Review of Battery State-of-Charge Estimation Algorithms

Kaustubh Kaushik, Devang Sureka, and H. V. Gururaja Rao

1 Introduction

Historical dependence on fossil fuels and subsequent overuse of traditional fuels has pushed environmental concerns to an all-time high. The single largest source of pollution is the combustion engines used primarily in vehicles. The alternative to the old internal combustion-based vehicles is electric or hybrid vehicles that replace combustible fuel engines with battery-based power units, keeping the carbon emissions in check. The use of batteries in place of traditional fuels presents a different set of challenges. The state of charge estimation largely governs the safety, robustness, durability, and reliability of batteries. Over the years, various algorithms have been put forward, like open circuit voltage (OCVMs), Coulomb counting method (CCMs), model-based methods (MBMs), and ANN-based methods (ANNBMs). Few algorithms use complementary methods for even more accurate estimation. To improve the BMS productivity and guarantee the battery's private use, we calculate the battery's SOC at each second during the activity. SOC cannot be calculated directly because the lithium-ion battery forms a closed-loop system. Hence, we calculate the SOC for the entire battery framework [1, 34].

Battery management systems include parameters like state of health (SOH), state of charge (SOC), state of power (SOP), and state of life (SOL) in its control circuit and an analog sampling circuit. The control circuit calculates parameters based on analog signals' readings and directs the information through various communication ports to the central control unit. The BMS forms the backbone of electric vehicle technology, and we judge the performance based on parameters like range, power, and service life. A BMS comprises a variety of sensors, actuators, regulators, and

K. Kaushik · D. Sureka · H. V. G. Rao (✉)
Department of Electrical and Electronics, Manipal Institute of Technology, Manipal Academy of Higher Education, Manipal, India
e-mail: gururaj.rao@manipal.edu

Sanjeevikumar et al. (eds.), *Advances in Renewable Energy and Electric Vehicles*,
Lecture Notes in Electrical Engineering 767,
https://doi.org/10.1007/978-981-16-1642-6_29

signature lines. An implementable BMS aims to make sure the battery's energy dispensation is judicious, and the data provided to the vehicle's energy management system is accurate as possible.

Additionally, proper interventions to the battery structure on the off chance that it works in adulterated conditions are secured, and this is achieved by monitoring the charging and delivering pattern of batteries. The model circuit's chief endeavor evaluates the current, voltage, and temperature according to the control circuit's gating signal. Moreover, the control circuit keeps checking the charge (SOC) state and other related parameters like SOH and SOP through analog signals. Subsequently, pass the data to the vehicular power management system, and it gives critical decision components to the heads and power appointment of vehicular energy [2, 3, 35].

State of charge (SOC) is the base parameter based on which a BMS specifies or calculates other parameters, including SOL and SOP. SOC is the proportion of remaining battery capacity about the battery's maximum capacity represented in percentage. SOC accuracy and delivery in real-time help eliminate catastrophic consequences and better manage various other sub-systems. We can draw an analogy between the SOC and traditional fuel gauge in combustion-based vehicles. SOC measurement is a challenging task. Internal and external factors play an important role in accurate SOC measurements like battery-aging, charging-discharging cycles, and differential characteristics between cells connected parallelly [4, 35].

Since BMS stays one of the most fundamental variables, different techniques have been proposed to estimate the SOC precisely. From the 1960s, scholastics, specialists, and researchers have performed broad examination to do the battery SOC assessment. In [7–10], authors have introduced a point by point SOC assessment as far as in general examination progress, future improvement patterns, and the beginning of SOC assessment.

Regardless, there is no perfect method of the SOC assessment cycle and estimation assurance and how to negate the atmospheric changes. Thus, this paper will explore the gaps by emphasizing the pre-existing estimation methods and focusing on the battery pack rather than a single cell [35].

2 State of Charge Estimation Methods

2.1 Classification of Estimation Methods

SOC estimation methods are broadly classified in four different forms, namely (a) look-up-table-based examples of which are open circuit voltage (OCV) and AC impedance, (b) Coulomb counting method (CCM), (c) model-based estimation methods (MBM), and (d) data-driven methods which are further classified into data training and data model fusion method. For this paper, we will explore each type of broad estimation method and then further delve into an example of each of those general classifications.

