A Comparative Study on Different Online State of Charge Estimation Algorithms for Lithium-Ion Batteries

Zeeshan Ahmad Khan 1,*, Prashant Shrivastava 2,*, Syed Muhammad Amrr 3, Saad Mekhilef 4,5,6, Abdullah A. Algethami 7, Mehdi Seyedmahmoudian 5 and Alex Stojcevski 5

1 CARAID SE, Volkswagen AG, 85053 Ingolstadt, Germany
2 Centre for Automotive Research and Tribology (CART), Indian Institute of Technology Delhi, New Delhi 110016, India
3 Department of Electrical Engineering, Indian Institute of Technology Delhi, New Delhi 110016, India; syedamrr@gmail.com
4 Power Electronics and Renewable Energy Research Laboratory (PEARL), Department of Electrical Engineering, University of Malaya, Kuala Lumpur 50603, Malaysia; saad@um.edu.my
5 School of Software and Electrical Engineering, Swinburne University of Technology, Melbourne, VIC 3122, Australia; mseyedmahmoudian@swin.edu.au (M.S.); astojcevski@swin.edu.au (A.S.)
6 Center of Research Excellence in Renewable Energy, and Power Systems, King Abdulaziz University, Jeddah 21589, Saudi Arabia
7 Department of Mechanical Engineering, College of Engineering, Taif University, Taif 21944, Saudi Arabia; a_algethami@tu.edu.sa
* Correspondence: zakhan.91@gmail.com (Z.A.K.); prashant.xev.ess@gmail.com (P.S.)

Abstract: With an accurate state of charge (SOC) estimation, lithium-ion batteries (LIBs) can be protected from overcharge, deep discharge, and thermal runaway. However, selecting appropriate algorithms to maintain the trade-off between accuracy and computational efficiency is challenging, especially under dynamic load profiles such as electric vehicles. In this study, seven different widely utilized online SOC estimation algorithms were considered with the following goals: (a) to compare the accuracy of the different algorithms; (b) to compare the computational time in the simulation. Since the 2-RC battery model is highly accurate and not very computationally complex, it was selected for implementing the considered algorithms for the model-based SOC estimation. The considered online SOC estimation performance was evaluated using measurement data obtained from experimental tests on commercial lithium manganese cobalt oxide batteries. The experimental analysis consisted of a dynamic current profile comprising a worldwide harmonized light vehicle test procedure (WLTP) cycle and constant current discharging pulses. In addition, the performance of the considered different algorithms was compared in terms of estimation error and computational time to understand the challenges of each algorithm. The results indicated that the extended Kalman filter (EKF) and sliding mode observer (SMO) were the best choices because of their estimation accuracy and computation time. However, achieving the SOC estimation accuracy depended on the battery modeling. On the other hand, the estimated SOC root mean square error (RMSE) using a backpropagation neural network (BPNN) was less than that using a Luenberger observer (LO). Moreover, with the advantages of BPNNs, such as no need for battery modeling, the estimation error could be further reduced using a large size dataset.

Keywords: lithium-ion battery; state of charge; electric vehicle; battery model; estimation

1. Introduction

In the last couple of years, the automotive industry has experienced a paradigm shift from conventional internal combustion engine (ICE) vehicles to electric vehicles (xEVs) [1]. The performance of xEVs highly depends on the energy storage systems used therein, and these systems share a significant portion of the overall cost. Though the technology is expanding, safe and reliable energy storage systems are still a considerable challenge.
Among all the existing energy storage system technologies, lithium-ion batteries (LIBs) have prominent features, such as high power/energy density, long cycle life, and low self-discharge, that make them suitable for xEV applications [2,3]. However, it is always recommended to operate in a safe operating range with the help of an electronic chip called a battery management system (BMS) [4]. For the proper functioning of BMSs, the battery state needs to be accurately monitored, especially the state of charge (SOC) [5,6]. The SOC refers to the ratio of a battery’s remaining capacity to its actual capacity [7]. Generally, estimation algorithms are utilized to estimate SOC, as SOC cannot be directly measured [8].

According to the literature, SOC estimation methods can be broadly classified into direct and indirect methods. Furthermore, the direct methods can be divided into the ampere-hour counting method [9] and the open-circuit voltage method [10]. The ampere-hour counting method is simple to implement in BMS; however, the possibility of drift in estimated SOC is high because of error accumulation under measurement inaccuracy. In the open-circuit voltage (OCV) method, an OCV vs. SOC lookup table is used for SOC estimation. However, it is difficult to achieve high SOC estimation accuracy during a flat voltage range [11].

The indirect methods can be classified into model-based and data-driven methods. In the model-based method, a battery model and an estimation algorithm are employed for SOC estimation. Different battery models that researchers have considered can be classified into empirical models (EMs) [12], electrical equivalent circuit models (EECMs) [13], electrochemical models (ECMs) [14], and electrochemical–thermal models (ECTMs) [15]. Among these, the second-order resistive and capacitive (RC) EECM has been widely utilized by researchers because of its low complexity and ability to mimic electrochemical behavior [16–18]. In recent years, for SOC estimation, different advanced algorithms have been developed for model-based SOC estimation [19]. Some of the commonly used algorithms are the Kalman filter (KF) [20,21], the particle filter (PF) [22], the H-infinity filter [23], the sliding mode observer (SMO) [24], and the Luenberger observer (LO) [25]. Furthermore, to improve the SOC estimation performance of model-based methods, several modified algorithms have been intensively studied, for example, extended KF (EKF) [26,27], adaptive extended KF (AEKF) [28,29], unscented KF (UKF) [30,31], sigma point KF (SPKF) [32,33], adaptive PF (APF) [34], and modified LO (MLO) [35].

