ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

Comparative Analysis and Estimation Techniques of BMS State Metrics: SoC and SoE

[1] Trupti Shende, [2] Dr. V S Kale, [3] Anjusha K. B.

[1] Department of Electrical Engineering, Visvesvaraya National Institute of Technology, Nagpur, Maharashtra, India
[2] Department of Electrical Engineering, Visvesvaraya National Institute of Technology, Nagpur, Maharashtra, India
[3] Electrification Practice Group, Transportation Business Unit, Tata Elxsi Ltd., Trivandrum, Kerala, India
Corresponding Author Email: [1] shendetg04@gmail.com, [2] vskale@eee.vnit.ac.in, [3] anjusha.k@tataelxsi.co.in

Abstract— This paper presents the research of the significance of the state of charge (SoC) and state of energy (SoE) metrics and their estimation methods for lithium-ion batteries used in an electric vehicle. SoC determines the remaining charge and SoE determines the remaining energy. The SoC-SoE variation is evaluated by simulating the factors while charging and discharging in different conditions. The larger the C rates the larger is the differences in the metrics. The SoC-SoE metric variation increases as the batteries age and hence it can be used as an indicator of the battery's state of health. This study helps to understand the correlation between both metrics and understand the importance of SoE, SoC, and their functions. Various state estimation methods and their challenges have been discussed. There are various methods that are currently used to estimate these metrics in the literature.

Index Terms— lithium-ion battery, state of charge, state of energy, state estimation methods.

I. INTRODUCTION

Electric vehicles (EVs) use recyclable lithium-ion batteries (LIBs) for energy storage as it has a large energy density and larger life cycle [1]. A battery management system (BMS) is required to ensure the safety and efficiency of lithium-ion batteries in electric vehicles. In BMS, state-of-charge (SoC) and state-of-energy (SoE) are two important aspects, which aid to estimate the range of the vehicle [2,3].

The most common way to estimate SoC is Coulomb Counting (or Ah counting) in which the technique of current integration is applied. However, simple coulomb counting does not consider battery aging (health), temperature or discharge rate. Because of these issues, academia and industry have worked to develop SoC forecasting methods that consider one or more of these factors [4].

SoC is a measure of the battery's remaining charge relative to its full capacity. It is a measure of how much energy can be supplied by the battery at a given moment in time. Let's consider an example, if the battery has capacity of 220 Ah and its SoC is 50%, then the battery has 110 Ah of energy remaining. On the other hand, SoE is a measurement of the total energy contained by the battery, expressed in watt-hours (Wh) or kilowatt-hours (kWh). Let us consider a scenario such that the battery has a capacity of 100Ah and a voltage of 12V, then its total energy storage capacity is 1.2 kWh.

Even though SoE has some similarities to SoC, it uses integrated power instead of discrete current. As such, it can be used to better monitor battery power than SoC metric [5,6]. In BMS, the SoC determines the level of charge remaining in the battery and hence prevents overcharge or over-discharge, which can damage the battery. The SoE indicates the total power a battery can provide, considering factors such as temperature [7].

The purpose of this research is to conduct experiments that explain the importance of the SoC and SoE metrics for lithium-ion battery to improve our understanding of how these metrics perform. Efforts have been taken to evaluate the current online estimation techniques for SoC and SoE, and to present the merits and demerits of each method of estimation.

II. EQUATIONS OF SOE AND SOC PARAMETERS

The SoC metric is estimated by load current integration and normalizing it with the nominal capacity Cn to give a dimensionless percentage value. The SoE is evaluated in the similar way by considering the integral of product of the instantaneous battery current and voltage and then converts this value into a percentage by normalization with nominal battery energy En [8]. For the tests conducted, the battery starts testing with fully charged state i.e. SoC and SoE will be considered as 100%. The equations of both the metrics has been stated below:

$$SoC(k+1) = SoC(k) + \frac{\int_k^{k+1} \eta I(k)dk}{Qr} \tag{1}$$

$$SoE(k+1) = SoE(k) + \frac{\int_k^{k+1} \eta P(k)dk}{Er} \tag{2}$$

SoC(k+1) is the SoC at the next instant, SoC(k) is SoC at current instant, I(k) is load current and Qr is total charge contained by the battery. SoE(k+1) is SoE at the next instant, SoE(k) is SoE at the current instant, I(k) is load current and Er is total charge capacity of the battery. η represents the charging or discharging efficiency. For now, considering it as 1, for simplicity of calculations and to focus better on the metrics functions.