2.1.1 Look-Up-Table-Based Method

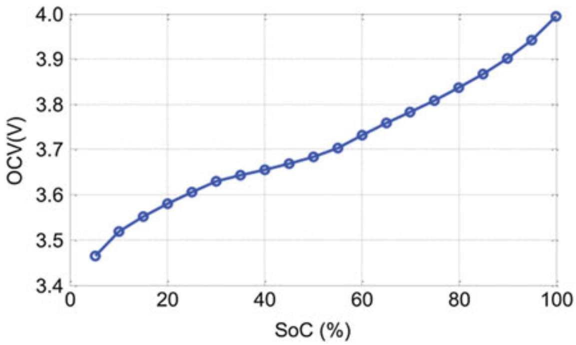
The state of charge of batteries directly correlates with their external fixed parameters like the open circuit voltage (OCV) and impedance. This way, we shall calculate their limits, and after that, tally it against the provided table, which is prepared with the associations among SOC and at any rate one limits, we can predict the SOC [11–14, 35].

We shall look at an OCV example for looking up a table-based model of state of charge estimation. Open circuit voltage is estimated under the condition that the battery is separated from any heap and has enough unwinding opportunity to arrive at its interior balance. The relationship between the open circuit voltage and SOC is the most effective strategy for assessing SOC if a precise estimation of open circuit voltage is already given. Since the Li-ion battery's unwinding time might even exceed 10 h or considerably more, which influences this method's real-time applicability. The connection between this method and SOC is found to alter temperature and used-age [15–18, 34]. Broad works zero in on improving the open circuit voltage method with higher accuracy and precision by considering external factors proposed in [16, 20–22]. Also, the qualities of the OCV-SOC bend are firmly identified with battery science. For instance, the open circuit voltage and state of the charge curve is moderately level for lithium-iron-phosphate batteries, which implies a little mistake in OCV will cause a significant SOC assessment blunder. As figured, the distinction of open circuit voltage is only 72 mV in the SOC scope of 30–80%. Hence, the traditional open circuit voltage method is not precisely satisfactory for real-world online applications. Analysts take a quick OCV shot to improve its utility in short, unwinding time [23, 24, 34].

The method suggested that the open circuit voltage method has higher computational accuracy and is apt for online assessment. Even though this method stands up to numerous downsides, it is still being perfected for better relevance during online applications.

Figure 1 shows that the OCV of a LiPB cell shows a monotonically growing example with its SOC. Thus, if we know the OCV, we can gather battery SOC by looking into the table among OCV and SOC [34].

Fig. 1 OCV curve of Lip cell



2.1.2 Coulomb Counting Method

The coulomb counting method, also known as ampere-hour integral method, is another efficient method of calculation of SOC of a cell. It is defined as:

$$z(t) = z(0) - \int_{0}^{t} \frac{n_i I_l(t)}{Q} \mathrm{d}t \tag{1}$$

where $z(t)$ is the SOC at time t and $z(0)$ is the underlying SOC; n_i is the battery's Coulombic proficiency. I_t is current, which is positive and negative for charging and discharging conditions, respectively. From Eq. (1), we can characterize SOC as the limit-integration of current. Consequently, the Coulomb counting method is close to the perfect SOC calculation methodology in principle [34]. Be that as it may, in all actuality, the underlying state of charge of the battery is not known ahead of time due to self-release and irregular utilization. Mistakes from current sensors likewise collect in the computation cycle. To beat these downsides, improving the CCM is proposed in [15, 16, 34]. Since Coulombic accuracy influences the productivity of Coulomb counting method in Eq. (1), changing the productivity count during the releasing cycle will assist in improving calculation exactness [12, 13]. In any case, it is generally challenging to acquire its worth because the battery's test tests under various current rates are required [26, 27, 34]. Joining the OCV state-of-charge relationship is additionally an excellent method to make up for the deficiencies of the Coulomb counting method. In [27], the creators proposed to reset the underlying state of charge of this method by anticipating open circuit voltage in a shorter duration and naturally remunerating the assessing blunder. Contrasted and the regular CCM, the proposed technique increments by 2.07% the SOC assessment precision when a UDDS profile is utilized. The battery's underlying charge levels are obtained for this method by thinking about the open circuit voltage, resting time, and temperature impact [29, 34]. By adding the release proficiency, the error of SOC assessment is additionally diminished. Eliminating the commotion from the current sensor will further reduce the discrepancies in the state-of-charge calculation. For simple applications, if the underlying charge is calculated ahead of time, and more accurate sensors are employed for the power management system, and this method is advantageous and appropriate for continuous state-of-charge assessment [34].