In the data-driven method, the machine learning model is referred to as the black-box model. In a black-box model, the relationships between input and output related to voltage, current, temperature, and SOC are used without understanding the underlying features of electrochemical behavior. Commonly used machine learning (ML) algorithms are feedforward neural networks (FNNs) [36], backpropagation neural networks (BPNNs) [37,38], convolutional neural networks (CNNs) [39], recurrent neural networks (RNNs) [40], long short-term memory (LSTM) networks [41,42], and extreme machine learning (EML) [43]. However, the accuracy and performance of the ML methods highly depend on the quantity and quality of the datasets used. Poor datasets may lead to over- and underfitting problems that can degrade SOC estimation accuracy.

Research statistics on battery SOC estimation methods introduced or developed by researchers in the last decade are shown in Figure 1. Data from published journals were collected from ScienceDirect (2021). These statistics reveal the importance of accurate SOC estimation methods in real-time applications. The data indicate that the number of publications on SOC estimation is gradually increasing. Model-based SOC estimation has been widely chosen by researchers because of its high accuracy. In model-based SOC estimation using adaptive algorithms, the KF and its advanced algorithms have been applied more often than other algorithms. On the other hand, with advancement in ML technology, the application of data-driven methods for SOC estimation is also increasing.
In the past years, several studies have been published on online SOC estimation [6,7,9,10,20,44–46]. However, for a detailed comparative assessment of the different SOC estimation algorithms, it is required to consider the same test environment, as the performance of SOC estimation may vary with operating conditions. Based on the trends in research on SOC estimation in the last couple of years, seven different algorithms, EKF, AEKF, SPKF, UKF, LO, SMO, and BPNN, were considered for SOC estimation. The performance of these algorithms in terms of SOC estimation error and complexity under the same operating conditions was analyzed and is presented herein. With the obtained estimation results, the best suitable algorithm as per system requirement can be chosen by researchers and engineers. Additionally, this study will be helpful in the development of estimations of other states and combined states.

Key Contributions

The main contributions of this study are given below:

- Seven different widely used SOC estimation algorithms, EKF, AEKF, SPKF, UKF, LO, SMO, and BPNN, were considered to develop a comparative study.
- The effect of temperature on two RC battery model parameters was analyzed, and the obtained parameters were utilized for model-based SOC estimation.
- An experimental dataset collected under a dynamic load profile test on commercial 25 Ah lithium-nickel-manganese-cobalt-oxide (LiNiMnCoO2) prismatic cells was considered for SOC estimation using different algorithms. Further, the estimated SOC accuracy and computational burden were compared.
- Based on the obtained results, future recommendations are explained to assist engineers and researchers in their work.

2. Description of Considered Online SOC Estimation Algorithms

Different methods of online SOC estimation were analyzed in this study. Model-based SOC estimation methods using EKF, SPKF, UKF, AEKF, LO, and SMO and a data-driven method using BPNN were considered, as shown in Figure 2.

Figure 1. Research statistics on battery state of charge estimation in the last decade. (Source: Science Direct, 2021 database).
2.1. Model-Based Method

In the model-based method of online SOC estimation, a battery model and an estimation algorithm play essential roles. The estimation algorithm modifies the gain and estimates the SOC in real-time conditions based on the voltage error, as shown in Figure 3. Different types of estimation algorithms, such as Kalman filters and their variants and observers, have been widely utilized for SOC estimation using the model-based method.

![Figure 3. Process of model-based online SOC estimation method [20].](image)

2.1.1. Extended Kalman Filter (EKF)

The EKF algorithm is a nonlinear version of the KF, and it works on the principle of linearization of the nonlinear function [47]. For this purpose, first-order or second-order terms of Taylor’s formula are used. In the past few years, EKF has been the most preferred method for state estimation. In [48], the robustness of EKF and that of UKF were compared, and both filters demonstrated high robustness against current noise. In [49], EKF was used for battery model parameter identification and state estimation. In this method, the computation of the Jacobian matrix is required, which degrades the estimated SOC value [50]. For the linearization cutoff process, first-order Taylor expansion is adopted in EKF, so it is possible to achieve only first-order accuracy.

In the last couple of years, several modifications have been performed to improve the performance of the EKF. In [47], an improved EKF was proposed for online SOC estimation that considered the aging factor to adaptively update the battery model parameters. The SOC estimated by the improved EKF (IEKF) method for a single-cell battery could accurately present the battery pack SOC of electric vehicles (EVs). In [51], SOC estimation was performed with the help of a robust EKF, and to evaluate the performance, five different types of RC models were selected. The sensitivity with different initial values was exam-
ined, and with this SOC estimation method, the error resulting from the SOC initial values was significantly reduced. In [52], experimental data were used to develop a battery model to minimize the effect of measurement and process noise. The outcomes confirmed that the proposed method could effectively eliminate the impact of measurement noise and process noise on the SOC estimation without prior knowledge of the initial SOC. However, it had a problem of significant error occurrence with highly nonlinear systems due to its approximation of distributed Gaussian random variables and ignorance of higher-order terms. Furthermore, EKF accuracy directly depends on the battery model and prior knowledge of the system noise variables. If the prior knowledge is not correct, then the estimation process error may lead to divergence [53].

