried on source gaussian for mapping them on target gaussian later propagating it through non-linear function for computing the mean and covariance of transformed gaussian. Such transformation is termed unscented transformation. Moreover, the SPKF implementation is independent of the model used. Hence, implementation is easier.

The robust SoC estimation with the SPKF algorithm for Li-ion batteries is accomplished against core problems such as unknown initial SOC, current noise, aging, and temperature effects is studied and the results are shown in the figure. The SOC estimation result will be more accurate because the capacity estimation result is relatively accurate. It is observed from the result that the rate of capability loss obtained is proportional to the increased number of cycles.

6. Simulation results and Analysis of Capacity and SoC estimation

The performance of the proposed SoC estimator has been assessed based on the measurement system, and the values obtained have been tabulated in Table 5. From Figure 6, it is found that after 1000 cycles, the amount of capacity faded to 20.5 Ah. Consistently, the major sources of capacity loss were noticed as a function of cycle count and temperature. To evaluate the SoC estimator performance, the three metric criteria preferred are maximum error (MAX), root mean square error (RMSE) and mean absolute error (MAE). Evaluation of RMSE is to check the robustness of the SoC estimation; MAX exemplifies SoC value in the abnormal system response; MAE indicates the accuracy of the SoC estimation.

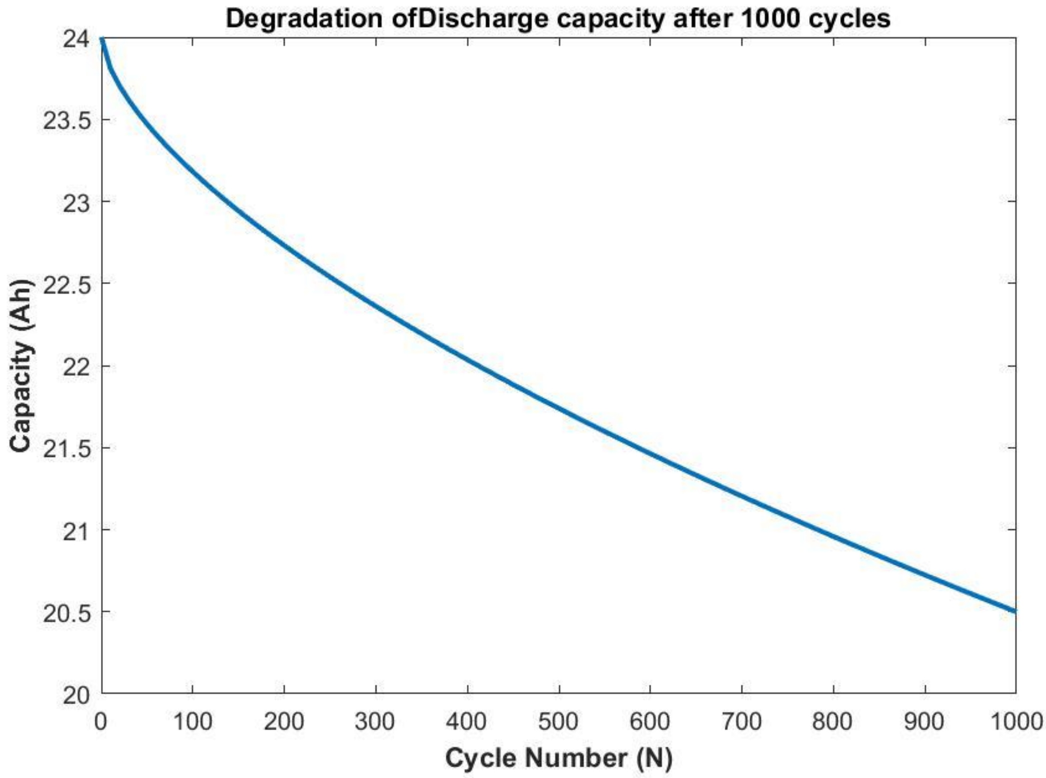

Fig. 6. Capacity degradation of Li-ion cell after 1000 cycles

$$\text{RMS}= \sqrt{\frac{1}{N}\sum_{j=1}^{N}(v[k]-\hat{v}[k])^2} \quad (16)$$

$$\text{MAE}= \frac{1}{N}\sum_{j=1}^{N}|v[k]-\hat{v}[k]| \quad (17)$$

$$\text{MAX}= \max\ |v[k]-\hat{v}[k]| \quad (18)$$

Additionally, it should be observed that the result obtained is based on the accurate model parameters. Consequently, the error never converges to zero, but it stays within the predicted bounds. For the reason that the actual system is constantly being excited by the process noise and the measurements, we make are going to constantly have the additive sensor noise on them. So, the error lies within the bounds seems correct operation of the Kalman filter. For illuminating the robustness of the proposed approach, the algorithm implements the full SPKF using the combined battery model in Octave for SOC estimation. It shows excellent stability and high precision rate under the combined battery and capacity model with dynamic conditions and aging stresses.

Generally, the estimation error bounds lie under the range of $\pm 3\sqrt{\Sigma_{\tilde{x},k}^{+}}$ (3 sigma bounds) for 99% assurance of estimate's accuracy.

Table 5. Robustness evaluation of SoC estimation using SPKF algorithm

Performance Metrics	Error in %
RMS	0.5101
MAE	0.3754
MAX	1.0029

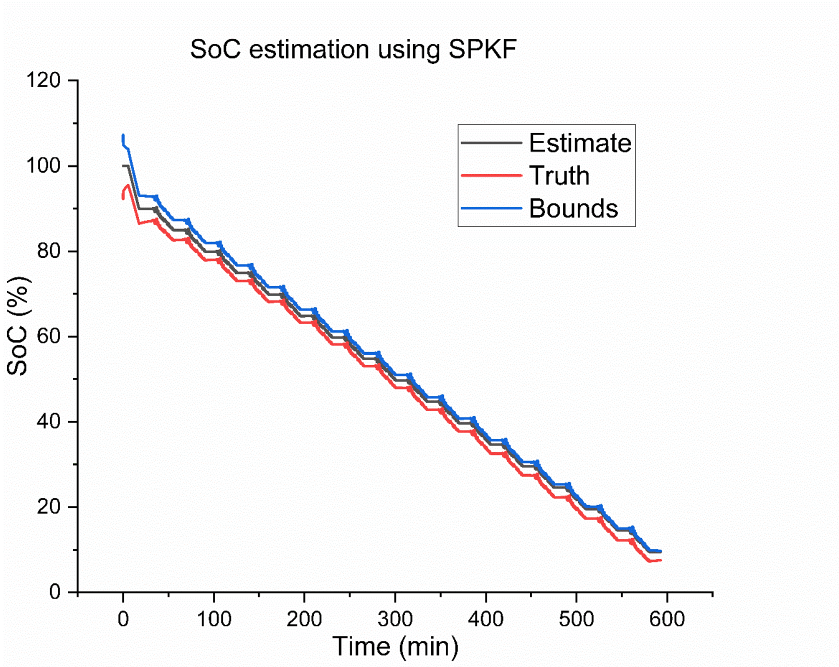

Fig. 7(a)

