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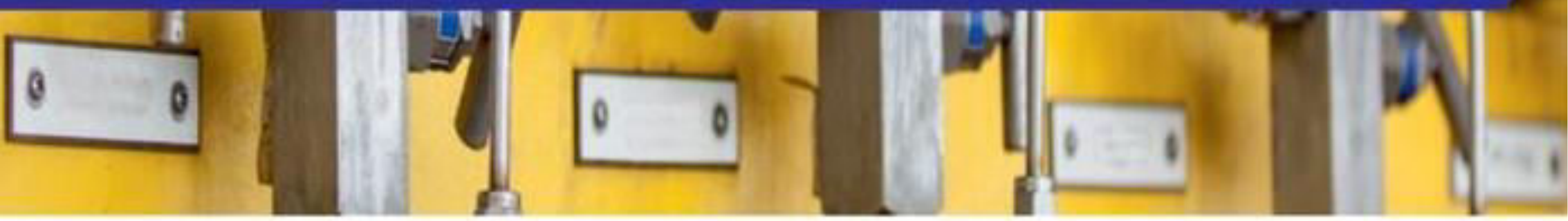

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State of Charge Estimation of Lithium-Ion Battery using Extended Kalman Filter

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ABSTRACT: Lithium-ion batteries are widely used in electric vehicles, stationary storage, and portable electronic equipment due to their excellent energy density, cycle life, and power performance. In order to ensure the reliable operation of lithium-ion batteries, a sophisticated Battery Management System (BMS) is necessary. The BMS can detect some physical and electrical states, such as voltage, current, temperature, and state of charge (SOC). SOC indicates how much capacity has remained in the battery. SOC is important for safety operation of the battery, for the better utilization of battery energy and to avoid over-charge or over-discharge states. SOC cannot be measured directly and is usually estimated using computational approaches based on some measurable electrical values. This paper presents a model-based SOC estimation approach using the Extended Kalman Filter (EKF). A second-order RC equivalent circuit model is employed to describe the electrical behaviour of a lithium-ion battery, and the EKF algorithm is used to estimate SOC using measured current and terminal voltage signals. The proposed method is implemented in the MATLAB/Simulink environment to evaluate estimation performance under dynamic operating conditions. According to the simulation results, the estimated result by EKF is of the high precision to follow the SOC and greatly decreased the error from traditional Coulomb counting method.

KEYWORDS: Battery modelling, Extended Kalman filter (EKF), Lithium-ion batteries, MATLAB/Simulink, and State of Charge (SOC) estimation.

I. INTRODUCTION

With the explosive growth of EVs, renewable energy systems and portable electronic devices, the demand for reliable and efficient energy storage system increases rapidly. Among available energy storage devices, Li-ion batteries are identified as one of the best candidates owing to their high energy density, long cycle life, low self-discharge and excellent charge/discharge capability. Therefore, they are adopted in many applications such as EVs, HEVs, on-grid renewable energy systems, and consumer electronics etc. Nevertheless, Li-ion batteries need to be monitored and controlled in order to ensure safety, enhance performance and extend their service life.

To fulfil the above needs, battery management system (BMS) has been introduced in the modern batteries for monitoring and controlling key parameters such as battery voltage, current, temperature, SOC and state of health (SOH). Among them, SOC is one of the most critical states that represent the amount of available capacity within the battery relative to the nominal capacity. Accurate estimation of SOC is of great importance for avoiding battery over-charging or over-discharging, optimizing energy management strategy, maximizing battery utilization and ensuring battery safety. However, the SOC cannot be directly measured through sensors and must be estimated based on detectable electrical parameters such as current and voltage using algorithms.

In recent decades, many SOC estimation methods have been proposed in literature and can be broadly classified into direct measurement methods, model-based estimation techniques and data-driven methods. The direct measurement techniques include open-circuit voltage (OCV) method and Coulomb counting method. The OCV method determines SOC based on the measurement of battery voltage when the battery is under a static condition. Although this method could achieve good accuracy, it is time consuming and unsuitable for dynamic applications that requires the battery to keep resting. The Coulomb counting technique is a very common method that SOC estimation is achieved by integrating battery current over time. This method is computationally simple but highly sensitive to initial SOC value and current measurement accuracy; as a result, the current measurement error accumulates rapidly and yields significant drift in SOC estimation.

Therefore, model-based estimation techniques are widely applied to overcome the shortages of direct measurement methods in the field of battery management. They utilize the mathematical model of battery's electrical characteristics in conjunction with estimation algorithms to determine the internal states of battery systems. The model that has been employed for SOC estimation could generally be divided into electrochemical models and equivalent circuit models. The electrochemical models describe the interior chemical reaction and ion transport mechanism inside a battery with high accuracy, but are generally complex and computationally expensive to implement on real-time control systems. The equivalent circuit models represent the dynamics of battery system using circuits composed of voltage sources, resistors and capacitors; they compromise modelling accuracy and computational burden for dynamic application widely.

A second order RC model, commonly referred to as the dual polarization model, has been adopted to describe the electric dynamics of Li-ion battery in the battery management systems. This model represents the battery by an open-circuit voltage, an internal resistance and two parallel RC networks which account for the electrochemical polarization and diffusion characteristics of the battery respectively. With these two RC networks, the second order RC model can capture both immediate and time-varying voltage characteristics of the battery dynamics effectively. When coupled with an estimation algorithm, it can be used to estimate internal states of the battery, such as SOC, from the easily-measurable external signals such as current and voltage.

Among the numerous estimation algorithms, state estimation in a battery generally uses Kalman filter. It is a recursive algorithm for obtaining an optimal estimate of the state of a dynamic system by combining system model with measured noisy data. However, the derivation of Kalman filter is based on linear systems, but actually, a battery is a dynamic system with nonlinearity which is due to complex electrochemical reactions that are dependent on states of battery and temperature. To resolve the issue of nonlinear battery dynamics, the extended Kalman filter (EKF) is developed as a nonlinear extension of the conventional Kalman filter.

EKF algorithm provides state estimations by linearizing the nonlinear state equations around the estimated state via first-order Taylor expansion. The operation consists of two recursive phases: a prediction phase and an update phase. In the prediction phase, the battery model is utilized to predict the next states of the system. The estimated state then is updated in the update phase by considering the actual measurements such as the battery voltage. The continuous correction process helps reduce errors from measurements and modelling.

This work developed an SOC estimation technique for Li-ion batteries using EKF algorithm. The electrical characteristics of the Li-ion battery are described by a second order RC equivalent circuit model, and then the SOC estimation is performed based on the measurement of current and voltage signals by utilizing the EKF algorithm. The proposed method is implemented in MATLAB/Simulink environment and tested under various conditions. The estimation performance of the EKF algorithm is compared with the conventional Coulomb counting technique and illustrated the improvement on accuracy.