2.1.2. Adaptive Extended Kalman Filter (AEKF)

The assumption of fixed measurement and process noise covariance in EKF estimation reduces the estimation process’s overall performance [54,55]. The problem of biased solutions may occur if the initial process and measurement noise covariance matrices are too small. On the other hand, if both the covariance matrices are too large, then the problem of divergence occurs [56]. The feature of adaptively updated covariance matrices is added with the EKF in the AEKF estimation method to overcome the problem of diverging and significant error. In [56], the new AEKF algorithm was proposed to estimate SOC. In this algorithm, the filter innovation matrix \( H_k \) based on the innovation sequence \( e_k \) inside the moving estimation window (\( M \)) is added in the estimation steps of the EKF. With the help of \( H_k \), the measurement \( P_{vk} \) and process \( P_{wk} \) covariance matrices are updated iteratively. Divergence is also an essential factor for the accuracy of EKF. In [17,57], a divergence judgmental condition was introduced in the AEKF to avoid filter divergence and improve stability.

2.1.3. Sigma-Point Kalman Filter (SPKF)

An alternative approach to the state estimation for nonlinear systems called the sigma-point Kalman filter (SPKF) was proposed to overcome the shortcomings of EKF and AEKF [58]. This method has at least second-order Taylor accuracy. In SPKF, linearization is performed via a statistical distribution approach to nonlinear systems with the application of deterministic sampling points called sigma points [59]. Sigma points are usually selected. The weighted mean and covariance of the posterior random variable must be matched with the prior mean and covariance of the random variables being modeled [58]. Based on this weighting factor, the SPKF algorithm has been classified into two categories: unscented Kalman filter (UKF) and central difference Kalman filter (CDFK) [58,59].

2.1.4. Unscented KF (UKF)

The UKF also uses the concept of sigma points to perform state and output estimation. This approach calculates the set of weighted sigma points on the original Gaussian (input space), maps them on the target Gaussian (output space) by passing them through the nonlinear function, and then calculates the mean and covariance of the transformed Gaussian [31,60]. These sigma points are representative of the whole system distribution. The UKF is based on the concept of “unscented transform”, which calculates the statistics (mean and covariance) of a variable after it goes through a nonlinear transformation [48]. The use of sigma points to calculate the mean and covariance indicated that the UKF and SPKF had higher accuracy than EKF [30].

2.1.5. Luenberger Observer (LO)

The concept of the observer can be applied to both linear and nonlinear systems. David G. Luenberger, in 1964 [61], published a research article introducing the concept of observers based on the state-space model of a linear system. In [61], the idea of nonlinear systems was discussed in regard to several variants for observers, including reduced-order observers and dual observers. From then on, the concept of observers was limited to control system problems and widely utilized in multiple engineering problems for state estimation of nonlin-
ear systems [35]. The observer requires the state-space model of the dynamic system being modeled. The working principle of the Luenberger observer is based on using the biased output of a closed-loop system to remove the state biases so that that the convergence of the observer error dynamic to the neighborhood is ensured, i.e., the error between the actual and the observed states is reduced. Hence, the observed state measurement can be used as the exact system state measurement for the feedback control system design [62].

2.1.6. Sliding Mode Observer (SMO)

Another commonly used observer-based estimation technique is the SMO. The SMO has a similar structural design as any other state observer. However, it is much more robust in its estimations against error due to system disturbances and model uncertainties. The robustness property of SMO is achieved because of the sliding motion on the estimation error between the observer and measured output. Consequently, the observer output state precisely estimates the real-time plant output information [24]. A nonlinear discontinuous switching term, the function of output error, is inserted into the observing system to obtain this sliding motion. As a result of this discontinuous function, the system trajectories are forced to remain on a user-defined sliding surface in the error space. The motion of system states on the sliding surface is known as the sliding mode phase [63]. The switching term enables the system to reject disturbances and system parametric uncertainties, and the observer model output is used to design state feedback estimation [63]. However, the discontinuous switching function of SMO generates rapid oscillations in the dynamic observer model. The estimated states can have a chattering effect due to fast oscillations, which creates deviation in the observed value from the actual value. The fluctuation in the observer output increases as the magnitude switching function increases. As a result, chattering suppression methods are incorporated to appropriately reduce the switching gain while maintaining the sliding mode phase. The first solution is to lower the magnitude as the system states decrease [64]. The second option is an adaptive-based tuning of magnitude, a low-pass filter-derived equivalent control function. This method can also be used for plants affected by unknown disturbances [65].

2.2. Data-Driven Method

Backpropagation Neural Network (BPNN)

Artificial neural networks (ANN) are data-driven models capable of modeling any nonlinear, complex input–output relationship. As the name suggests, these networks are designed like the human brain, with neurons representing nodes and weights expressing the intensity of connection between different neurons. The higher the value of the weight is, the greater the influence on the final output is. The learning of neural networks (NNs) is nothing but simple changes in the values of weights between different neurons to achieve an optimal value [66]. The learning of an NN is typically performed by an algorithm that adjusts the values of weights until they are optimized so that the network output converges to the actual output [36,67].