Variation of SoC and SoE can be well understood from Fig. 1. It is assumed that ΔSoC1=ΔSoC2, however the

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

ΔSoE1>ΔSoE2. That is, smaller SoC has more SoE, i.e., it has more energy. Hence, it is realized that SoC and SoE are two different parameters and SoE can appropriately predict EV mileage compared to SoC [9].

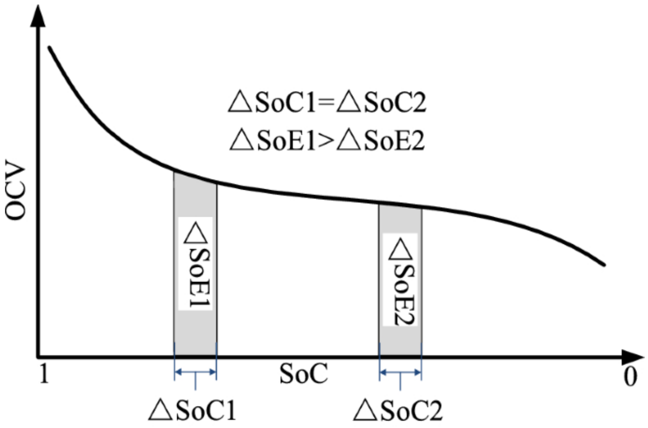

Figure 1: Discharge Curve OCV vs SOC

III. RELATION BETWEEN SOC AND SOE

SoC is the charge remaining after use, compared to the total charge present in the cell.

$$\mathrm{SoC} = \frac{\mathrm{Qrem}}{\mathrm{Qtotal}} \tag{3}$$

Where Qrem is the remaining charge and Qtotal is the total charge present in the cell. SoE is the energy present after use, compared to the total energy that is delivered by the cell.

$$SoE = \frac{Erem}{Etotal} \tag{4}$$

Where Erem is the remaining energy and Etotal is the total charge energy in the cell.

The mathematical relation between the SoE and the SoC can be stated as:

$$SoE = SoC * \frac{Uocv,curr}{Uocv,max} \tag{5}$$

Where $Uocv, curr$ is the current value of open circuit voltage that varies proportionally with SoC and $Uocv, max$ is the max value of open circuit voltage [10,11]. The open circuit voltage (Vocv) is calculated based on the external voltage (Vt), series resistance voltage (Vr) and polarization voltage (Vp) i.e.

$$Vocv = Vt + Vr + Vp \tag{6}$$

The voltages vary as the parameters vary with the varying conditions. Hence. the voltages have to be calculated in real time.

IV. EXPERIMENTAL EVALUATION OF METRIC DIFFERENCES AND RESULTS

To understand how both the metrics function differently, let's look at the practical scenario. The specifications for the Lithium-ion INR 18650-25R NMC cell, that is used to present the difference between SoC and SoE, is given in Table 1.

Table 1 : Specifications of the INR 18650-25R cell [12]

Parameters	Specifications
Type	INR 18650-25R
Nominal capacity	2.5 Ah
Actual energy	8.7488 Wh
Current range	1C-5C
Voltage range	2.5V - 4.2V
SoC functional scale	10%-90%
SoE functional scale	10%-90%

To get the SoC-SoE differences, we are first evaluating the SoC and SoE for a cell with the simulation model of the Li–ion battery. To calculate the SoC, we will require the load current, that is integrated over time to achieve the capacity used, the total capacity of the cell is known from datasheet. To calculate the SoE, we will require the load current and terminal voltage. Integrating it over time will give the energy used, the total energy of the cell is known from datasheet.

A. Load current conditions

The cell was tested for charging, discharging, mixed and still load current. The results were observed for SoC and SoE to understand the difference in performance of both the metrics, over a period of time (3600 secs).