The main contributions of this work are summarized as follows. First, a second-order RC equivalent circuit model is developed to represent the dynamic electrical behaviour of a lithium-ion battery suitable for SOC estimation. Second, an EKF-based estimation framework is formulated to estimate the battery SOC using measurable current and terminal voltage signals. Third, the proposed SOC estimation approach is implemented in the MATLAB/Simulink environment to analyse the dynamic performance of the estimator under varying operating conditions. The estimation performance of EKF is analysed, compared with the standard Coulomb counting approach and showed good performance in practical battery management system application.

The remainder of this paper is organized as follows. Section II presents the literature review on state-of-charge estimation techniques for lithium-ion batteries. Section III describes the battery equivalent circuit modelling used to represent the electrical behaviour of the battery. Section IV describes the EKF-based SOC estimation algorithm. Section V presents the simulation results of proposed estimation method based on MATLAB/Simulink and the simulation setup. Section VI gives simulation and comparison results. At last, the conclusions are given in Section VII.

II. LITERATURE REVIEW

The accurate estimation of SOC is a critical prerequisite for the safe, efficient operation of battery systems especially the lithium-ion battery used in electric vehicles, renewable energy storage and modern battery management systems (BMS). Since SOC cannot be measured directly, it is obtained by means of mathematical model and signal processing methods. The research of SOC estimation based on the mathematical model and signal processing algorithms has been

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carried out very extensively for the past ten years; effective SOC estimation methods capable of solving the nonlinear dynamics of the battery, parameters variations, measurement noise and environmental uncertainties have been developed.

Early approaches for SOC estimation are mainly based on empirical and measurement-based method such as open-circuit voltage (OCV) method and ampere-hour (Ah) integration method. The above-mentioned methods are simple to implement; however, they possess the following disadvantage. OCV-based methods require long rest periods to reach voltage equilibrium, which is impractical in real-time applications. Likewise, the accumulated errors in Ah counting are increased with time due to sensor errors and undefined initial SOC [9],[29]. This drawback of Ah counting drove the researchers to search for model-based state estimation approach which combines battery models and recursive filtering algorithm in order to have more accurate and robust estimation.

Among various model-based approaches, Kalman filter-based state estimation techniques are one of the most widely used techniques for SOC estimation which combines system models and correction with real-time measurements via state-space model. Through recursive prediction and correction steps, Kalman filtering continuously updates SOC estimates based on measured voltage and current signals, and several studies have demonstrated practical implementation frameworks for such filtering algorithms in real-time systems [8].

Several studies demonstrated that Kalman filtering significantly improves SOC estimation accuracy compared with conventional Coulomb counting methods by effectively mitigating measurement noise and modelling errors [1], [2], [7], [21]. In such frameworks, equivalent circuit models (ECMs), particularly Thevenin and Randle-type models, are commonly used to represent battery behaviour because they provide a practical balance between modelling accuracy and computational simplicity [2], [11], [18].

The models commonly adopted are open-circuit voltage source in series with internal resistance and one or more parallel RC circuits for electrochemical polarization. Different orders of RC circuits (first-order or second-order RC circuits) have been used to describe the diffusion and charge transfer process within the battery and embedded in EKF algorithms to provide SOC estimates on the basis of measurable current and terminal voltage signals [3], [5], [18]. Validations have demonstrated that SOC estimation algorithms based on EKF can provide estimation error as low as under 1-4% during dynamic loading, and thus hold great promise for practical battery management system applications [3], [11], [16]. Despite these advantages, early EKF-based approaches often assumed constant battery parameters and simplified battery behaviour, which can reduce estimation accuracy under varying operating conditions.

Lithium-ion batteries exhibit complex nonlinear characteristics influenced by factors such as temperature variations, hysteresis effects, and dynamic charge-discharge behaviour. To tackle these issues, various studies have suggested improved models of the battery and adaptation filtering techniques. By considering temperature dependency into the parameters and the OCV-SOC relationship, a better estimation of the battery performance across different ambient temperatures is achieved [4], [13].

Also, by taking hysteresis into account, the performance in predicting the battery voltage and the SOC could be enhanced due to the difference between charging and discharging behaviour [10], [17]. Thus, the models are improved and the performance of the EKF based estimator is enhanced. A second area of research is related to the adaptation filtering techniques, where parameters of the system or noise covariance matrix are adapted in order to improve estimation accuracy and robustness. An AEKF, an iterative EKF or a variational EKF algorithm have been designed in order to track the battery states under unknown operating conditions.

They adapt their filtering parameters by using the innovation sequences or through an iterative procedure of minimizing a cost function, making them adaptable to the model inaccuracies and measurement noises [6], [20], [23]. These adaptive filters have shown to be much better than a classical EKF approach for SOC estimation by reducing the estimation error.

Besides of the adaptive filtering approach, there are many studies dealing with accurate modelling of the battery. The application of the fractional-order EC to characterize both polarization and memory effects is one of the solutions suggested to overcome limitation of integer order EC models [15]. The model using fractional-order dynamic has also shown a good result for voltage prediction and SOC estimation.

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For an effective representation of the battery, it may be necessary to account for the rate and temperature dependency. The nonlinear EC which takes the two conditions into account have been used to better represent the battery behaviour [19]. The improved models can contribute to a better estimation performance when it is based on model-based approaches.

Model based EKF is a popular algorithm for SOC estimation, the precision of which strongly relies on the quality of the model parameters. A number of experiments methods like HPPC, pulse discharging, DST tests cycles have been proposed for model identification, and OCV-SOC characterization [5], [13], [18]. However, the model parameters could change over time, for example due to the wear of the battery. Therefore, on-line parameter identification algorithms have been developed in order to dynamically update the model parameters [12]. These methods increase robustness to variations due to changes in the parameters due to operational conditions and aging of the battery.

The application of optimization methods in the field of SOC estimation has also been studied in some works. It's also possible to use optimization techniques to tune the Kalman filter covariance matrices or the battery model parameter identification. Metaheuristic optimization methods have been demonstrated to reduce the error in the voltage prediction and adjust filter parameters according to noisy measurement conditions [30].

However, such optimization-based approaches often result in increased computational cost, and their real-time implementation in the battery management system of embedded devices may be severely restricted. The other major emerging research trend is the fusion of electrochemical battery models with Kalman filtering approaches. In contrast to equivalent circuit models, electrochemical models represent the battery state by considering the lithium diffusion process within the particles of the electrode materials and the electrochemical reactions between the lithium ions and electrode active materials. For instance, the single particle model (SPM) can be employed to describe the diffusion of lithium ions within electrode particles with diffusion equations, and the estimated states such as lithium concentration and SOC can be predicted by using extended Kalman filter (EKF) [26].

In general, although the electrochemical models possess better physical accuracy than equivalent circuit models, their real-time implementation in the BMS are hindered by their computation intensive nature and elaborate parameter identification processes.

Similar to the hybrid approaches, the combination of Kalman filtering with machine learning algorithms is also another research trend. The reason why hybrid approaches such as these are being increasingly concerned is due to the ability of these approaches to combine the advantage of model-based approaches with data driven approaches.