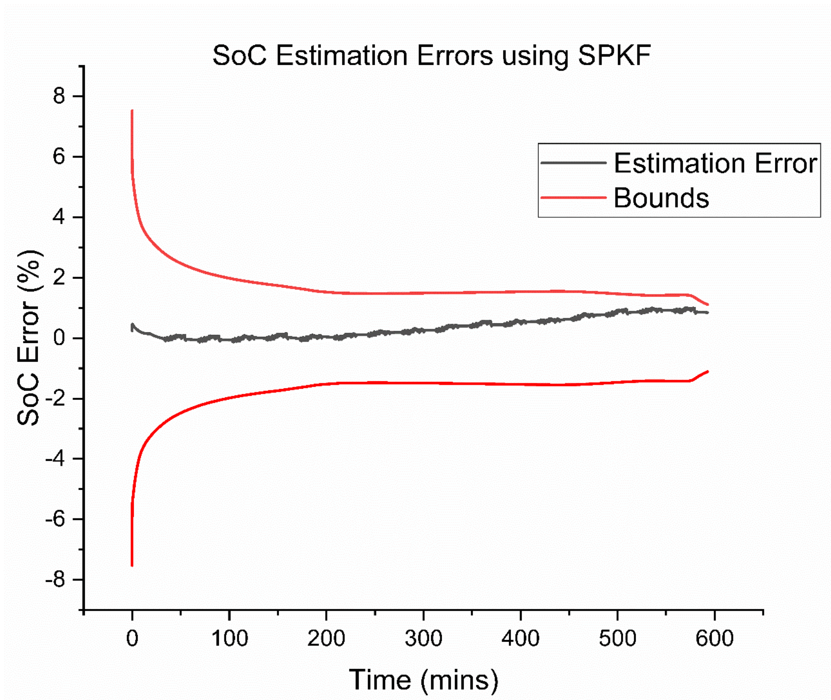

Fig. 7(b)

Fig. 7 (a) & (b). SoC Estimation with consideration of battery ageing effect using SPKF algorithm

From the simulation results depicted in Figure 7 and Table 5, the RMSE value of the SoC estimation error obtained is 0.5101%, and the Percent of time error outside bounds is 0%. Thus, to work under the highly non-linear case, the SPKF approach provides better accuracy and robustness under accuracte modelling of Li-ion battery sondiering the model uncertainties, capacity fading and temperature effect. Hence, it is concluded that SPKF performs effectively as an SoC estimator using the ESC model.

Table 6: Performance Analysis

Method	Estimation Accuracy % (MAX)	Run Time (Iterations)
EKF	0.899	35560
SPKF	1	46535

Table 6 signifies the quantitative comparison for the estimation accuracy and response time for the state estimation techniques. To make the comparison sensible, only non-linear KFs are considered.

7. Conclusion

To understand the performance characteristics of Li-ion rechargeable batteries, a thorough investigation of modelling, estimation, and prognostics was examined. Furthermore, modelling the capacity degradation effect explains the uncertainty of determining capacity loss as the battery's life expectancy is reduced under the influence of specific charge and discharge cycles. Given this, capacity loss has been defined as a proportion of the cycle count. The study predicted and demonstrated the battery's capacity fading after 1000 cycles. With an estimation error of less than 1%, the proposed SPKF approach effectively evaluated the capacity values, providing improved convergence, precision, and stability. This technique is better for BMS of EV applications because it has a lower error rate. This method's main strengths are real-time estimation, suitability for various LIB chemistries, and robust and accurate SoC estimation.

This research provides numerous recommendations for achieving accurate and reliable SOC estimation to solve the issues currently faced in real-time EV applications. Conversely, the approach's drawback is that a rigorous study of an experimental dataset is necessary to comprehend and identify input parameters for various battery chemistries. Different datasets through real-world electric vehicle driving patterns, running at various temperatures and with high-current discharge circumstances, are necessary. To construct a model-based and data-driven SOC estimate technique, the appropriate quantity of battery model parameters and hyperparameters must be set with precision. Extensive research needs to be done to construct an electrochemical battery model that includes thermal and mechanical wear and inner reaction kinetics. In real-time execution, substantial research is required into advanced SoC estimation methodologies (such as cubature Kalman filter (CKF), a non-derivative estimator and highly effective and operative numerical integration technique that diminishes computational load) using the prototype of a BMS embedded system. Eventually, our subsequent research focuses on the dual or co-estimation of SoC and SoH for Li-ion rechargeable batteries throughout their complete lifecycle.

According to the authors, these proposals will significantly contribute to the future advancement of the SOC estimate algorithm.

References

[1] F. Nadeem, S. S. Hussain, P. K. Tiwari, A. K. Goswami and T. S. Ustun, “ Comparative review of energy storage systems, their roles, and impacts on future power systems”, IEEE Access, vol. 7, pp. 4555-4585, December 2018.

[2] S. B. Wali, M. A. Hannan, M. S. Reza, P. J. Ker, R. A. Begum, M. S. Abd Rahman, and M. Mansor, “Battery storage systems integrated renewable energy sources: A biblio metric analysis towards future directions”, Journal of Energy Storage, vol. 35, p. 102296, March 2021.