2.1.3 Model-Based Estimation Methods.

In the SOC assessment strategies, the model-based one appears to be the most accurate and suitable for online SOC assessment as of now. Much work is defined and identified with model-based methods. Various online-based models for SOC assessment strategies are introduced and summed up in the accompanying section. The standard calculations are Kalman channel, Luenberger observer, PI (extent combination) observers, H∞, sliding–mode observer. The Kalman channel is the most preferred for nonlinear assessment and artificial intelligence-based applications. The authors in [35] talk about a PNGV model based on an improved SOC estimation method with Kalman filtering.

Reasoned in Eq. (1), the model-based SOC assessment strategies can likewise generally represented by [30]:

$$\{Z = \frac{n_i}{C_n}\dot{I}_t - L(\widehat{v_t} - v_t)v_t = h(Z, i_t, \ldots) \quad (2)$$

whereas the voltage at time t given by the voltage sensors, $\widehat{v_t}$ is defined as the voltage assessed by battery setup, $h(.)$, is the representation of the model of the battery [30, 34]. From Eq. (3), we can deduce that the feedback remuneration used in assessing the state of charge is given by the difference between the voltage estimated by the sensor and the one calculated by the model the battery. Considering the non-open loop structure, MBMs can manage obscure starting charge levels. In Eq. (2), the gain of remunerating the charge levels determined by Coulombic count is denoted by L. The model proposed in [31] consists of two equivalent RC circuits, depicts a straightforward structure and highly viable SOC assessment technique utilizing two free PI observers where one of them helps further improve the demonstrating exactness. Simultaneously, the second one calculates the open circuit voltage for SOC assessment all the while. Then again, H∞ observer is proposed for diminishing the impact of commotion and boundary vulnerability on the assessment precision [34]. A versatile H∞ channel is presented in [32] that improves the accuracy of charge levels assessment values opposing the sensor's clamor and incorrectness from the battery model. Using recursive least square for boundary refreshing, this strategy shows exact assessed charge levels in a piece of equipment tuned in the analysis [34]. Nonetheless, the Kalman channel is the most famous model-based assessment calculation because of its vigor to the commotion in the academic circles. Extended Kalman filter (EKF) is utilized in [33] to deduce battery internal temperature and charge levels simultaneously dependent on a novel thermoelectric model. He et al. [31] approve unscented Kalman filter (UKF)-based state-of-charge assessment on an embedded system [34]. As dangerously portrayed in this paper, MBMs depend on an exact battery model for acquiring precise SOC assessment. Nonetheless, the battery's internal characteristics alter while it charges and discharges and is a very complicated process. It is trying to develop a model that can be accurate and depicts all the battery attributes. Particularly, for non-offline applications, the battery model's computational intricacy should be limited to a sensible reach. Being harsh toward introductory SOC and influential to estimation clamor, MBMs are incredibly mainstream for various online SOC assessment applications [34].

2.1.4 Data-Driven Estimation Methods

Data-driven estimation methods are broadly classified into two sub-categories, namely data training (DT) and data model fusion method (DMF). The DT method is further based on two models first support vector machines and the second neural network-based estimation model [35]. Data-driven control techniques just utilize the info yield data of the framework to build up a regulator. Since these techniques do not need a precise plant model, the assessments and suppositions presented in the plant demonstrating step are excluded. Nonlinear measurable data displaying apparatuses are reasonable. They can show complex connections among data sources and yield or discover designs in the data. In [35], the neural organization is utilized to build up the SOC assessor, where the data layer is made up of parameters like current, temperature, and the charge level of the battery. The yield layer represents the voltage. Experiments have shown high levels of exactness with the given arrangement. Various types of fake neural organization (ANN) strategies and a few techniques like ANN are common in planning the nonlinear connection among data sources and yields. In SOC assessment, ANN can legitimately set up the relationship among state-of-charge-related values, including current, voltage, and temperature. Subsequently, designers can make an assessor with no prior data available about the battery [34]. The connection among the inputs (voltage, current, temperature) and charge levels is straightforwardly settled using a structure that is nonlinear and ANN-based. ANNBMs ought to be prepared to build up a nonlinear relationship and can operate continuously [34]. Two distinct ANN-based structures are applied to assess SOC in [32]. Using computed the limit blur, precise SOC is deduced from the ANN assessor during the battery's life expectancy. If suitable examples are chosen and improved boundaries are picked for the preparation cycle, the ANNBMs can introduce a precise SOC assessment for the preparation test [34].