3. Experimental Setup and Test Conduct

3.1. Experimental Setup

The experimental setup utilized for testing the battery cell is shown in Figure 4. It consisted of a 25 Ah lithium-nickel-manganese-cobalt-oxide (LiNiMnCoO2) prismatic cell, abbreviated as Li-NMC; an EA-PSI 9080–510 power supply; an EA-EL 9500–60 B electronic load; a Vötsch Industrietechnik VTL 4006 climate chamber; and a laptop running the MATLAB software for data acquisition. Each sample of the battery variables, including current, voltage, and the temperature of the cell during charging, discharging, and rest phases, was obtained every 0.05 s (measurement frequency = 20 Hz). The upper (4.2 V) and lower (2.5 V) safety limits for battery voltage were also monitored throughout the experiments. The battery cell was placed inside the climate chamber to test under controlled temperature conditions. The climate chamber had a temperature range of −40 to +180 °C with a heating
rate of 2.5 K/min and a cooling rate of 3.5 K/min. The power supply and electronic load had an inbuilt function generator that could apply constant current pulses with subsequent rest phases in between. These constant current pulses were applied to obtain the voltage response of the battery when subjected to constant current pulses followed by a long rest phase. The instruments were connected and controlled using a prototype graphical user interface (GUI) developed on the app designer development environment in MATLAB, which ran on the laptop.

![Experimental setup](image)

**Figure 4.** Experimental setup.

### 3.2. Stepwise Test Description

A complete step involved in the test conducted on the considered cell is presented in Figure 5. Each step consisted of a pulse discharge test and a dynamic load profile test under controlled operating conditions.

![Complete test steps involved in testing](image)

**Figure 5.** Complete test steps involved in testing.

### 3.3. Pulse Charge/Discharge Test

Exhaustive characterization tests were performed on the fresh 25 Ah Li-NMC prismatic cell at three different temperatures, 5 °C, 25 °C, and 45 °C. Constant current pulse tests were
performed for both charging and discharging conditions. During charging, the cell was charged from 0 to 100% SOC in steps of 5%, whereas in discharging, the cell was discharged from 100 to 0% SOC in steps of 5%. The obtained test current and terminal voltage profile were used to evaluate the OCV–SOC relationship and extract the 2-RC electrical equivalent circuit battery model parameters.

3.4. Dynamic Load Profile Test

After the pulse charge/discharge test and the identification of battery 2-RC model parameters $R_0$, $R_1$, $R_2$, $C_1$, and $C_2$, it was necessary to validate the results. For validation, a dynamic current profile was chosen, and the voltage response of the cell was recorded. As shown in Figure 6, the dynamic profile involved a combination of the Worldwide Harmonized Light Vehicle Test Procedure (WLTP) class 3 drive cycle and the constant current discharge pulses. The current profile under the WLTP drive cycle is depicted in Figure 6a. The steps involved in dynamic discharging were:

- The cell voltage was measured before the start of the test. The voltage across the terminals was checked to be 4.10 V as specified by the manufacturer for the cell to be completely charged. If the voltage was 4.10 V, the test was started at 25°C. If not, the cell was charged with a very low C-rate (C/30 or C/50) to bring the voltage to 4.10 V and then allowed to rest for at least 2 h to reach equilibrium.
- A discharging pulse of 25 A (1 C-rate) for 12 min was applied to discharge the cell by 20%, as shown in Figure 6b.
- A resting phase of 15 min was applied during which there was no current flow and the cell could relax.
- Figure 6b shows that a programmed WLTP class 3 drive cycle was applied to the cell under test. The drive cycle lasted for 1800 s, and during this test, the full cycle was applied.
- A resting phase of 15 min was applied again to allow the cell to relax. The above four steps were repeated multiple times until the voltage reached 3.0 V, which was the lower limit specified by the cell manufacturer.

![Figure 6. Dynamic load profile: (a) WLTP current profile; (b) combined WLTP and pulse discharge current profile.](image-url)
4. Evaluation Method and Battery Modeling

4.1. Evaluation Matrices

Three different evaluation metrics were considered to analyze the performance of considered SOC estimation algorithms under dynamic load profiles. The SOC estimation error was analyzed in terms of maximum absolute error (MaxAE), root means square error (RMSE), and computation time (in seconds). The values of MaxAE and RMSE were calculated by using Equations (1) and (2), respectively. The SOC estimation error denotes the difference between the experimental data and the online estimated value.

\[
\text{MaxAE} = \max |(\text{Estimated})_k - (\text{Experimental})_k| \quad (1)
\]

\[
\text{RMSE} = \sqrt{\frac{1}{N} \sum_{k=1}^{N} ((\text{Measured})_k - (\text{Estimated})_k)^2} \quad (2)
\]

4.2. Battery Modeling

The 2-RC battery model is used in this study for battery modeling, as shown in Figure 7. The presence of two RC branches in the model enables it to capture the slow and fast time constants during the relaxation period of the battery. The parameter \( R_0 \) is the internal resistance of the battery, and \( i_k \) shows the current flowing through the battery. \( \tau_1 \) represents the fast time constant for the battery and is equal to the product of \( R_1 \) and \( C_1 \), and \( \tau_2 \) represents the slow time constant for the battery and is equal to the product of \( R_2 \) and \( C_2 \). \( V_t \) and \( V_{OCV} \) is the voltage source to represent the battery terminal voltage and open circuit voltage, respectively. Due to the presence of fast and slow polarization effects, the model is sometimes also referred to as the dual-polarization model. This model offers the advantage of ease of implementation in real-time applications and provides sufficiently accurate estimation results.