For charging scenario, there are two ways to charge i.e. charging with constant current and charging with gradual increase in load current (fig 2 and fig 3). Similarly, for discharging, the two scenarios are discharging with constant current and discharging with gradual decrease in current (fig 4 and fig 5). The third load current condition is low load current i.e., the current is very low but not zero, for a small time period (fig 6). The fourth load current condition is real time varying load current condition i.e. the load current in actual scenario is never constant and is always varying with time, so the load current is changing randomly with real life kind of condition (fig 7).

The simulation results are presented in the form of graphs. It can be clearly seen that in every load current condition, there is variation in SoC and SoE value over a time period. SoC value presents the charge contained by the cell whereas the SoE metric presents the energy contained by the cell at that particular time.

Hence it can be understood that the variation of SoC and SoE metric is quite significant and should be calculated by the BMS to understand the cell/battery charge and energy supplied by the cell/battery.

The cell model was simulated to achieve the state parameters, SoC and SoE. The various load current conditions are given as input and the simulation results are displayed in every figure.

In the next section the effect of various C rates on these metrics is evaluated experimentally and the results are presented in the form of graphs.

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

1) Charging condition:

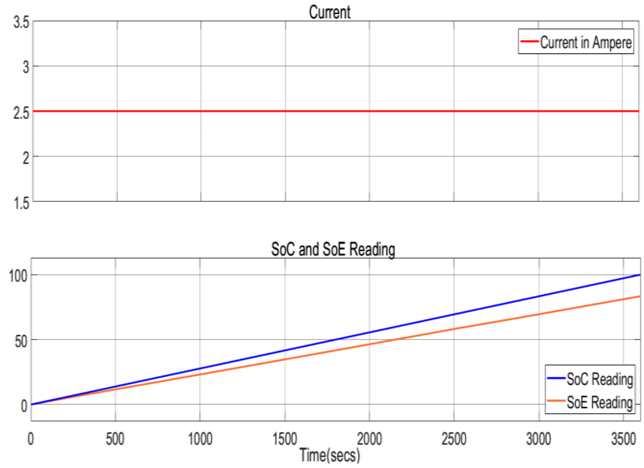

Figure 2: Charging with constant current

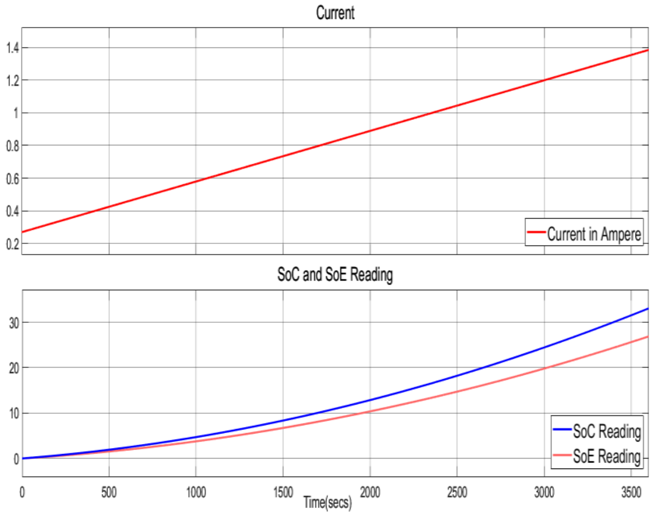

Figure 3: Charging with varying load current

2) Discharging Condition :