Nonetheless, it is handily discovered that these techniques' practicability is firmly identified with the preparation cycle and the set of data, given that the test surrounding shift, the determination of ANN-based methods is limited to online forms. By and large, ANN-based processes are handily relocated for online usage in the wake of having been prepared disconnected [34]. A review of various model-based and data-driven methods for SOC estimation of batteries is discussed in [36]. In [37], various artificial intelligence and direct measurement techniques for SOC estimation are explored.

2.2 Argument

In the wake of presenting every one of the SOC assessment techniques' highlights, their appropriateness for online use is talked about in this part. As appeared by the past locale's evaluation, the fittingness for online utilization of the four essential SOC examination techniques. From Fig. 2, we can see that all these procedures have their central focuses and hindrances. Be that as it may, for non-offline applications

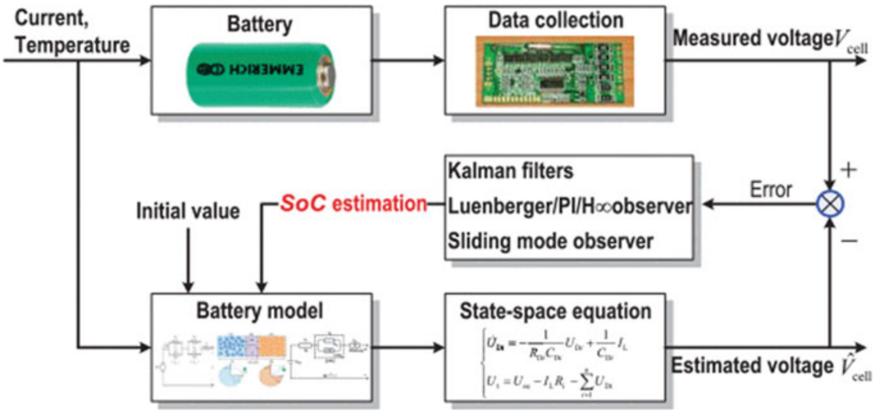
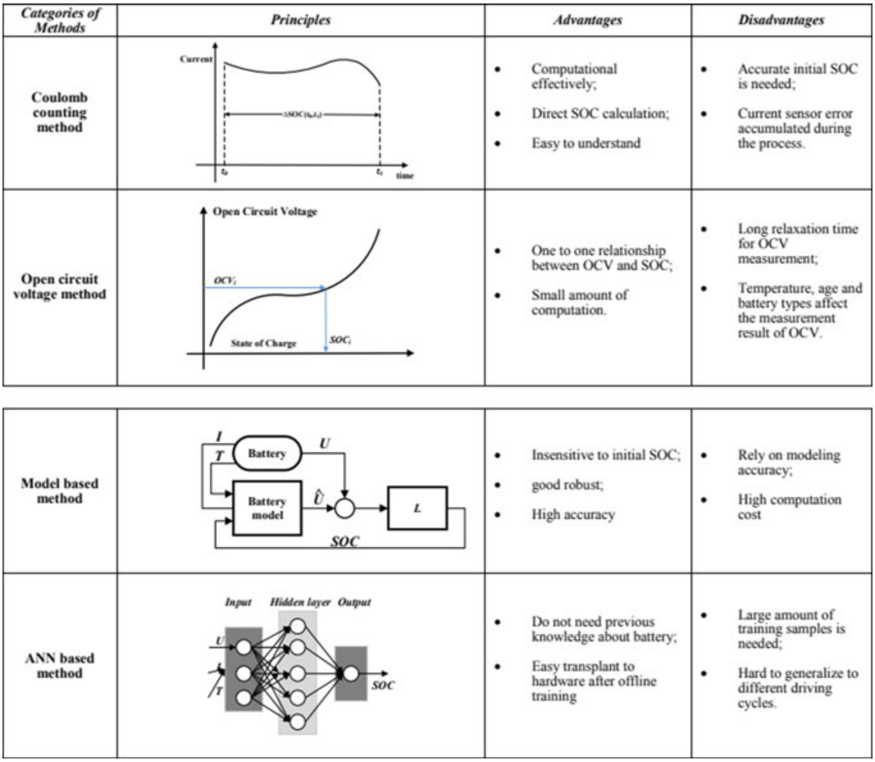


Fig. 2 General model-based estimation method

on battery management systems, exactness, stiffness, and computation expense are the three most significant elements to consider [34]. The electric vehicle application is based as an example to investigate and analyze these various techniques. From a clear perspective, every procedure can accomplish fantastic outcomes under exact circumstances. Since the Coulomb counting method is a non-closed-loop structure, starting charge level and estimation of current are, without a doubt, critical for its precision. Commonly, in hybrid applications, some current sensors' exact starting charge level and high exactness are deemed impractical [34] (Fig. 3).