![Figure 7: Second-order RC equivalent circuit model.](image)

The associated state equation and output voltage equation for the battery in discrete time is provided below.

\[
\begin{bmatrix}
Z_{k+1} \\
V_{1,k+1} \\
V_{2,k+1}
\end{bmatrix} =
\begin{bmatrix}
1 & 0 & 0 \\
0 & 1/e^{-\Delta t/\tau_1} & 0 \\
0 & 0 & 1/e^{-\Delta t/\tau_2}
\end{bmatrix}
\begin{bmatrix}
Z_k \\
V_{1,k} \\
V_{2,k}
\end{bmatrix} +
\begin{bmatrix}
-\eta_i \Delta t / C_n \\
0 \\
0
\end{bmatrix} i_k
\]

\[
V_{t,k} = V_{OCV}(Z_k) - V_{1,k} - V_{2,k} - i_k R_0 \quad (4)
\]

where \( \Delta t \) stands for the sampling time, \( \eta_i \) is the coulombic efficiency for the circuit (generally taken as 1 during discharging and 0.99 during charging), \( C_n \) represents the nominal battery.
capacity, and $Z_k$ is the SOC, which is the state variable to be determined. The OCV ($Z_k$) is the open-circuit voltage for the battery under test and is taken as a function of SOC.

In this study, the forgetting factor recursive least square (FFRLS) method, as discussed in [68], is considered to extract the battery model parameters. The variation in identified battery model parameter profiles relating to the change in SOC and operating conditions at three different temperatures—5 °C, 25 °C, and 45 °C—for example, charging current, discharging current, and temperature, are shown in Figure 8.

**Figure 8.** Extracted battery model parameters profiles for SOC under three different temperatures: (a) $R_0$ during charging; (b) $R_0$ during discharging; (c) $R_1$ during charging; (d) $R_1$ during discharging; (e) $R_2$ during charging; (f) $R_2$ during discharging; (g) $\tau_1$ during charging; (h) $\tau_1$ during discharging; (i) $\tau_2$ during charging; (j) $\tau_2$ during discharging.
The battery’s internal resistance is one of the most important parameters when performing SOC estimation, and it varies substantially with SOC and the cell temperature. The $R_0$ is the sum of resistances offered by the electrolyte, the separator, and the electrodes. As shown in Figure 8a,b, the values of $R_0$ are relatively high at lower values of SOC ($SOC \leq 10\%$). This is because lithium ions are stored at the electrodes at the start of the charging or discharging process. $R_0$ values decrease continuously when the SOC is $0.2 \leq SOC \leq 0.9$. As the charge continues to be added or removed during charging and discharging due to the constant application of current, the internal resistance keeps on decreasing. It is recommended that a battery be operated in the SOC range (20–90%) when used in an electric vehicle (EV) or hybrid EV (HEV). Furthermore, the variation in $R_1$, $R_2$, $C_1$, $C_2$, $\tau_1$, and $\tau_2$ with SOC and temperature during the constant current charging and the discharging tests is demonstrated in Figure 8c–j.

4.3. OCV vs. SOC Relationship

The variation in OCV with SOC for different cell temperatures during the charging and discharging tests is shown in Figure 9a,b, respectively. The relationship between OCV and SOC varies with the change in operating conditions, especially temperature values. This relationship is obtained by allowing the battery to relax to the OCV after excitation by a current pulse. From the zoomed-in portion attached in both the figures, it is observed that for a given SOC, the OCV value when the cell temperature is $5^\circ C$ is the highest (red line) while the OCV value is recorded at $45^\circ C$ is the lowest (yellow line). These differences in values are attributed to the effect of temperature on the internal chemical reactions of the cell. The chemical reactions happening inside the cell represent the movement of charged particles from the cathode to the cell’s anode, and vice versa is responsible for the production of electricity. Lower temperatures mean that the mobility of the ions is reduced as the rate of chemical reaction decreases with increasing temperature. The OCV is obtained as the last value of the relaxation part, and the duration for which the cell can relax in these tests is the same (30 min) for all the temperatures. Thus, at lower temperature values, we have a higher value of the voltage caused by the slower diffusion of the lithium ions into the graphite anode. This phenomenon occurs inside the cell irrespective of the charging or discharging conditions. Therefore, from the zoomed-in portion attached with Figure 9a,b, for a given SOC, OCV values for $5^\circ C$ are the highest while OCV values for $45^\circ C$ are the lowest. The difference between the OCV values for $25^\circ C$ and $45^\circ C$ is not very high.

\[
V_{OCV} = a_1 \cdot \exp\left(-\frac{(x - b_1)}{c_1}\right) + a_2 \cdot \exp\left(-\frac{(x - b_2)}{c_2}\right) + a_3 \cdot \exp\left(-\frac{(x - b_3)}{c_3}\right) + a_4 \cdot \exp\left(-\frac{(x - b_4)}{c_4}\right) + a_5 \cdot \exp\left(-\frac{(x - b_5)}{c_5}\right)
\]

The dependence of OCV on SOC needs to be empirically determined in OCV-based SOC estimation and model-based SOC estimation. The fitting for the charging OCV at $25^\circ C$ has been performed using the fifth-order Gaussian with 15 constants as expressed by Equation (5). The fitting has been performed in MATLAB using the Curve fitting toolbox and the Gaussian expression that fits the measured OCV data.