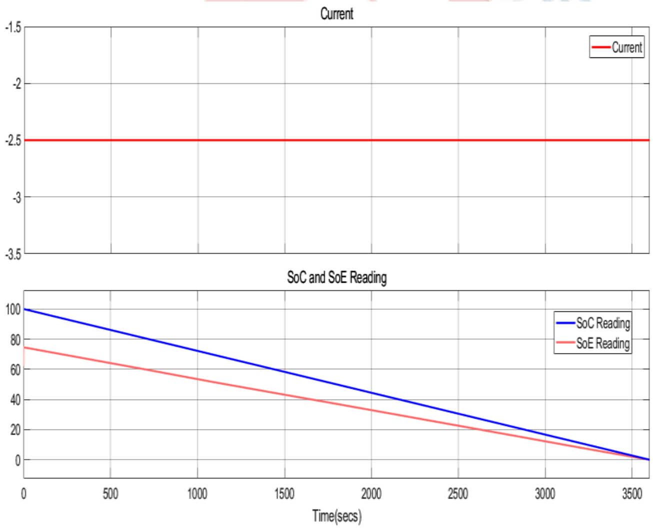

Figure 4: Discharging with constant current

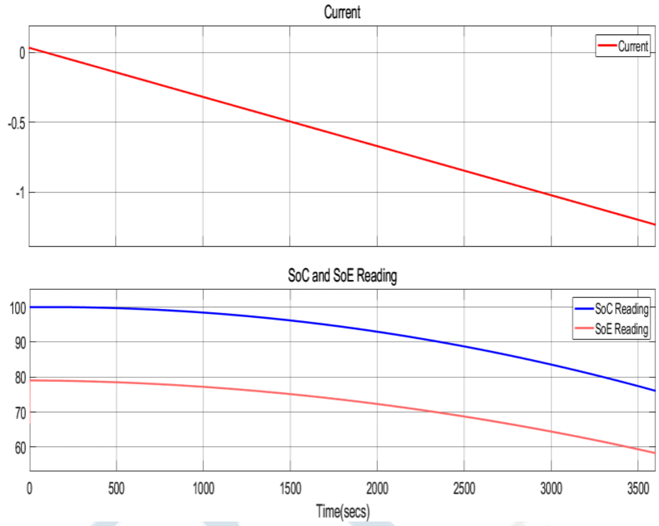

Figure 5: Discharging with varying load current

3) Still load current condition:

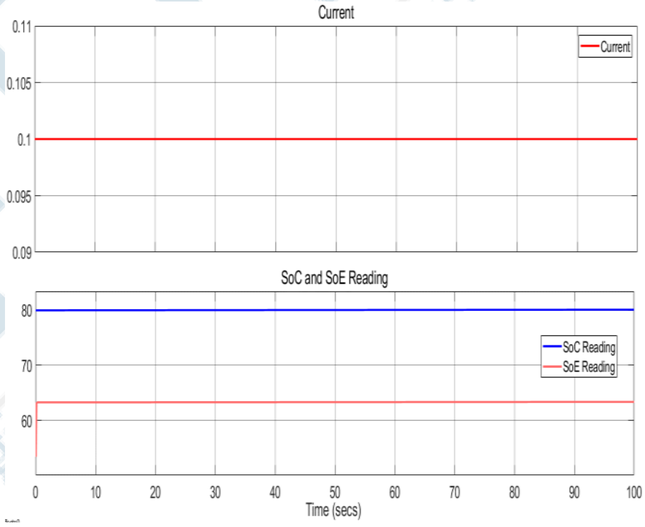

Figure 6: Low load current condition

4) Mixed load current condition:

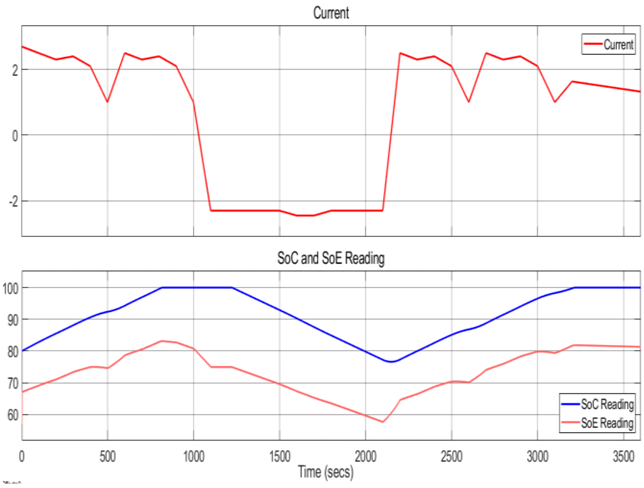

Figure 7: Real time varying load current condition

B. Effect of C-rate on SoC-SoE metric differences

As the C value increases, it is seen that the SoE-SoC metric difference increases. Understanding and analyzing this through a charging experiment on 2.5 Amp-hr cell. The load current for the charging scenario is varied according to C rate.