OCVM depends on the exact OCV esteem for acquiring the assessed state of charge. The open circuit voltage could still be reached even after the EV left a while ago. Nonetheless, amidst the driving cycle, the current interference could likewise occur while the EV halts at the traffic signal. The current interference during the conditions is typically immensely small for battery unwinding. Subsequently, quick open circuit voltage assessment is pressing for the use of OCV-based method continuously [34]. Besides, the OCV and state of charge bend ought to be steep to ensure assessment precision. The exactness of MBM depends on building up an exact model of the battery in the assessment cycle. Choosing the apt model of the battery structure will improve assessment precision. Nonetheless, it is difficult to replicate the complex electrochemical process of battery by the equal circuit model, typically utilized in the MBM. Besides, the adjusted calculation's exhibition and combination are likewise firmly identified with an exact assessed SOC. This way, the precision of MBMs appears to be adequate for EV applications if the correct battery model and the appropriate assessment calculation are picked [34]. ANNBMs are amazingly precise if the whole EV driving cycle's present profile is like the preparation dataset. The viable application consistently experiences a wide range of working conditions, implying that power is an essential factor to mull over [35]. For EV applications, the battery pack ought to satisfy the extra force prerequisites of a continuous drive. The current, temperature, and age change frequently. A shut circle framework is generally



Categories of Methods	Principles	Advantages	Disadvantages
Coulomb counting method	Current; time	• Computational effectively; • Direct SOC calculation; • Easy to understand	• Accurate initial SOC is needed; • Current sensor error accumulated during the process.
Open circuit voltage method	Open Circuit Voltage; State of Charge	• One to one relationship between OCV and SOC; • Small amount of computation.	• Long relaxation time for OCV measurement; • Temperature, age and battery types affect the measurement result of OCV.
Model based method	Battery; Battery model; L; SOC	• Insensitive to initial SOC; • good robust; • High accuracy	• Rely on modeling accuracy; • High computation cost
ANN based method	Input; Hidden layer; Output; SOC	• Do not need previous knowledge about battery; • Easy transplant to hardware after offline training	• Large amount of training samples is needed; • Hard to generalize to different driving cycles.

Fig. 3 Comparison of various SOC estimation algorithms

heartier than an open-circle framework. Accordingly, MBMs have prevalent vigor contrasted and the other three. Notwithstanding, different strategies can likewise accomplish better strength by taking a few measures. It tends to be induced using Eq. (1) that the Coulomb count method strength under different operating cycles can be improved by thinking about the temperature and maturing impacts. Likewise, adding these impacts to the open circuit voltage state-of-charge bend helps change the OCV-based method under other working conditions. MBMs have better heartiness due to the input rectification. Since the battery model's exactness might be diminished during battery utilization, Internet refreshing of the battery model boundaries is essential for guaranteeing its vigor. Moreover, the assessment calculations ought to likewise be inhumane toward demonstrating and sensor blunders. Much preparing data under various working conditions ought to be gathered to improve the power of ANNBMs. The preparation cycle boundaries must be upgraded, and different approval cycles ought to be performed to keep away from the ideal nearby consequences of ANNBMs. Computational over-burden is always considered for equipment execution. Coulomb counting method and OCV-based methods are computationally effective because they include a straightforward count measure. MBMs are tedious, particularly, the Kalman channel containing framework activity in the assessment cycle. Ease applications will pick PI spectator or SM observer for lower calculation trouble. The ANN-based method is less complicated when disconnected before relocating to the installed framework. In outline, steps could be implemented to improve the exactness, vigor, and multifaceted computational nature of charge level's assessment strategies for online execution. For continuous applications, the most appropriate way is a decent compromise of all affecting components (e.g., the prerequisite of exactness, power, and computational exertion) [34].

3 Conclusion

The state of charge of batteries has a quick arranging relationship with their external fixed characteristics, like OCV and impedance. It might be gainfully used to change the inaccurate SOC. By the by, it is difficult to check the specific OCV always since the assessment of OCV of a battery is done by removing power and making sure the battery's rest for a widely inclusive period. Of course, the proportion of battery impedance relies upon the assessment contraption. Consequently, it cannot be executed for running electric vehicles. Such a SOC evaluation methodology is better for being applied to the laboratory atmosphere [35].