[3] M. Akhil, E. Dokur, and R. Bayindir, “Impact of electric vehicle charging profiles in data-driven framework on distribution network”, 9th International Conference on Smart Grid (icSmartGrid), IEEE, pp. 220-225, 29 June 2021.

[4] U. Cetinkaya, R. Bayindir, and S. Ayik, “Ancillary services using battery energy systems and demand response”, 9th International Conference on Smart Grid (icSmartGrid), IEEE, pp. 212-215, 29 June 2021.

[5] M. U. Ali, A. Zafar, S. H. Nengroo, S. Hussain, M. Junaid Alvi, and H. J. Kim, “Towards a smarter battery management system for electric vehicle applications: A critical review of lithium-ion battery state of charge estimation”, Energies, Vol. 12, No. 3, p.446, January 2019.

[6] M. Armand, P. Axmann, D. Bresser, M. Copley, K. Edstrom, C. Ekberg D. Guyomard, B. Lestriez, P. Novak, M. Petranikova, and W. Porcher, “Lithium-ion batteries– Current state of the art and anticipated developments”, Journal of Power Sources, vol. 479, p.228708, December 2020.

[7] S. Gherairi, “Zero-Emission Hybrid Electric System: Estimated Speed to Prioritize Energy Demand for Transport Applications”, International Journal of Smart Grid-ijSmartGrid, Vol. 3, No. 4, December 2019.

[8] D. N. How, M. A. Hannan, M. H. Lipu, and P. J. Ker, “State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A review”, IEEE Access, vol. 7, pp. 136116-136136, September 2019.

[9] R. Xiong, J. Cao, Q. Yu, H. He, and F. Sun, “Critical review on the battery state of charge estimation methods for electric vehicles”, IEEE Access, vol. 6, pp. 1832-1843, December 2017.

[10] Y. Song, M. Park, M. Seo, and S. W. Kim, “Online state-of-charge estimation for lithium-ion batteries considering model inaccuracies under time-varying current conditions”, IEEE Access, vol. 8, pp. 192419-192434,October 2020.

[11] Y. Gao, K. Liu, C. Zhu, X. Zhang, and D. Zhang, “Co-estimation of state-of-charge and state-of-health for lithium-ion batteries using an enhanced electrochemical model”, IEEE Transactions on Industrial Electronics, vol. 69, no. 3, pp. 2684-2696, March 2021.

[12] R. Xiong, Y. Zhang, J. Wang, H. He, S. Peng, and M. Pecht, “Lithium-ion battery health prognosis based on a real battery management system used in electric vehicles”, IEEE Transactions on Vehicular Technology, vol. 68, no. 5, pp. 4110-4121, August 2018.

[13] M. Safari, M. Morcrette, A. Teyssot, and C. Delacourt, “Multimodal physics-based aging model for life prediction of Li-ion batteries”, Journal of The Electrochemical Society, vol. 156, no. 3, p.A145, December 2008.

[14] R. Fu, S. Y. Choe, V. Agubra, and J. Fergus, “Development of a physics-based degradation model for lithium-ion polymer batteries considering side reactions”, Journal of Power Sources, vol. 278, pp. 506-521, March 2015.

[15] M. Uitz, M. Sternad, S. Breuer, C. Täubert, T. Traußnig, V. Hennige, I. Hanzu, and M. Wilkening, "Aging of tesla's 18650 lithium-ion cells: Correlating solid-electrolyte-interphase evolution with fading in capacity and power", Journal of The Electrochemical Society, vol. 164, no. 14, p. A3503, November 2017.

[16] B. Y. Liaw, E. P. Roth, R. G. Jungst, G. Nagasubramanian, H. L. Case, and D. H. Doughty, "Correlation of Arrhenius behaviors in power and capacity fades with cell impedance and heat generation in cylindrical lithium-ion cells", Journal of power sources, vol. 119, pp. 874-886, June 2003.

[17] C. Chen, R. Xiong, and W. Shen, "A lithium-ion battery-in-the-loop approach to test and validate multiscale dual H infinity filters for state-of-charge and capacity estimation", IEEE Transactions on power Electronics, vol. 33, no. 1, pp. 332-342, February 2017.