For instance, Kalman filter-based SOC estimation can be integrated with machine learning models to predict battery state of health (SOH) or detect abnormal cell behaviour using real-time battery management system data [27]. Some techniques for analysing data, clustering, and time series pattern matching have been also used to identify the battery degradation pattern and improved the battery diagnostics.

A series of review studies have concluded that no SOC estimation method alone is appropriate for all real operation conditions. Though the easy-to-use technique (like Coulomb counting) are fast in computation but accumulates errors over the time. In contrast, advanced estimation algorithms offer improved accuracy, but their implementation requires extensive modelling and computational resources [9], [25], [29]. As a result, many works underline the benefits of a hybrid SOC estimation architecture which integrates model-based methods with intelligent techniques in order to increase robustness with respect to real operating conditions. However, although great progress has been made on SOC estimation research, several obstacles persist. For instance, a lot of the research has been performed on simplified conditions like static temperature, static battery parameters, or on small data-sets acquired under stable test conditions. In practice however, lithium-ion batteries operate under dynamic conditions: changing temperatures, battery degradation, load changes, all of these factors contribute to uncertainties on battery parameters which can impair SOC estimation. Therefore, there is a continuing need for SOC estimation techniques that can simultaneously address nonlinear battery dynamics, parameter drift caused by aging, and computational constraints associated with real-time battery management systems.

Overall, the literature demonstrates that Kalman filter-based estimation techniques combined with appropriate battery modelling approaches provide a promising framework for accurate SOC estimation in lithium-ion battery systems. The EKF has become one of the most widely accepted techniques for SOC estimation owing to its robustness to the nonlinear battery dynamics and recursive correction of estimated errors using prediction and measurement updates,

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which is well suited for precise and robust battery state estimation for the purpose of advanced battery management and energy storage applications.

III. BATTERY EQUIVALENT CIRCUIT MODEL

Accurate modelling of lithium-ion batteries is an essential requirement for developing reliable state estimation algorithms such as the EKF. A battery model provides a mathematical representation of the electrical behaviour of the cell and enables the estimation of internal states that cannot be measured directly, such as the SOC. Battery model is employed in the BMS for the prediction of battery voltage behaviour under different operational circumstances, and for mapping measurable electric quantities to the internal states of the battery. Consequently, selection of the battery model is vital in obtaining accurate SOC estimation.

Battery models can generally be classified into two main categories: electrochemical models and equivalent circuit models. Electrochemical models characterize the chemical reactions and ion transport inside a battery as well as its thermodynamic characteristics. Electrochemical models can simulate battery dynamics with a great degree of physical realism but they necessitate comprehensive knowledge of Electrochemical parameters and have to cope with complex partial differential equations with huge computational cost. Thus, they can mainly be used for analysing experiments, not for real-time battery management.

Equivalent circuit models approximate battery as a collection of electric elements, such as voltage source, resistors and capacitors. They can provide a straightforward yet sufficient depiction of battery electrical behaviour with much lower computational cost. Equivalent circuit models can be applied for real-time SOC estimation and BMS application due to their good balance between modelling accuracy and computational load.

Among the common equivalent circuit models, second-order RC equivalent circuit model (dual polarization model) is widely adopted for lithium-ion battery modelling. Second-order RC model represents an instant potential drop caused by Ohmic resistance and a gradual change attributed to electrochemical polarization phenomenon in a Li-ion battery. As shown in Fig. 1, a second-order RC model typically comprises open-circuit voltage source, Ohmic resistance, and two RC sections modelling the electrochemical processes in a battery.

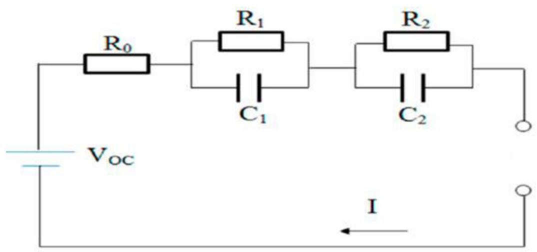

Fig1 Second-order RC battery equivalent model

The open-circuit voltage (OCV) source represents the equilibrium voltage of the battery and is primarily dependent on the SOC. The OCV-SOC relationship is usually obtained experimentally by measuring the battery voltage under open-circuit conditions at different SOC levels. This relationship plays a crucial role in SOC estimation since it establishes a connection between the internal battery state and the measurable terminal voltage.

The internal resistance, often denoted as R_0, represents the instantaneous voltage drop that occurs when current flows through the battery. This resistance accounts for various physical phenomena including electrolyte resistance, electrode material resistance, and contact resistance between battery components. The voltage across the internal resistance, is the instant potential drop, and it has to be there immediately charging or discharging is done.

The second order RC model contains two parallel RC networks to represent the polarization; it captures the voltage dynamic response of the electrochemical internal phenomena. First RC pair, normally R_1 and C_1 which represent the activation polarization which are charge transfer responses in electrode/electrolyte interface and reflect rapid response of the battery potential when current is charged or discharged at short time. Second RC pair is generally represented as R_2 and C_2. They capture the concentration polarization related to ion diffusion within electrolyte and electrodes, so

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represent long term response of battery potential, when current is charged or discharged at longer term. Terminal voltage can be written as,

$$V_t = V_{oc} - V_1 - V_2 - I\,R_0 \qquad (1)$$

where V_{oc} is the open-circuit voltage, V_1 and V_2 represent the voltages across the RC networks, I is the battery current, and R_0 is the internal resistance. The negative sign indicates that voltage drops occur due to internal resistive and polarization effects when the battery is delivering current.

The dynamic behaviour of the RC networks is described by differential equations that relate the polarization voltages to the battery current. These equations describe how the voltages across the capacitors evolve over time in response to current variations. The SOC variation is also related to the battery current through a charge balance equation that integrates the current over time relative to the battery capacity.

To estimate SOC the model has to be transformed to the states space representation. Internal states variables are usually polarization voltages and SOC; states input is battery current and state output is terminal voltage. The state-space model will allow us to apply state estimation technique like the EKF for estimation. The identified model must provide reasonable accuracy of parameters like resistance values R_0, R_1, R_2, capacitance values C_1, C_2 and OCV-SOC relationship. All the parameters are identifiable through experiments like pulse discharge method and hybrid pulse power characterization (HPPC) test method etc.

Although the model described is a simplification, it contains major electrochemical and electrical characteristics and has sufficient accuracy for the SOC estimation. The complexity is low, suitable for embedded application like BMS. With accurate identified parameter values, it is feasible to provide good estimation of the battery SOC, using algorithms like EKF based on the above electrical model. The model second-order RC equivalent circuit is utilized to describe electrical behaviour of lithium-ion battery in this work. The model is implemented in a MATLAB/Simulink environment and integrated with the EKF-based estimation framework to estimate the SOC in real time using measured voltage and current signals.

IV. STATE OF CHARGE ESTIMATION USING EKF

Accurate estimation of the SOC requires an estimation framework capable of handling nonlinear battery dynamics and measurement uncertainties. In this work, the EKF is employed to estimate the SOC of a lithium-ion battery using the electrical equivalent circuit model described in the previous section. The EKF is particularly suitable for battery applications because it can estimate internal states that cannot be measured directly while accounting for process disturbances and measurement noise.