The CCM is otherwise called the Coulomb checking strategy. This methodology turns out for batteries because there are no essential outcomes during ordinary action. Nevertheless, for this strategy's evaluation by this strategy, three disadvantages ought to be overseen first. In any case, the initial state of charge must be known. Second, the battery current's assessment bumbles from sporadic aggravations, for instance, uproar and temperature drift, which are inevitable [35].

Lastly, Q should be recalibrated as the assortment of the battery's working conditions and developing levels. The mix of the recently referenced components would also decrease the steady nature of this method. Along these lines, the vital ampere-hour system can work with other supporting strategies, for example, model-based methods [35].

Model-based strategies have been the most robust assessment strategy. MBMs work best on blend methodology. It joins the CCM necessary procedure and battery open circuit voltage limits table-based investigating system by the batteries' state condition. It can be deduced that the system's charge levels probably go like some platform between the CCM and the investigating table-based procedures. An off-base state of charge check dictated by the ampere-hour vital procedure brings an off-base battery's open circuit voltage, and a while later, it grows the gauge bumble of the terminal voltage. The base estimate slip-up of the battery terminal voltage can be deduced accurately best when the charge's state has been deduced this way. The OCV can be used to address the evaluation botch [35].

Specifically, the DD approach can show critical points of interest in the accompanying cases:

1. The worldwide numerical model of the controlled framework is altogether obscure.
2. The vulnerabilities of the controlled framework model are huge.
3. The numerical model cannot be worked for characterizing the controlled framework with a questionable structure in its working cycle.
4. The component model of the controlled framework is excessively convoluted, or the quantity of the request is overly restrictive, or it is unrealistic to break down and plan.

3.1 Recommendation

Battery SOC assessment is vital for battery management system utilized in EV. This paper audits and looks at ordinary SOC assessment strategies, zeroing in their utilization in electric vehicles. Four types of state of charge assessment techniques for a pack of batteries have been efficiently assessed and summed up. Albeit multiple SOC estimation methods have been proposed and comparing progress and applications have been depicted, and the precise prediction and strategies for the correct administration of a pack of batteries cannot be resolved. The hypothetical exploration and innovative utilization of the SOC assessment are remaining difficulties [34, 35].

1. Multi-requirement, multi-scale, and multi-state joint/double assessment. Assessment of battery state of charge includes the exactness of beginning qualities and the estimation and comprises recognizing the way of limit debasement and the warm conduct of batteries. The current techniques predominantly work to amend the underlying mistake of state of charge or accomplish the joint/double assessment for battery limit and the state of charge. Nonetheless, they only occasionally think about the mechanical properties (exhaustion harm), electrical properties (corruption way of intensity), and warm properties (warm disappointment track) of batteries. The combination technique consolidates a DD control system, multi-scale multi-measurement improvement hypothesis, and ideal assessment hypothesis to give a viable answer for the multi-oblige multi-scale state joint assessment [35].
2. Usually, utilized models of the battery pack for EVs contain electrochemical models, equivalent circuit models, and electrochemical impedance models. EMs can display the unpredictable substance response cycle of batteries, yet they cannot give an extensive portrayal of limit corruption, warm disappointment, and batteries' mechanical exhaustion measure. The quality of the equivalent circuit models and electrochemical impedance models is that the models' structure and request are moderately straightforward. The restrictions are that they cannot outline the internal response energy and the limit corruption and maturing way of batteries. Every type of battery model has its pros and cons; hence, a combination of more than one model by brushing various sorts of battery models with calculated combination rule can accomplish excellent prescient execution

under questionable battery maturing levels, operating conditions, and materials used for fabrication of a battery [34, 35].

3. State of charge assessment for a hybrid association battery framework with solid time changing, nonlinear, and non-uniform qualities. The battery pack utilized in the electric vehicles comprises many battery cells. It is trying to guarantee the consistency of the boundary and state for all cells. What is awful, because of the unsettling influence of dubious working conditions, age levels, and the adjusting procedures, SOC assessment strategies intended for battery cells cannot guarantee the SOC assessment precision of the multi-cell battery pack. Therefore, this will, at last, prompt wasteful energy use. Hence, the battery pack's SOC assessment can be identical to a state assessment issue for a half-breed framework with solid time-differing, nonlinear, and non-uniform attributes. Hence, we can look for arrangements from the vulnerability displaying hypothesis, the framework ID hypothesis, and the data-driven control hypothesis [35].

SOC estimation algorithms based on both current and voltage values are ideal. The algorithm should be modeled such that its failure should accurately correspond to the battery/cell failure. The mixed SOC would have the highest applicability for almost all the cases combined, as it takes advantage of the complementary behavior of the other algorithms, i.e., it is more flexible and can take into account failure scenarios better.