[18] J. Meng, D. I. Stroe, M. Ricco, G. Luo, and R. Teodorescu, "A simplified model-based state-of-charge estimation approach for lithium-ion battery with dynamic linear model", IEEE Transactions on Industrial Electronics, vol. 66, no. 10, pp. 7717-7727, November 2018.

[19] G. S. Misyris, D. I. Doukas, T. A. Papadopoulos, D. P. Labridis, and V. G. Agelidis, "State-of-charge estimation for li-ion batteries: A more accurate hybrid approach", IEEE Transactions on Energy Conversion, vol. 34, no. 1, pp. 109-119, August 2018.

[20] O. Rezaei, R. Habibifar, Z. Wang, "A robust kalman filter-based approach for soc estimation of lithium-ion batteries in smart homes", Energies, vol. 15, no. 10, p. 3768, May 2022.

[21] Y. Chen, Y. He, Z. Li, and L. Chen, "A Combined Multiple Factor Degradation Model and Online Verification for Electric Vehicle Batteries", Energies, vol. 12, no. 22, p. 4376, November 2019.

[22] G. G. Ravali, K. N. Raju, "Technological developments in batteries: a survey of modelling, estimation, and management strategies for EV application", International Journal of Electric and Hybrid Vehicles, vol. 13, no. 2, pp. 194-209, September 2021.

[23] G. Dong, J. Wei, "A physics-based aging model for lithium-ion battery with coupled chemical/mechanical degradation mechanisms", Electrochimica Acta, vol. 395, p. 139133, November 2021.

[24] S. Barcellona, and L. Piegari, "Lithium-ion battery models and parameter identification techniques", Energies, vol. 10, no. 12, p. 2007, December 2017.

[25] S. S. Choi, and H. S. Lim, "Factors that affect cycle-life and possible degradation mechanisms of a Li-ion cell based on LiCoO2", Journal of Power Sources, vol. 111, no. 1, pp. 130-136, September 2002.

[26] Q. Zhang, and R. E. White, "Capacity fade analysis of a lithium-ion cell", Journal of Power Sources, vol. 179, no. 2, pp. 793-798, May 2008.

[27] L. Barote, and C. Marinescu, "Li-Ion energy storage capacity estimation in residential applications with EV" In 2019 8th International Conference on Renewable Energy Research and Applications (ICRERA), pp. 326-330, IEEE, 3 November 2019.

[28] W. Vermeer, G. R. Mouli, and P. Bauer, "A Comprehensive Review on the Characteristics and Modelling of Lithium-ion Battery Ageing", IEEE Transactions on Transportation Electrification, vol. 8, no. 2, pp. 2205-2232, December 2021.

[29] J. M. Reniers, G. Mulder, and D. A. Howey, "Review and performance comparison of mechanical-chemical degradation models for lithium-ion batteries", Journal of The Electrochemical Society, vol. 166, no. 14, pp. A3189-A3200, September 2019.

[30] E. Martinez-Laserna, E. Sarasketa-Zabala, I. V. Sarria, D. I. Stroe, M. Swierczynski, A. Warnecke, J. M. Timmermans, S. Goutam, N. Omar, P. Rodriguez, "Technical viability of battery second life: A study from the ageing perspective", IEEE Transactions on Industry Applications, vol. 54, no. 3, pp. 2703-2713, February 2018.

[31] S. B. Peterson, J. Apt, and J. F. Whitacre, "Lithium-ion battery cell degradation resulting from realistic vehicle and vehicle-to-grid utilization", Journal of Power Sources, vol. 195, no. 8, pp. 2385-2392, April 2010.

[32] M. Broussely, "Aging mechanisms and calendar-life predictions in lithium-ion batteries", Advances in Lithium-Ion Batteries, pp. 393-432. Springer, Boston, MA, 2002.

[33] K. Thirugnanam, H. Saini, P. Kumar, "Mathematical modeling of Li-ion battery for charge/discharge rate and capacity fading characteristics using genetic algorithm approach", In 2012 IEEE Transportation Electrification Conference and Expo (ITEC), pp. 1-6, IEEE, 18 June 2012.