a) 2C = 5Amps

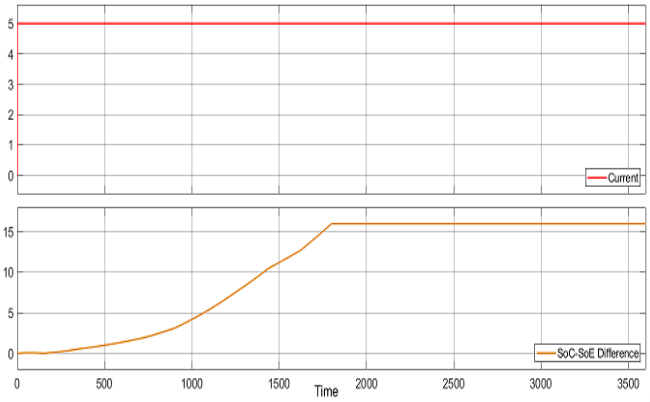

Figure 8: Load current is 5 amps

b) 1C=2.5 Amps

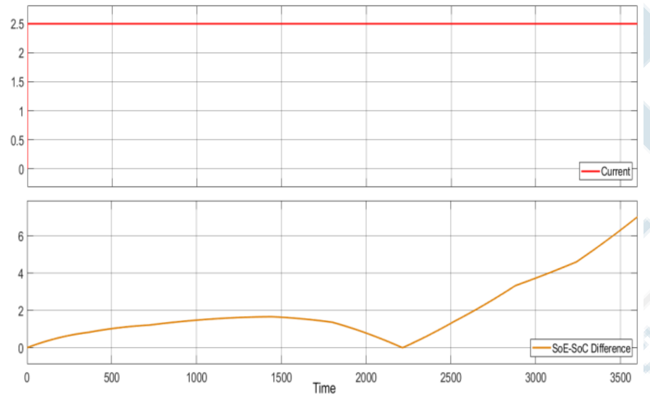

Figure 9: Load Current is 2.5 Amps

c) 0.5 C=1.25 Amps

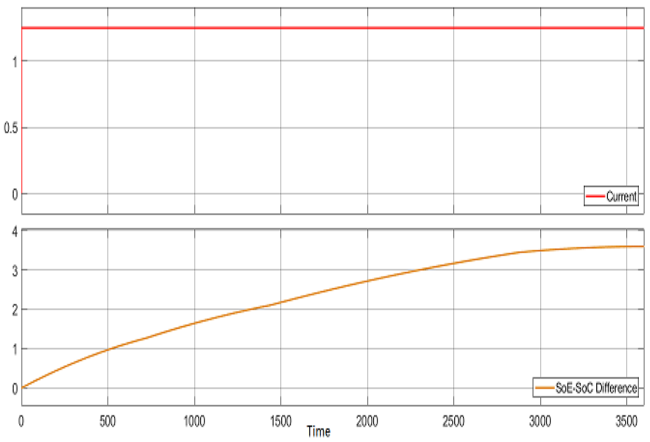

Figure 10: Load current is 1.25 Amps

d) 0.2C= 0.5 Amps

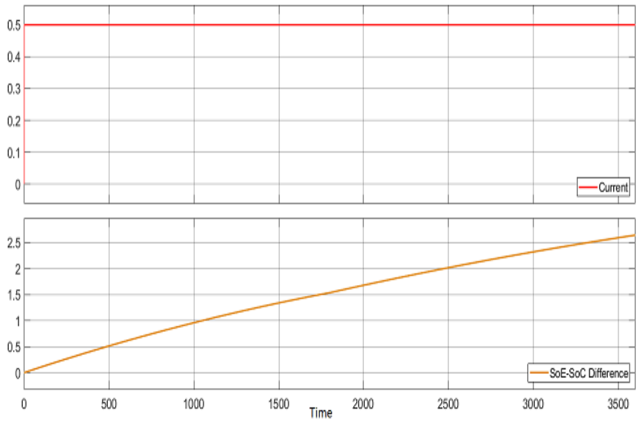

Figure 11: Load Current is 0.5 Amps

The simulation results are presented in the form of table (Table 2), where the SoE-SoC difference is provided for each C rate.