References

1. J. Meng, M. Ricco, G. Luo, M. Swierczynski, D.-I. Stroe, A.-I. Stroe, R. Teodorescu, An overview of online implementable SOC estimation, in *A Treatise on Electricity and Magnetism,* vol. 2, 3rd ed., ed. by C. Maxwell. (Clarendon, Oxford, 1892, 2017), pp.68–73.
2. R. Yang, R. Xiong, H. He, H. Mu, C. Wang, A novel method on estimating the degradation and state of charge of lithium-ion batteries used for electrical vehicles. Appl. Energ. **207**, 331–340 (2017)
3. S. Peng, C. Chen, H. Shi, Z. Yao, State of charge estimation of battery energy storage systems based on adaptive unscented Kalman filter with a noise statistics estimator. IEEE Access **5**, 13202–13212 (2017)
4. X. Hu, R. Xiong, B. Egardt, Model-based dynamic power assessment of lithium-ion batteries considering different operating conditions. IEEE Trans. Ind. Inform. **10**(3), 1948–1959 (2014)
5. M. Lurie, H.N. Seier, R.C. Shair, State of charge indicators for nickel-cadmium batteries. State Charg. Indic Nickel Cadmium Batter. (1963)
6. C.W. Lillehei, A.B. Cruz, I. Johnsrude, R.D. Sellers, A new method of assessing the state of charge of implanted cardiac pacemaker batteries. Amer. J. Cardiol. **16**(5), 717 (1965)
7. X. Hu, C. Zou, C. Zhang, Y. Li, Technological developments in batteries: a survey of principal roles types and management needs. IEEE Power Energ. Mag. **15**(5), 20–31 (2017)
8. L. Lu, X. Han, J. Li, J. Hua, M. Ouyang, A review on the key issues for lithium-ion battery management in electric vehicles. J. Power Sour. **226**, 272–288 (2013)
9. M.A. Hannan, M.S.H. Lipu, A. Hussain, A. Mohamed, A review of lithium-ion battery state of charge estimation and management system in electric vehicle applications: challenges and recommendations. Renew. Sustain. Energ. Rev. **78**, 834–854 (2017)
10. Z. Li, J. Huang, B.Y. Liaw, J. Zhang, On state-of-charge determination for lithium-ion batteries. J. Power Sour. **348**, 281–301 (2017)