The numerical values of the different coefficients in the Gaussian-expression fitted curve for charging and discharging OCV are listed in Table 1. Generally, the low-value RMSE and R-square value closer to 1 demonstrate high fitted-curve accuracy. For charging, the value of fitting curve RMSE = 0.006382 and R-square value = 0.9998. For discharging, the value of fitting curve RMSE = 0.006457 and R-square value = 0.9994.
The parameter values of $V_{OCV}$ are obtained from measurement and are then used in a MATLAB function to provide the model output voltage. As shown in Figures 9b and 10a, the modeling reports a mean error of 3.7569 mV and a maximum error of 132.5739 mV for charging. As shown in Figure 10c,d, the model has a mean error of 1.2279 mV and a maximum error of 40.7734 mV under discharging conditions. These low errors indicate a high accuracy in obtained parameter values used to obtain the model output voltage.

**Table 1. Different coefficients values of the gaussian expression of the fitted curve of charging and discharging OCV.**

<table>
<thead>
<tr>
<th>Mode</th>
<th>Coefficients in the Gaussian Expression Fitted Curve</th>
</tr>
</thead>
<tbody>
<tr>
<td>Charging OCV</td>
<td>$a_1 = 3.761$  $a_2 = 1.543$  $a_3 = 3.294$  $a_4 = 1.368$  $a_5 = 0.1842$</td>
</tr>
<tr>
<td></td>
<td>$b_1 = 1.132$  $b_2 = 0.7436$  $b_3 = 0.3469$  $b_4 = 0.00292$  $b_5 = 0.04179$</td>
</tr>
<tr>
<td></td>
<td>$c_1 = 0.3507$  $c_2 = 0.2674$  $c_3 = 0.3965$  $c_4 = 0.2271$  $c_5 = 0.05305$</td>
</tr>
<tr>
<td>Discharging OCV</td>
<td>$a_1 = 4.282$  $a_2 = 1.954$  $a_3 = 1.599$  $a_4 = 0.4318$  $a_5 = -$</td>
</tr>
<tr>
<td></td>
<td>$b_1 = 1.4$  $b_2 = 0.4647$  $b_3 = 0.0852$  $b_4 = 0.0373$  $b_5 = -$</td>
</tr>
<tr>
<td></td>
<td>$c_1 = 0.8515$  $c_2 = 0.5143$  $c_3 = 0.3252$  $c_4 = 0.0965$  $c_5 = -$</td>
</tr>
</tbody>
</table>

**5. Results and Discussion**

**5.1. Battery Model Parameter Validation**

To verify the obtained parameter values, the measured output voltage and the model output voltage for charging and discharging conditions at 25 °C are plotted in Figure 10. The parameter values of $V_{OCV}$ $R_0$, $R_1$, $R_2$, $C_1$, $C_2$, $τ_1$, and $τ_2$ obtained from measurement are interpolated for the whole interval and are then used in a MATLAB function to provide the model output voltage. As shown in Figures 9b and 10a, the modeling reports a mean error of 3.7569 mV and a maximum error of 132.5739 mV for charging. As shown in Figure 10c,d, the model has a mean error of 1.2279 mV and a maximum error of 40.7734 mV under discharging conditions. These low errors indicate a high accuracy in obtained parameter values used to obtain the model output voltage.
The accuracy of EKF is also not low, with the maximum error remaining under 1% for both charging and discharging conditions. Additionally, the time required by LO is also quite high for charging and discharging conditions. The LO performs the worst in this case with an RMS error of 1.2709% under the experimented discharging conditions. Additionally, the time required by LO is also quite high for charging and discharging conditions. The LO has only observer poles for tuning; however, it involves a greater number of additional quantities to calculate.

The estimation of SOC and absolute errors of the considered algorithms are demonstrated in Figure 11. All the methods performed with good accuracy (RMSE 2%) for estimating SOC after applying a dynamic current pulse to the cell test under charging and discharging test conditions. The value of the estimated SOC RMSE, MAE, and computation time is listed in Table 2.

As shown in Figure 11, the SPKF and UKF outperform EKF in RMS error and maximum error for both charging and discharging conditions. Additionally, it can be observed that SPKF has a lower RMS error than UKF only by a very low margin. Despite EKF having a more significant RMS error and maximum error values than its Kalman filter counterparts, the ease of implementation is relatively higher. The accuracy of EKF is also not low, with the maximum error remaining under 1% for both charging and discharging conditions. AEKF and SMO stand out from other algorithms due to their shallow RMS errors, as demonstrated in Table 2. However, these algorithms are complex to implement in MATLAB and contain several tunable parameters. The mathematical design of AEKF involves the step of adapting matrix Q. In contrast, for SMO, the Ricatti equation needs to be solved and the Lyapunov stability criterion needs to be satisfied. As a result, SMO has a very high computation time of 330.013 s. The LO performs the worst in this case with an RMS error of 1.2709% under the experimented discharging conditions. Additionally, the time required by LO is also quite high for charging and discharging conditions. The LO has only observer poles for tuning; however, it involves a greater number of additional quantities to calculate.
Figure 11. SOC estimation results: (a) SOC estimation using EKF; (b) absolute error using EKF; (c) SOC estimation using AEKF; (d) absolute error using AEKF; (e) SOC estimation using SPKF; (f) absolute error using SPKF; (g) SOC estimation using UKF; (h) absolute error using UKF; (i) SOC estimation using SMO; (j) absolute error using SMO; (k) SOC estimation using LO; (l) absolute error using LO; (m) SOC estimation using BPNN; (n) absolute error using BPNN.
Table 2. Comparison of SOC estimation results using considered algorithms and their limitations.