Table 2: SoE-SoC difference at various C rates

C rate	SoE-SoC Difference
0.2C	2.643
0.5C	3.601
1C	7.023
2C	15.95

From the table shown above, it can be observed that as the C rates increases the difference between both the metrics also increase. As C rate increases the health of the battery degrades and hence the difference between both the metrics can be used as an indicator of health [13].

V. STATE ESTIMATION METHODS AND KEY CHALLENGES

One of the prime task of the BMS is state estimation for the efficient and reliable use of EV. Many methods are discussed in literature to calculate SoC and SoE online. Each estimation technique has pros and cons and the usage depends on the application and data present initially.

1) SoC estimation techniques and key challenges:

Accurately estimating the SoC within desired limits can prevent overcharging or over discharging, thus extending battery life. However, SoC can't be measured directly and hence has to be derived from physical quantities i.e. current and voltage [14]. The SoC estimation methods that are usually preferred are: the Coulomb counting method where the value of the current is the main quantity to estimate SoC [15-17]; Open circuit method (OCV) using the OCV-SoC lookup table to estimate SoC [18]; An artificial intelligence method that determines data such as battery current and voltage and creates models using machine learning [19-21]; and the physical model

IFERP connecting engineers... developing research

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

based methods such as equivalent circuit models and electrochemical models that use the power electronics components to reflect the changes taking place in battery [22-27]. There are many challenges with these techniques.

a) Coulomb Counting Method

This method can be used to compute the SoC easily and directly, but the initial SoC should be accurate. The SoC value calculated using this method has sensor errors and calculation errors hence the estimated value is deviated from the actual value [28].

b) OCV-SoC method

Another widely used method is OCV-SoC method, the SoC metric can be estimated from the SoC-OCV lookup table. The OCV Method is quite laborious in a practical situation. The sensor should have high resolution to measure the voltage accurately. Also, long relaxation hours are required to reach an equilibrium state. The OCV–SOC graph for Li-batteries is almost flat, which indicates that a slight error in OCV measurement might result in a large estimation error [29].

c) Electrochemical impedance spectroscopy method

Electrochemical impedance spectroscopy (EIS) is used to reflect the electrochemical reactions occurring in the battery to determine the SoC. The procedure is to inject small amplitude AC signals at various frequencies into the battery [30]. Many parameters such as ohmic resistance, charge transfer and polarization capacitance can be examined from EIS measurement data. The process is inexpensive, but the equipment is expensive. Although the EIS results are accurate, they are hard to clone because the system must operate in a steady state condition. The effects of battery aging and temperature changes will cause the estimate to differ from the actual value, resulting in an understatement. These parameters vary with varying SoC and therefore can be used to estimate SoC [31].

d) Model based method

Among all the SoC estimators, the method based on model (MBM) seems to be the best option for real time SoC estimation at the moment. The whole MBM process is classified into two steps, namely (i) Designing the battery model with parameters such as resistances and capacitances; (ii) Implementation of algorithm. In fact, it estimates SoC indirectly, as it first creates the appropriate model and then uses a power algorithm to predict the online battery SoC. The MBM uses KVL equation (Equation 6) to form battery modelling equations. In particular, the filter method and the observer base methods can be used to estimate SoC in MBM [32]. The most used battery models are electrochemical model and the equivalent circuit model. The electrochemical battery model is often used to analyse battery performance as it captures the kinetics and charge transfer in the battery and reflects the thermodynamic effects. However, the accuracy estimation of the model parameters is still a challenge and requires computational efforts to reflect the aging and temperature effect [33,34].

Another popular model is the equivalent circuit model (ECM), which uses electronic components to simulate battery dynamics. It looks promising for real time SoC estimation as it has simple structure. However, it has been determined that ECM parameters may change over time, at different temperatures, SoC or aging levels [35,36]. The MBM overcomes the disadvantage of some of the direct estimation methods mentioned earlier, such as using the OCV-SOC method and CCM which requires SoC initialization.

e) Artificial Neural Network based method

Artificial intelligence (AI) is one of the powerful tools to predict the various states of any system. Has the ability to learn independently. It may be used to predict SoCs without previous knowledge of the battery's contents. Artificial neural networks (ANNs) are one of the branches of AI. Fuzzy logic has similar properties to ANN and is therefore also used for SoC estimation [37]. The actual SoC obtained by ANN estimator over the entire battery life, including the potential loss of the battery. The ANN has three layers, that are input layer, hidden layer, and the output layer. The input process is powered by battery physical quantities such as current, voltage and temperature. The output process generates SoC for a given state. The algorithm consists of a feed forward transition and a back-propagation process. A cascading process runs from the initial layer to the final layer with bias via the hidden layer [38].