The SOC estimation problem can be formulated using a nonlinear state-space model derived from the second-order RC equivalent circuit representation of the battery. In this representation, the internal battery states include the polarization voltages associated with the RC branches and the battery SOC. The measurable quantities available for estimation are the terminal voltage and the current flowing through the battery.

A. Coulomb Counting Based SOC Estimation

The One of the most commonly used method for SOC estimation of a battery is the Coulomb counting method. SOC is calculated as time integral of current flow over the nominal capacity of the battery. The technique is widely adopted for battery monitoring systems, as well as for portable applications, due to the low computation complexity.

The concept on which Coulomb counting depends on is the principle of conservation of charge. Where there is current flowing in or out of the battery, it must mean that there has been a change in the amount of charge the battery contains, which will be calculated from integrating the current over time, and so expressing the SOC at time t as,

$$SOC(t) = SOC(t_0) - \frac{1}{Q_n}\int_{t_0}^{t} \eta\, I(\tau)\, d\tau \qquad (2)$$

Where,

$SOC(t_0)$ = initial SOC at time t_0

Q_n = nominal battery capacity

$I(\tau)$ = battery current

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η = Coulombic efficiency factor

A positive current typically corresponds to battery discharge, while a negative current represents charging. The Coulombic efficiency parameter accounts for losses that occur during the charging and discharging processes.
For digital implementation in battery management systems, the continuous equation is commonly expressed in discrete form as

$$SOC_k = SOC_{k-1} - \frac{\eta \Delta t}{Q_n} \times I_k \qquad (3)$$

Where,
Δt = sampling interval
I_k = measured battery current at time step k

This recursive definition gives us the ability to update SOC continuously using the measured current signal.
Coulomb counting is computationally simple, but several intrinsic errors make this technique unreliable for real-world applications. An important problem is the need of an exact initial SOC. If there is any error in the initially calculated SOC, it carries throughout the whole estimation process since it is a system in an open-loop. Another major limitation is the sensitivity to current measurement errors. The value of SOC, being the integral of the measured current over time, is dependent on accurate current measurements; inaccuracies accumulate, causing great errors over a large interval of operation.

Another weakness of the Coulomb counting method is that it completely ignores battery aging, varying temperature and changes in internal battery parameters. In a practical battery system these can greatly affect the real capacity and dynamics of the battery. As the Coulomb counting technique assumes the capacity of the battery is fixed, its estimate of the SOC will not be accurate in variable conditions.

As the shortcomings listed above, it is obvious that Coulomb counting technique cannot fulfil the demanding requirements for estimation of SOC in modern BMSs. In response to these drawbacks, model-based estimation methods are developed, which use dynamic models of the battery with measurements to estimate SOC more accurately. Among all model-based estimation methods, EKF is the one that most commonly used, which can deal with both nonlinear system dynamics and measurement noise.

In the following section, the SOC estimation scheme based on the EKF is introduced. The EKF integrates the equivalent circuit battery model with the measured data (current and voltage) in real-time to perform better and robust estimation of the battery SOC.

B. Open-Circuit Voltage-SOC Relationship
The open-circuit voltage of a lithium-ion battery is defined as the steady state voltage across the battery when there is no current flowing. The OCV of a cell is directly proportional to the electrochemical state of the battery and hence very strongly dependant on the SOC of the battery. The relation between OCV and SOC is a non-linear one, the accurate modelling of which is essential to be able to determine the SOC reliably.

In a realistic battery modelling scenario, the OCV-SOC relation is typically found from experiment. It can be obtained from the experimental result during charge-discharge testing of the battery. The battery is kept at each of the SOC value to stabilize then the value for OCV is recorded. The fitting of an analytical function to the OCV-SOC curve with experimental data is performed. In the context of estimation, the OCV-SOC is approximated by a polynomial,

$$V_{oc}(SOC) = a_0 + a_1 SOC + a_2 SOC^2 + a_3 SOC^3 + \dots + a_n SOC^n \qquad (4)$$

Where,
$V_{oc}(SOC)$ = open-circuit voltage as a function of SOC
$a_0, a_1, a_2, \dots, a_n$ = polynomial coefficients determined from experimental data.
In many practical applications, a polynomial of order three or four is sufficient to capture the nonlinear characteristics of the OCV-SOC relationship. Alternatively, the OCV-SOC curve can be represented using lookup tables obtained from experimental measurements.

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This OCV-SOC function is important for the EKF estimation process, as it is the function relating the internal state of the battery (SOC) to the terminal voltage that can be measured. During the EKF update phase, the predicted terminal voltage is derived using the estimated SOC and the OCV-SOC function, enabling the filter to compare it to the measured terminal voltage and correct the estimate for the SOC.

C. Discrete-Time RC Model for EKF Implementation

The derived continuous-time dynamic equations for the second-order RC equivalent circuit model shown above must first be converted to discrete-time equations due to the discrete-time nature of the EKF, using sampling time T_s.

Let V_1 and V_2 be the voltages across the capacitors C_1 and C_2 respectively. The discrete form of these state equations may be determined by integrating the continuous-time differential equations over the sampling interval.

The evolution of the voltage V_1 across the first RC branch is given by:

$$V_1(k+1) = e^{-\frac{T_s}{R_1C_1}} V_1(k) + R_1\left(1 - e^{-\frac{T_s}{R_1C_1}}\right) I(k) \quad (5)$$

Similarly, the voltage across the second RC branch is given by

$$V_2(k+1) = e^{-\frac{T_s}{R_2C_2}} V_2(k) + R_2\left(1 - e^{-\frac{T_s}{R_2C_2}}\right) I(k) \quad (6)$$

These equations describe how the polarization voltages change between successive sampling instants in response to the applied current.

The SOC state is updated using the discrete form of the charge balance equation

$$SOC(k+1) = SOC(k) - \left(\frac{\eta\, T_s}{Q}\right) I(k) \quad (7)$$

Where,

T_s = sampling period

Q = nominal battery capacity

η = Coulombic efficiency.

The terminal voltage predicted by the model can then be expressed as

$$V_t(k) = V_{oc}\left(SOC(k)\right) - V_1(k) - V_2(k) - R_0\, I(k) \quad (8)$$

This equation represents the measurement function used in the EKF estimation process.

D. State-Space Representation for EKF

Using the discrete equations above, the system states can be defined as

$$x_k = \begin{bmatrix} V_{1(k)} \\ V_{2(k)} \\ SOC(k) \end{bmatrix} \quad (9)$$

The input to the system is the battery current

$$u_k = I(k) \quad (10)$$

The nonlinear state equation can therefore be expressed as

$$x_{k+1} = f(x_k, u_k) + w_k \quad (11)$$

where w_k represents process noise associated with modelling uncertainties.