11. R. Xiong, J. Tian, H. Mu, C. Wang, A systematic model-based degradation behavior recognition and health monitoring method for lithium-ion batteries. Appl. Energ. **207**, 367–378 (2017)
12. V. Pop, H.J. Bergfeld, D. Danilov, P.P.L. Regtien, P.H.L. Notten, *Battery Management Systems: Accurate State-of-Charge Indication for Battery-Powered Applications*, vol. 9. (Springer 2008)
13. S. Rodrigues, N. Munichandraiah, A.K. Shukla, Review of state-of-charge indication of batteries by means of a.c. impedance measurements. J. Power Sour. **87**(1), 12–20 (2000)
14. X. Hu, F. Sun, Y. Zou, Comparison between two model-based algorithms for Li-ion battery SOC estimation in electric vehicles. Simul. Model. Pract. Theor. **34**, 1–11 (2013)
15. L. Lavigne, J. Sabatier, J.M. Francisco, F. Guillemard, A. Noury, Lithium-ion open-circuit voltage (OCV) curve modelling and its ageing adjustment. J. Power Sour. **324**, 694–703 (2016)
16. M.W. Cheng, Y.S. Lee, M. Liu, C.C. Sun, State-of-charge estimation with aging effect and correction for lithium-ion battery. IET Electr. Syst. Transp. **5**(2), 70–76 (2015)
17. S. Tong, M.P. Klein, J.W. Park, Online optimization of battery open circuit voltage for improved state-of-charge and state-of-health estimation. J. Power Sour. **293**, 416–428 (2015)
18. Y. Xing, W. He, M. Pecht, K.L. Tsui, State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures. Appl. Energ. **113**, 106–115 (2014)
19. B. Pattipati, B. Balasingam, G.V. Avvari, K.R. Pattipati, Y. Bar-Shalom, Open circuit voltage characterization of lithium-ion batteries. J. Power Sour. **269**, 317–333 (2014)
20. W. Waag, D.U. Sauer, Adaptive estimation of the electromotive force of the lithium-ion battery after current interruption for an accurate state-of-charge and capacity determination. Appl. Energ. 416–427 (2013.)
21. N. Lin, S. Ci, D. Wu, A novel low-cost online state of charge estimation method for reconfigurable battery pack, in *2016 IEEE Applied Power Electronics Conference and Exposition (APEC)*, 20–24 March 2016, pp. 3189–3192
22. L. Pei, R. Lu, C. Zhu, Relaxation model of the open-circuit voltage for state-of-charge estimation in lithium-ion batteries. IET Electr. Syst. Transp. **3**(4), 112–117 (2013)
23. E. Leksono, I.N. Haq, M. Iqbal, F.X.N. Soelami, I.G.N. Merthayasa, State of charge (SOC) estimation on $LiFePO_4$ battery module using coulomb counting methods with modified peukert, in *2013 Joint International Conference on Rural Information and Communication Technology and Electric-Vehicle Technology (rICT & ICeV-T)*, 26–28 November 2013, pp. 1–4
24. K.S. Ng, C.-S. Moo, Y.-P. Chen, Y.-C. Hsieh, Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries. Appl. Energ. **86**(9), 1506–1511 (2009)
25. A. Purwadi, A. Rizqiawan, A. Kevin, N. Heryana, State of charge estimation method for lithium battery using combination of coulomb counting and adaptive system with considering the effect of temperature, in *The 2nd IEEE Conference on Power Engineering and Renewable Energy (ICPERE) 2014*, 9–11 December 2014, pp. 91–95
26. Y. Zhang, W. Song, S. Lin, Z. Feng, A novel model of the initial state of charge estimation for $LiFePO_4$ batteries. J. Power Sour. **248**, 1028–1033 (2014)
27. Z. Caiping, W. Le. Yi, L. Xue, C. Wen, G.G. Yin, J. Jiuchun, Robust and adaptive estimation of the state of charge for lithium-ion batteries. IEEE Trans. Ind. Electron. **62**(8), 4948–4957 (2015)
28. M. Cacciato, G. Nobile, G. Scarcella, G. Scelba, Real-time model-based estimation of SOC and soh for energy storage systems. IEEE Trans. Power Electron. **32**(1), 794–803 (2017)
29. Y. Zhang, R. Xiong, H. He, W. Shen, A lithium-ion battery pack state of charge and state of energy estimation algorithms using a hardware-in-the-loop validation. IEEE Trans. Power Electron. **32**(99), 1–1 (2016)
30. C. Zhang, K. Li, J. Deng, S. Song, Improved real-time state-of-charge estimation of $LiFePO_4$ battery based on a novel thermoelectric model. IEEE Trans. Industr. Electron. **64**(1), 654–663 (2017)
31. H. He, R. Xiong, J. Peng, Real-time estimation of battery 579 state-of-charge with unscented kalman filter and rtos μcos-ii platform. Appl. Energ. **162**, 1410–1418 (2016)
32. Y. Shen, Adaptive online state-of-charge determination based on neuro-controller and neural network. Energ. Convers. Manag. **51**(5), 1093–1098 (2010)

33. M. Xu, J. Deng, S. Quan, SOC estimation of lithium battery based on improved kalman filtering algorithm, in *2016 International Conference on Industrial Informatics—Computing Technology, Intelligent Technology, Industrial Information Integration (ICIICII)* (2016)
34. J. Meng et al., An overview of online implementable SOC estimation methods for Lithium-ion batteries, in *2017 International Conference on Optimization of Electrical and Electronic Equipment (OPTIM) and 2017 Internationall Aegean Conference on Electrical Machines and Power Electronics (ACEMP)*, Brasov (2017), pp. 573–580. https://doi.org/10.1109/OPTIM.2017.7975030.
35. R. Xiong, J. Cao, Q. Yu, H. He, F. Sun, Critical review on the battery state of charge estimation methods for electric vehicles. IEEE Access **6**, 1832–1843 (2018). https://doi.org/10.1109/ACCESS.2017.2780258
36. D.N.T. How, M.A. Hannan, M.S. Hossain Lipu, P.J. Ker, State of charge estimation for lithium-ion batteries using model-based and data-driven methods: a review. IEEE Access **7**, 136116–136136 (2019). https://doi.org/10.1109/ACCESS.2019.2942213
37. P. Tejeswini, P. Sivraj, Artificial intelligence based state of charge estimation of li-ion battery for EV applications, in *2020 5th International Conference on Communication and Electronics Systems (ICCES)*, Coimbatore, India (2020), pp. 1356–1361. https://doi.org/10.1109/ICCES48766.2020.9137999