<table>
<thead>
<tr>
<th>Method</th>
<th>Tunable parameters</th>
<th>RMSE (%)</th>
<th>Max AE (%)</th>
<th>Computational Time (sec)</th>
<th>Limitations</th>
</tr>
</thead>
<tbody>
<tr>
<td>EKF</td>
<td>$P$ ($3 \times 3$), $Q$ ($3 \times 3$), $R$ ($1 \times 1$)</td>
<td>0.5368</td>
<td>0.9721</td>
<td>145.134</td>
<td>Linearizes the state and measurement equations using the first-order Taylor expansion; dependence on battery model parameters; prior knowledge of system noise signals is necessary; dependence on experimental conditions</td>
</tr>
<tr>
<td>AEKF</td>
<td>$P$ ($3 \times 3$), $Q$ ($3 \times 3$), $R$ ($1 \times 1$)</td>
<td>0.3176</td>
<td>0.4184</td>
<td>199.908</td>
<td>Complex tuning of the filter performance when simultaneously adapting matrices $Q$ and $R$; dependence on battery model parameters; dependence on experimental conditions</td>
</tr>
<tr>
<td>SPKF</td>
<td>$P$ ($3 \times 3$), $Q$ ($3 \times 3$), $R$ ($1 \times 1$), $h$ ($1 \times 1$)</td>
<td>0.5574</td>
<td>0.94</td>
<td>208.152</td>
<td>High value of measurement noise causes filter divergence; estimation errors, and slow convergence when the dataset is too large; dependence on battery model parameters; dependence on experimental conditions</td>
</tr>
<tr>
<td>UKF</td>
<td>$P$ ($3 \times 3$), $Q$ ($3 \times 3$), $R$ ($1 \times 1$), $\alpha$ ($1 \times 1$), $\beta$ ($1 \times 1$), $\kappa$ ($1 \times 1$)</td>
<td>0.5585</td>
<td>0.91</td>
<td>213.308</td>
<td>High value of measurement noise causes filter divergence; estimation errors, and slow convergence when the dataset is too large; dependence on battery model parameters; dependence on experimental conditions; 3 additional tunable parameters apart from $P$, $Q$, and $R$ matrices</td>
</tr>
<tr>
<td>LO</td>
<td>Observer poles ($3 \times 1$)</td>
<td>1.2709</td>
<td>29.39</td>
<td>354.972</td>
<td>Incorrect determination of observer poles can lead to estimation errors, and noise problems can arise when observer poles are placed farther to the left in the complex plane; dependence on battery model parameters; dependence on the experimental condition</td>
</tr>
<tr>
<td>SMO</td>
<td>$R$ ($1 \times 1$), $Q$ ($3 \times 3$), $W$ ($1 \times 1$), $Q_f$ ($3 \times 3$), $\rho$ ($1 \times 1$)</td>
<td>0.0439</td>
<td>0.0963</td>
<td>330.013</td>
<td>Ricatti Equation constants; Lyapunov stability constants; observer switching; gain constant</td>
</tr>
<tr>
<td>BPNN</td>
<td>$\alpha$ ($1 \times 1$), network size, lambda ($1 \times 1$)</td>
<td>0.8172</td>
<td>46.99</td>
<td>160.142</td>
<td>Computationally expensive; requires advanced techniques for optimization</td>
</tr>
</tbody>
</table>

A BPNN also presents an alternative to the existing methods and can be used for SOC estimation, provided sufficient data are available for training the network. Once the network is trained, it can be used for testing an unknown measurement set to perform SOC estimation. However, the implemented network in this study is an offline network. The BPNN could also be an online network that could provide SOC estimation results instantaneously. BPNN estimates SOC with more than 98% accuracy in both cases; however, the maximum error is the highest among all the networks. BPNN has a very high offset, and
as the iterations progress, the network SOC estimation converges to the measured value. BPNN also acts as a viable alternative if the data-based SOC estimation is considered.

The study aims to suggest an optimal method for SOC estimation. Therefore, this could represent a trade-off between accuracy and ease of implementation. The methods with more tunable parameters and additional calculations will yield accurate results. However, these would be complex to implement, integrate, and stabilize into the existing BMS software for implementation. Considering these points from the model-based approach, two methods can be recommended for SOC estimation. The first is EKF because of its good accuracy and ease of implementation. Another method that can be recommended is SMO. Even though it has a higher number of tunable parameters and involves the most additional calculations, the strong analytical structure of the method allows it to supersede other algorithms in terms of accuracy. Additionally, with such a strong analytical equation-based structure, the method is more robust and can provide accurate SOC estimations even when the drive cycles are incorporated into the applied current profile. The EKF has the least computation time amongst all the methods while SMO has the best accuracy. The recommendation of two methods allows the user freedom to decide which method is most suitable for them based on their requirements. For an application wherein the computation time, memory requirements, and complexity are not as important as the accuracy, SMO can be the optimal algorithm from the studied group. However, when the accuracy is not as crucial as the computation time, complexity, and memory requirements, EKF can provide the desired results.

6. Future Recommendations

Based on the comparison of the obtained results for the considered algorithms for SOC estimation, recommendations for future research are listed below:

- As the battery model parameters change with the battery aging, it is recommended to simultaneously estimate the battery model parameters to improve the SOC estimation accuracy using the model-based method further.
- By considering the adaptive value of sampling time, it would be possible to improve the SOC estimation accuracy and reduce the computational burden.
- Based on the obtained results, it is recommended to develop a hybrid algorithm by combining the algorithms to achieve higher SOC estimation accuracy and lower computational time.
- To achieve high accuracy of online SOC estimation in a real-time application, combining the model-based and data-driven methods in future studies is recommended.
- Because of the advancement of machine learning algorithms, the concept of a digital twin would be a good choice for online battery SOC estimation.
- To improve the efficiency of the BMS, it would be useful to develop a combined state estimation method using a data-driven as well as model-based approach.
- With the advancement of ML algorithms, it is recommended to develop a cloud-based BMS to reduce the overall cost of xEVs.