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The measurement equation describing the terminal voltage is

$$y_k = g(x_k, u_k) + v_k \tag{12}$$

Where, $y_k = V_{t(k)}$ is the measured battery voltage and v_k represents measurement noise.
This nonlinear state-space formulation serves as the basis for implementing the EKF.

E. EKF-Based SOC Estimation Algorithm

The EKF estimates the internal battery states through a recursive procedure consisting of two major stages: prediction and correction.

During the prediction stage, the state estimate and the corresponding covariance matrix are propagated forward using the nonlinear system model

$$\hat{x}_{(k|k-1)} = f\left(\hat{x}_{(k-1|k-1)}, u_{\{k-1\}}\right) \tag{13}$$

$$P_{(k|k-1)} = A_k\, P_{(k-1|k-1)} A_k^T + Q \tag{14}$$

where A_k is the Jacobian matrix of the state transition function.
In the correction stage, the predicted state estimate is adjusted using the measured terminal voltage. The Kalman gain is computed as

$$K_k = P_{(k|k-1)}\, C_k^T \left(C_k\, P_{(k|k-1)} C_k^T + R\right) \tag{15}$$

where C_k is the Jacobian matrix of the measurement function.

The updated state estimate is then obtained using

$$\hat{x}_{(k|k)} = \hat{x}_{(k|k-1)} + K_k\left(y_k - g\left(\hat{x}_{(k|k-1)}, u_k\right)\right) \tag{16}$$

Finally, the covariance matrix is updated according to

$$P_{(k|k)} = (I - K_k C_k)\, P_{(k|k-1)} \tag{17}$$

Through this recursive estimation process, the EKF continuously refines the SOC estimate by combining the dynamic battery model with real-time measurement data.

F. Implementation of EKF in MATLAB/Simulink

The Simulink model integrates the battery equivalent circuit model, current and voltage measurement blocks, and the EKF estimation algorithm into a unified simulation framework. This structure allows the interaction between the physical battery model and the estimation algorithm to be analysed under dynamic operating conditions.

In the developed simulation model, the second-order RC equivalent circuit represents the electrical behaviour of the lithium-ion battery. The inputs to the battery model are the battery current and it's output is the terminal voltage. The states within the battery model are the two RC networks' polarization voltages and SOC of the battery which evolve in discrete-time as equations determined in the previous subsection.

The battery model has three major subsystems namely battery model subsystem, measurement subsystem and EKF estimation subsystem. The battery model subsystem determines the response of the terminal voltage based on the applied input current profile and also determines the actual SOC of the battery which is then taken as the reference to determine the algorithm's performance.

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The measurement subsystem simulates sensing in a real BMS. The battery current and terminal voltage signals are processed by measurement blocks which can emulate signals read from current and voltage sensors. In practical scenario, the signals are usually subject to noise and disturbances hence a noise can be introduced to both the measurement signals and algorithm's robustness can be assessed. The EKF estimation subsystem accepts both the measurement current and terminal voltage and then runs the estimation recursively at each sampling instance. Initially the prediction is done followed by the correction. During prediction stage, the states are updated by using the battery model equations. The error covariance matrix is also updated during this stage.

During the correction stage, a difference between the predicted voltage and the measurement terminal voltage is calculated. The difference between these two quantities, known as the innovation or residual, is used to update the state estimate through the Kalman gain. This feedback mechanism enables the EKF to continuously adjust the SOC estimate and reduce the influence of modelling inaccuracies and measurement noise.

Accurate setting of the parameters for the EKF is a critical requirement for stable operation of the estimation. The initial SOC is defined depending on the assumed initial condition of the battery. The process noise covariance and measurement noise covariance are used to define the uncertainties of the battery model and measurements respectively. By appropriately tuning these parameters, the filter can compromise between the model forecast and measurement update.

The simulation model is driven by time with a fixed sampling rate. In every time step the current input is applied to the circuit model and the terminal voltage is calculated; then the state estimation using EKF is updated. The SOC estimated by the EKF is compared to the actual SOC output from the battery model.
The SOC estimation by EKF is compared with the Coulomb counting method. They are both given the same current input, to compare estimation accuracy and stability. The simulation of the battery system provides evidence of a satisfactory estimation based on EKF. The simulation based on MATLAB/Simulink could serve as a verification process before implementation in real battery systems. The proposed state estimation methodology combines the equivalent circuit model and EKF to develop a reliable battery SOC estimation, which can be integrated into battery management systems for applications of energy storage systems.

V. MATLAB/SIMULINK IMPLEMENTATION AND SIMULATION

In order to analyse the performance of the proposed method for SOC estimation, the simulation framework was built under MATLAB/Simulink environment. MATLAB/Simulink provides a flexible platform for modelling, simulation, and analysis of dynamic systems, making it well suited for battery modelling and estimation algorithm implementation. In this study, the lithium-ion battery equivalent circuit model and the EKF algorithm were implemented in Simulink to estimate SOC based on measured current and voltage signals.

The simulation structure consisting of the lithium-ion battery model, the current and voltage measurement system is shown in Fig. 2. These components are integrated within the Simulink environment to create a closed-loop estimation framework in which the battery model generates terminal voltage responses while the EKF algorithm estimates the internal battery states.

In the context of this section, the presented lithium-ion battery model of section III is implemented and simulated in the MATLAB/Simulink environment. The equivalent circuit model covers instantaneous voltage drops on the internal resistance and time-dependent voltage variations caused by electrochemical phenomena occurring in the battery.

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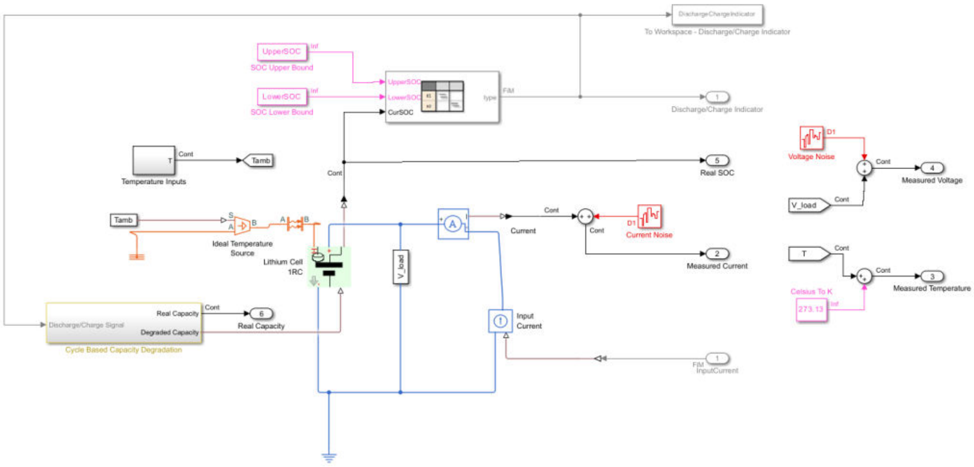

Fig 2 Lithium-ion battery model including current input, temperature effects, and measurement signals

The battery current is represented as a input signal to the Simulink block diagram, as depicted in Fig. 2. The current signal reflects the charge or discharge states of the battery during operation. In the simulation, a dynamic current signal is fed into the battery model. The current signal can be modelled to reflect the changing loads applied to the battery during use. To test the accuracy of the algorithm, different current signals with varying load conditions are applied to the battery model.