[34] Z. Chen, J. Xiao, X. Shu, S. Shen, J. Shen, Y. Liu, "Model-based adaptive joint estimation of the state of charge and capacity for Lithium–Ion batteries in their entire lifespan", Energies, vol. 13, no. 6, p. 1410, March 2020.

[35] X. Shu, G. Li, Y. Zhang, S. Shen, Z. Chen, Y. Liu, "Stage of charge estimation of lithium-ion battery packs based on improved cubature Kalman filter with long short-term memory model", IEEE Transactions on Transportation Electrification, vol. 7, no. 3, pp. 1271-1284, December 2020.

[36] Z. Wei, J. Zhao, D. Ji, and K. J. Tseng, "A multi-timescale estimator for battery state of charge and capacity dual estimation based on an online identified model", Applied energy, vol. 204, pp. 1264-1274, October 2017.

[37] C. Yang, X. Wang, Q. Fang, H. Dai, Y. Cao, and X. Wei, "An online SOC and capacity estimation method for aged lithium-ion battery pack considering cell inconsistency", Journal of Energy Storage, vol. 29, p. 101250, June 2020.

[38] C. Wang, N. Lu, S. Wang, Y. Cheng, B. Jiang, "Dynamic long short-term memory neural-network-based indirect remaining-useful-life prognosis for satellite lithium-ion battery", Applied Sciences, vol. 8, no. 11, p. 2078, October 2018.

[39] R. Spotnitz, "Simulation of capacity fade in lithium-ion batteries", Journal of power sources, vol. 113, no. 1, pp. 72-80, January 2003.

[40] L. Lam, P. Bauer, "Practical capacity fading model for Li-ion battery cells in electric vehicles", IEEE transactions on power electronics, vol. 28, no. 12, pp. 5910-5918, December 2012.

[41] H. Wang, S. Frisco, E. Gottlieb, R. Yuan, J. F. Whitacre, "Capacity degradation in commercial Li-ion cells: The effects of charge protocol and temperature", Journal of Power Sources, vol. 426, pp. 67-73, June 2019.

[42] G. E. Jung, J. Baek, J. Liu, M. C. Dinh, C. S. Kim, M. K. Lee, J. Bae, "The Precision SOC Estimation for Fire Prevention of the EES Using ANN", In 2021 10th International Conference on Renewable Energy Research and Application (ICRERA), pp. 231-234, IEEE, 26 September 2021.

[43] Y. Ko, K. Cho, M. Kim, and W. Choi, "A Novel Capacity Estimation Method for the Lithium Batteries Using the Enhanced Coulomb Counting Method with Kalman Filtering", IEEE Access, vol. 10, pp. 38793-38801, April 2022.

[44] X. Lai, W. Yi, Y.Cui, C. Qin, X. Han, T. Sun, L. Zhou, and Y. Zheng, "Capacity estimation of lithium-ion cells by combining model-based and data-driven methods based on a sequential extended Kalman filter", Energy, vol. 216, p. 119233, February 2021.

[45] C. J. Lee, B. K. Kim, M. K. Kwon, K. Nam, and S. W. Kang, "Real-time prediction of capacity fade and remaining useful life of lithium-ion batteries based on charge/discharge characteristics", Electronics, vol. 10, no. 7, p. 846, April 2021.

[46] C. Yang, X. Wang, Q. Fang, H. Dai, Y.Cao, and X. Wei, "An online SOC and capacity estimation method for aged lithium-ion battery pack considering cell inconsistency", Journal of Energy Storage, vol. 29, p. 101250, June 2020.

[47] R. Yang, R. Xiong, H. He, H. Mu, C.Wang, "A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles", Applied Energy, vol. 207, pp. 336-345, December 2017.

[48] H. F. Khan, A. Hanif, M. U. Ali, A. Zafar, "A Lagrange multiplier and sigma point Kalman filter based fused methodology for online state of charge estimation of lithium-ion batteries", Journal of Energy Storage, vol. 41, p. 102843, September 2021.