7. Conclusions

Based on the application and requirements, a suitable estimation algorithm needs to be selected to implement in a BMS because of its limitations. In this study, different estimation algorithms, EKF, AEKF, SPKF, UKF, LO, SMO, and BPNN, were utilized for online SOC estimation to perform a comparative analysis. A 2-RC battery model was considered because of its high accuracy and property of mimicking battery characteristics. For accurate battery model parameter estimation and betterment of the dynamic performance simulation precision of the battery model, pulse characterization tests were performed at three different temperatures, 5 °C, 25 °C, and 45 °C. Furthermore, parameter identification was performed to build a battery model using the FFRLS algorithm [68]. The temperature dependency of the model parameters was also evaluated through an exhaustive testing process. The obtained low value of battery model terminal voltage error (i.e., mean error less than 4 mV and maximum error less than 135 mV) validated the high accuracy of the
2-RC battery model. The performance of the different algorithms was verified against measurements from the dynamic load profile test. The dynamic load profile test applied at 25 °C comprised the WLTP drive cycle combined with constant current discharging pulses. Per a comparison of the estimation results, EKF and SMO are recommended for real-time BMS implementation. EKF provided the least computation time (145.134 s) and low estimation errors (RMSE = 0.5368% and MaxAE = 0.9721%), whereas SMO had a higher computation time (330.013 s) but the lowest errors in estimation (RMSE = 0.0439% and MaxAE = 0.0963%).


Funding: This work is financially supported by the Ministry of Higher Education, Malaysia, under the Long Term Research Grant Scheme (LRGS): LRGS/1/2019/UKM-UM/01/6/3.

Institutional Review Board Statement: Not applicable.

Informed Consent Statement: Not applicable.

Data Availability Statement: The data presented in this study are available on request from the corresponding author.

Acknowledgments: This work is financially supported by the Ministry of Higher Education, Malaysia, under the Long Term Research Grant Scheme (LRGS): LRGS/1/2019/UKM-UM/01/6/3.

Conflicts of Interest: The authors declare no conflict of interest.

References
2. Xavier, M.A.; Trimboli, M. Lithium-ion battery cell-level control using constrained model predictive control and equivalent circuit models. J. Power Sources 2015, 285, 374–384. [CrossRef]
6. Lu, L.; Han, X.; Li, J.; Hua, J.; Ouyang, M. A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sources 2013, 226, 272–288. [CrossRef]
7. Li, Z.; Huang, J.; Liaw, B.Y.; Zhang, J. On state-of-charge determination for lithium-ion batteries. J. Power Sources 2017, 348, 281–301. [CrossRef]

15. Wu, B.; Yufit, V.; Marinescu, M.; Offer, G.; Martinez-Botas, R.F.; Brandon, N.P. Coupled thermal–electrochemical modelling of uneven heat generation in lithium-ion battery packs. *J. Power Sources* 2013, 243, 544–554. [CrossRef]


25. Li, J.; Barillas, J.K.; Guenther, C.; Danzer, M.A. A comparative study of state of charge estimation algorithms for LiFePO4 batteries used in electric vehicles. *J. Power Sources* 2013, 230, 244–250. [CrossRef]


32. Li, D.; Ouyang, J.; Li, H.; Wan, J. State of charge estimation for LiMn2O4 power battery based on strong tracking sigma point Kalman filter. *J. Power Sources* 2015, 279, 439–449. [CrossRef]


34. Ye, M.; Guo, H.; Cao, B. A model-based adaptive state of charge estimator for a lithium-ion battery using an improved adaptive particle filter. *Appl. Energy* 2017, 190, 740–748. [CrossRef]


37. Ee, Y.-J.; Tey, K.-S.; Lim, K.-S.; Shrivastava, P.; Adnan, S.; Ahmad, H. Lithium-Ion Battery State of Charge (SoC) Estimation with Non-Electrical parameter using Uniform Fiber Bragg Grating (FBG). *J. Energy Storage* 2018, 259, 1217–1230. [CrossRef]


62. Barillas, J.K.; Li, J.; Günther, C.; Danzer, M.A. A comparative study and validation of state estimation algorithms for Li-ion batteries in battery management systems. *Appl. Energy* 2015, 155, 455–462. [CrossRef]


64. Chen, Q.; Jiang, J.; Ruan, H.; Zhang, C. Simply designed and universal sliding mode observer for the SOC estimation of lithium-ion batteries. *IET Power Electron.* 2017, 10, 697–705. [CrossRef]


66. Xiao, F.; Li, C.; Fan, Y.; Yang, G.; Tang, X. State of charge estimation for lithium-ion battery based on Gaussian process regression with deep recurrent kernel. *Int. J. Electr. Power Energy Syst.* 2021, 124, 106369. [CrossRef]


68. Sun, X.; Ji, J.; Ren, B.; Xie, C.; Yan, D. Adaptive Forgetting Factor Recursive Least Square Algorithm for Online Identification of Equivalent Circuit Model Parameters of a Lithium-Ion Battery. *Energies* 2019, 12, 2242. [CrossRef]