The battery voltage measured at the terminals is given as an output of the equivalent circuit model. The voltage reflects the sum of the open circuit voltage, the internal resistance voltage drop and the dynamic voltage due to polarization. Real world battery measurements include random noise and potential measurement errors. To accurately simulate real world applications a random signal could be added to the terminal voltage signal. This is done in the Simulink model to assess the robustness of the EKF under measurement noise conditions.

The EKF algorithm itself is a separate estimation block within the Simulink model. The estimation block takes the current input and terminal voltage measurement as input, and uses a state space model to derive state estimations of the internal parameters. The state parameters chosen to be modelled were the voltages across the two RC networks and the SOC of the battery.

The estimation of the states is done recursively in each simulation time step. At the prediction step, the state estimation is computed using a prior state estimate and the current input signal in order to predict the future states of the system (predicted polarization voltages and SOC). State covariance is then propagated forward with the modelling uncertainty. In the update step, the predicted state is refined with use of the terminal voltage measurement and the Kalman gain is computed and used to update the state estimate in a way that minimizes errors between the predicted and actual terminal voltages.

Initialization procedures are important when using EKF. Initial SOC value, initial state covariance matrix, process noise covariance matrix and measurement noise covariance matrix must be provided before running the EKF. The initial SOC can be chosen as known from the initial battery conditions, and the covariance matrices reflect the uncertainties of the modelled system and the measurements respectively.

The simulation time step plays an important role in the performance of the estimation algorithm. In this study, a sufficiently small sampling time is selected to accurately capture the dynamic behaviour of the battery system. At each sampling instant, the EKF algorithm processes the measured signals and updates the estimated states. This discrete-time implementation closely resembles the operation of real-time battery management systems used in practical applications. The results obtained by using the Coulomb counting and the EKF for the SOC estimation are compared in order to determine the performance of the proposed SOC estimation approach. In the Coulomb counting method, the SOC is computed by integrating the battery current and dividing it by the battery capacity. Although this method is simple and widely used, it is sensitive to measurement errors and inaccurate initial conditions. As a result, estimation errors tend to accumulate over time.

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Within the simulation environment, the Coulomb counting algorithm is implemented as a reference method for comparison. Both estimation techniques receive the same current input signal, and their SOC estimates are compared with the actual SOC obtained from the battery model. This comparison allows the evaluation of estimation accuracy under identical operating conditions.

The simulation results generated by the MATLAB/Simulink model include the actual SOC of the battery, the SOC estimated using the Coulomb counting method, and the SOC estimated using the EKF. It is thus possible to estimate how the different algorithms track the true SOC value by examining the result obtained.

The MATLAB/Simulink implementation provides a convenient environment for analysing the dynamic performance of SOC estimation algorithms before deploying them in real battery management systems. Through simulation, the effectiveness of the EKF algorithm can be evaluated under various operating conditions, including varying current profiles and measurement noise. The presented method also enables to verify the proposed estimation scheme and to obtain good insights on its applicability to the lithium-ion battery monitoring system.

VI. RESULTS AND DISCUSSION

The validity of the suggested SOC estimation method is assessed through simulation in MATLAB/Simulink environment. The objective of this analysis was to investigate the capability of the EKF algorithm to estimate the SOC of a lithium-ion battery under dynamic operating conditions. The estimation performance of the EKF was also compared with that of the conventional Coulomb counting technique in order to demonstrate the improvement obtained through model-based estimation.

A. Simulation Framework

The lithium-ion battery was modelled using the second-order RC equivalent circuit described earlier is modelled as shown in Fig. 3. This model captures both the instantaneous voltage drop caused by internal resistance and the transient voltage behaviour associated with polarization effects. The model parameters were selected to represent the electrical characteristics typically observed in lithium-ion cells.

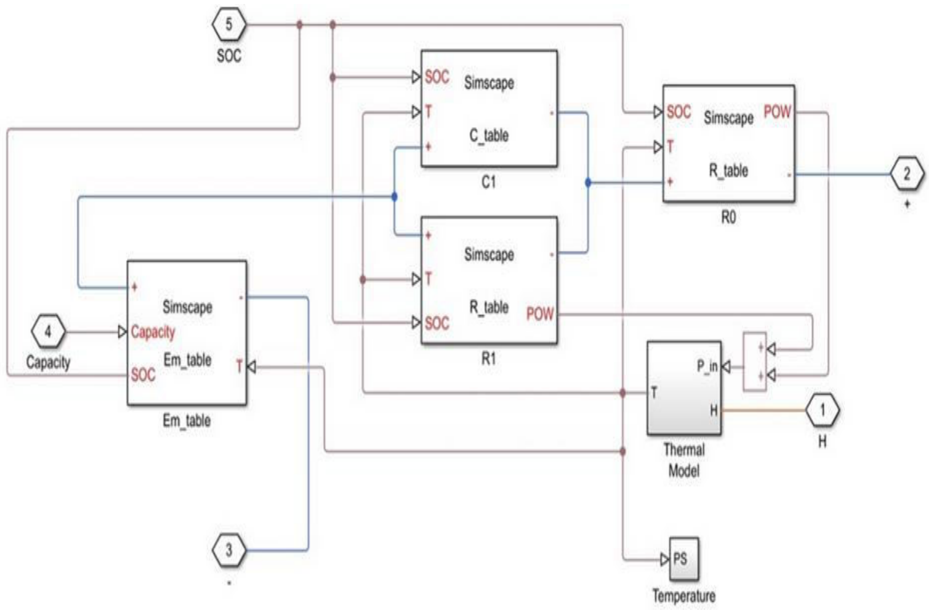

Fig.3 MATLAB/Simulink implementation of the lithium-ion battery equivalent circuit model used for SOC estimation

In the simulation environment, the battery current was defined as the primary excitation signal. The battery model was driven with a time-variant current profile, which included charge and discharge phases to mimic the real working condition. Changes in the current value like these is typically encountered in applications like the electric vehicles and the renewable energy storage systems, as the load applied is always fluctuating. The output signal of the SOC estimation algorithm was taken as the terminal voltage produced by the equivalent circuit model. In real life battery management systems, terminal voltage measurements would include sensor errors and environmental interference.

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Therefore, a noise component was introduced in the voltage measurement signal to simulate real measurement conditions and to evaluate the robustness of the estimation algorithm.

The EKF-based SOC estimator was implemented using the state-space representation of the battery model. The algorithm processed the measured current and voltage signals at each sampling instant and recursively updated the estimates of the internal battery states. In parallel, the Coulomb counting method was implemented using the same current signal in order to provide a reference for performance comparison.

B. SOC Estimation Using Coulomb Counting

This technique is computationally simple and therefore widely used in practical battery monitoring systems. However, the method relies heavily on the accuracy of current measurements and the knowledge of the initial SOC value.

According to the simulation results, the SOC estimation obtained by Coulomb counting drifts away from the true value with time. The cause of the error is due to the accumulation of errors from the noise from the sensors, and numerical integration. Tiny errors in the current measurements may lead to great errors if they are integrated for a long time. The other drawback of Coulomb counting method is that it is a open loop method, meaning that the voltage cannot be used to check for estimation errors as it doesn't provide feedback to correct the estimation errors when it happens. As a result, once an estimation error appears, it continues to increase with time.

The simulation results clearly demonstrate this limitation. The SOC curve obtained from Coulomb counting progressively deviates from the true SOC trajectory generated by the battery model. This behaviour indicates that the method may not be suitable for applications that require high estimation accuracy over extended operating periods.

C. SOC Estimation Using EKF

The simulation results show that the SOC estimation based on EKF can accurately estimate the true SOC of the battery. From the simulation results, we can see that the estimated SOC by EKF well tracks the real SOC of the battery during whole simulation time. During the whole simulation process, the current is in variable conditions.

The main feature of EKF algorithm is to reduce estimation errors by measurement feedback. At each sampling step, the estimated terminal voltage is compared with measured voltage, then the estimated states are adjusted based on this comparison. In this recursive correction way, estimation errors cannot grow with the simulation steps, so the accuracy is very high.

Another characteristic of EKF algorithm is its robustness to noise and modelling errors. EKF algorithm uses the information of process noise and measurement noise, which are included in two covariance matrices. With proper choices of these parameters, the EKF can compromise between model prediction and measurement correction well.

D. Comparative Analysis

This technique A comparative evaluation was performed to assess the estimation performance of the two SOC estimation methods. The SOC values obtained from the EKF and Coulomb counting techniques were compared with the actual SOC generated by the battery model are shown in Fig. 4.

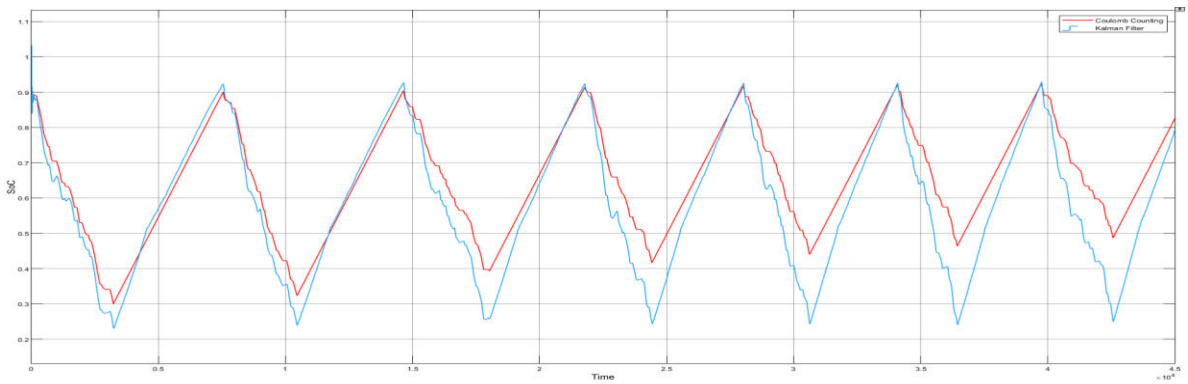

Fig.4 Comparison of SOC estimation using EKF and Coulomb counting methods

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As shown by the above comparison, estimation accuracy is greatly enhanced with EKF. The SOC profile calculated by EKF has close agreement with the true value. In contrast, deviation between Coulomb counting estimated value and true value goes on increasing over time.

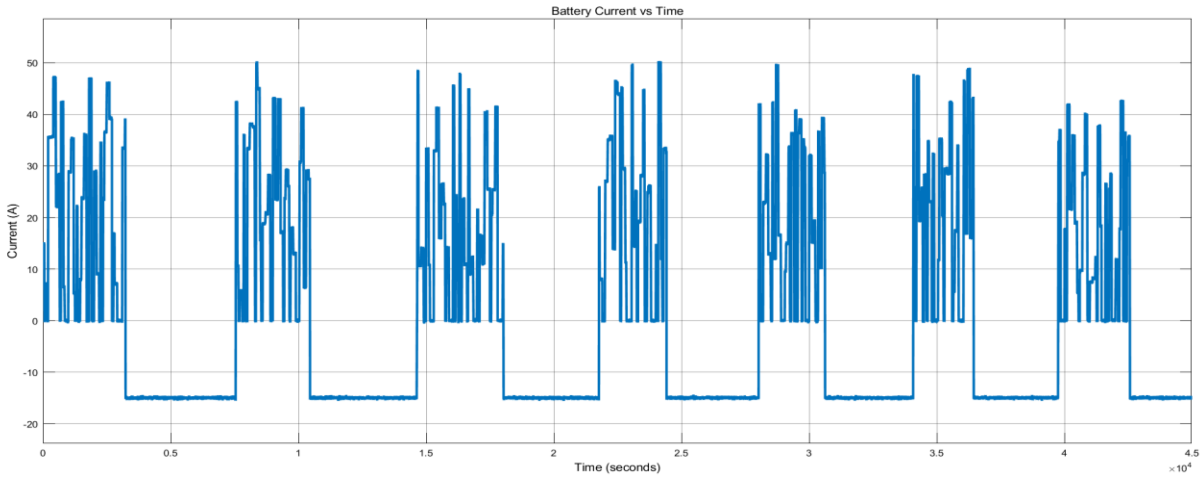

Fig.5 Battery current profile showing charging and discharging cycles.

Fig. 5. shows the battery current progress where charging and discharging current are the flows of electric charge into and out of a battery, respectively

The EKF algorithm also demonstrates improved robustness under noisy measurement conditions. Even when disturbances are introduced in the measurement signals, the EKF maintains stable estimation performance due to its recursive correction mechanism.

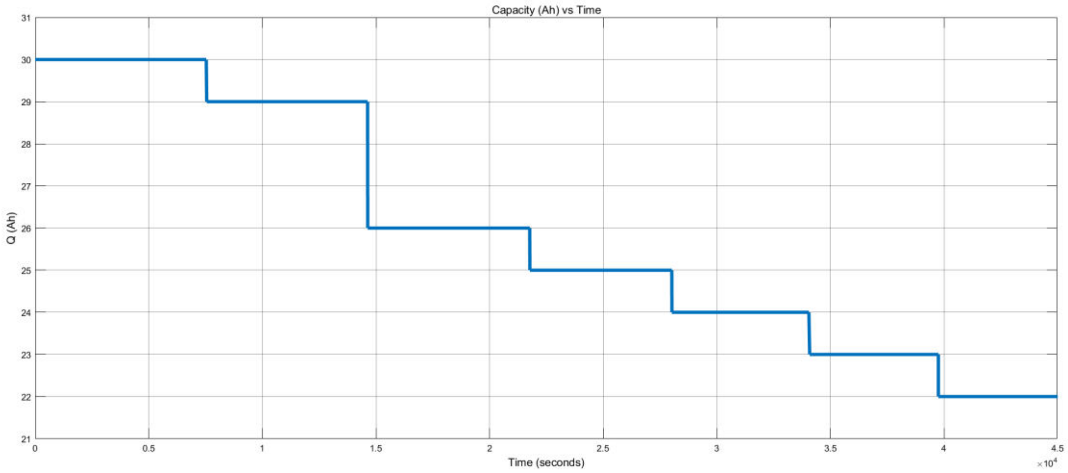

Fig.6 Battery capacity (Ah) variation over the simulation time period.

Lithium-ion cell capacity. Lithium-ion cell capacity is defined as the amount of electric charge that a lithium-ion cell can store or deliver during its operational life. Fig. 6 shows battery capacity decrease (Ah) over simulation period.
In terms of estimation accuracy, the EKF method maintains a relatively small error throughout the simulation period. These results show that the framework of model-based SOC estimation can indeed offer the precise SOC values that are acceptable for practical BMS.

The results of the simulation work clearly show the benefits of the EKF in SOC estimation. Combining the battery model with real-time measured information, the EKF is capable of overcoming the shortcomings of the traditional methods like coulomb counting. The second-order RC equivalent circuit model has shown a sufficiently accurate

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representation of the dynamics of lithium-ion batteries with acceptable computational burden. This balance between modelling accuracy and computational efficiency makes the model suitable for real-time battery management applications.

Overall, the EKF-based SOC estimation method provides accurate tracking performance, strong robustness against measurement noise, and reduced estimation error compared with conventional techniques. All the features make the proposed method convenient to be realized by using the modern battery management system, which can be used for electric vehicles, renewable energy storage, and other applications

VII. CONCLUSION

In a modern energy storage system based on a Li-ion battery, an accurate estimation of SOC is required to insure a reliable operation and control. Since SOC cannot be directly measured, estimation techniques based on mathematical modelling and signal processing are required to determine the remaining capacity of a battery during operation. In this work, a model-based SOC estimation approach using the EKF has been presented and evaluated.

A second-order RC equivalent circuit model was employed to represent the electrical behaviour of the lithium-ion battery. This model captures both the instantaneous voltage drop caused by internal resistance and the transient voltage dynamics associated with electrochemical polarization effects. The battery model was integrated with the EKF algorithm in a MATLAB/Simulink environment to estimate SOC using measured current and terminal voltage signals. The performance of the EKF-based estimator was analysed under dynamic charging and discharging conditions.

From simulation results, it can be concluded that EKF can produce an accurate and steady estimation for the SOC, especially with the measurement noise and arbitrary current inputs. In comparison to the traditional Coulomb counting method, the EKF algorithm will result in smaller cumulative errors in the estimation through continuously updating state prediction with measurement values of voltage. Thus, the estimation of the SOC by the EKF has followed well with the true value for the whole simulation time range.

The simulation shows that the proposed model-based SOC estimation method, EKF, has great performance enhancement in estimation accuracy and robustness in comparison to those open-loop methods. The presented method therefore is a feasible and reliable solution for battery real time estimation and control.

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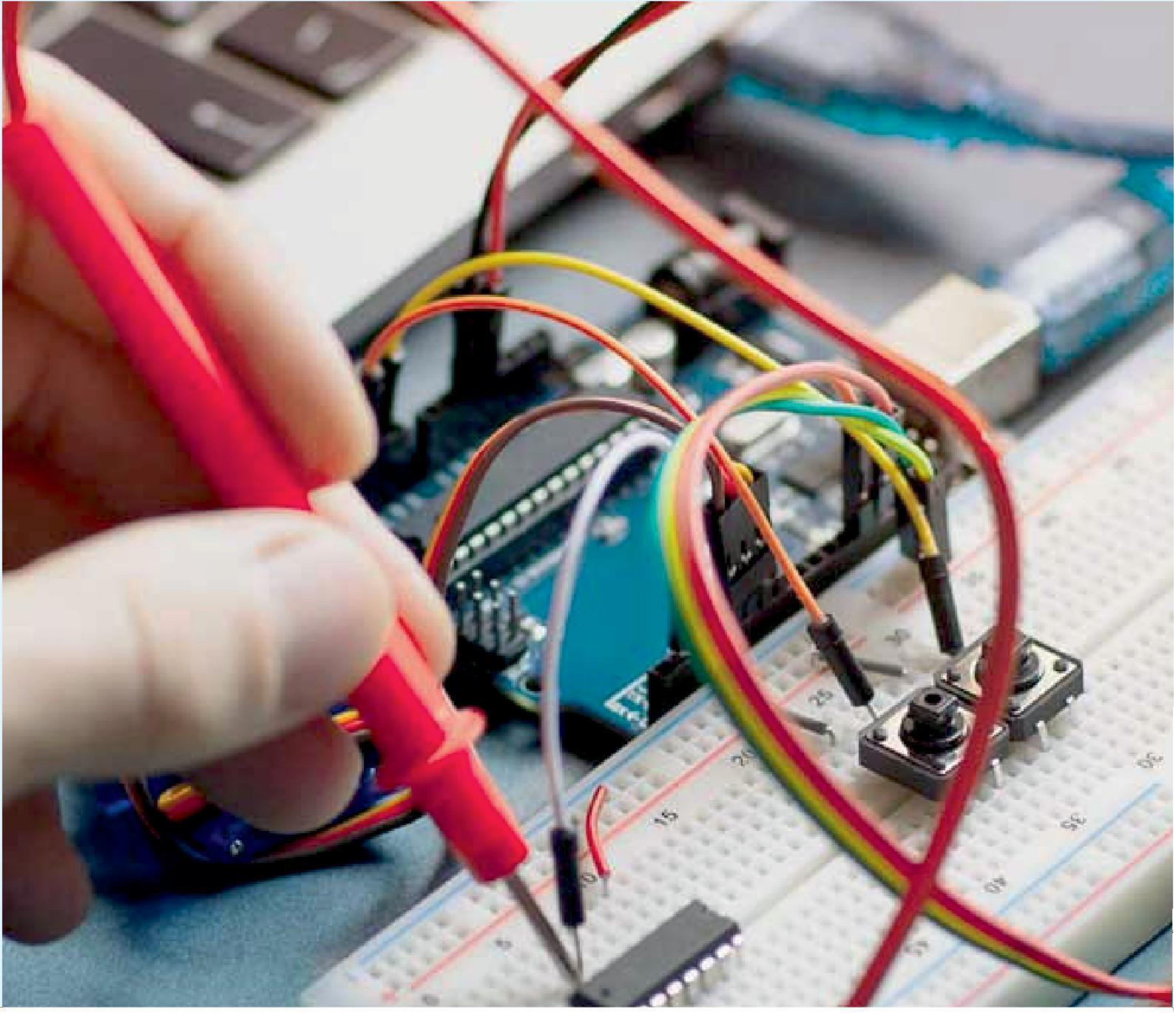

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