Back propagation technique is used to reduce the error close to the target function by adjusting the weights of the output and input parameters. This process runs continuously until the closest value for the objective function is achieved. The disadvantages of the ANN are that it needs more neurons to improve accuracy, which limits the success of the model over time. In addition, every neural network needs to be trained and lot of iterations are required due to which it consumes a lot of time. Therefore, well trained ANNs can be used for specific applications. The algorithm must store a lot of information for training, which not only requires a large amount of memory, but also overloads the entire system.

f) Filter-based method

Approach using filters for SoC estimation of EVs are commonly used for noise rejection. It can achieve desired results with high accuracy. Usually the SoC and SoE value are affected by noises in the system and errors may arise due to sensor inaccuracy. There are various types of filter that can be used to estimate SoC, such as Kalman filter (KF), Extended KF, Unscented KF and Particle filter. Studies have shown that KF is the best option for metric estimation in EVs [39]. The main idea of the generalized KF used is, to construct a set of state-space modelling equations based on the appropriate ECM. The metric is considered as a state variable, the current as input variable and voltage and the output variable. The Kalman gain is calculated based on the error between the measured value and the estimated value. It can also be used in situations where the system is affected by external noises.

However, the basic KF cannot be used for the non-linear systems and also involves lot of complex mathematical calculations. To overcome this shortcoming of KF, EKF was introduced. It is used for metric estimation using partial derivatives and Taylor series expansion [40]. If the system becomes very nonlinear then it can result in linearization errors.

g) Observer-based method

Similar to filters, the observer-based approach aims to reduce the error between the observed state and the actual state using the feedback closed loop. Few observers that are used for SoC estimation are Proportional-integral observer (PIO), Sliding mode observer (SMO) and Non-linear Observers (NLO).

The PIO is a very robust state estimator and is considered capable to improve the accuracy and is relatively faster than other methods. A 2RC ECM model is used with PIO to increase accuracy in [41-43]. Another observer is SMO, which can achieve high accuracy and has fast response time. It is resistant to environmental influences the model uncertainties [44]. A NLO is used to reduce the errors in the grid with the help of nonlinear analysis. This method outperforms the EKF and SMO, with regard to accuracy, computational speed and price. However, finding the appropriate gain matrix to reduce the error is difficult.

Methods for SoC estimation are been listed in Table 3. Each method has advantages and disadvantages, that would help to understand its need depending on the application.

2) SoE estimation techniques and key challenges:

Accurate SoE estimation can relieve users' anxiety about running out of battery power. Finding the correct SoE estimation techniques is considered to be difficult than SoC estimation task [45]. So far, many attempts have been made to improve the performance of the SoE estimation. The main estimation techniques are summarized below:

a) Power Integration method

A type of SoE estimation is the power integration method, which can effectively reduce the computational load [46]. However, due to its open-loop nature, this approach leads to uncertainty, low resolution, and measurement error. Suitable characteristic mappings have been used to improve the accuracy [47].

Although these techniques show the improvement in the performance of power integration method, these methods are expensive and require time consuming calibration.

b) Joint estimation based method

Wang et al. [48] developed a quantitative relation between the SoC and SoE, and these two quantities were jointly estimated using the particle filter (PF) algorithm. Zheng et al. [49] proposed a joint estimation framework for SoC and SoE with high accuracy and robustness, and the total available energy was estimated using the sliding window moving energy integration method. However, the above methods require an accurate SoC as an input. If there is an error in the SoC estimation, it will result in an SoE estimation error.

Table 3: Merits and Demerits of Different SoC Estimation Methods

Methods	*Merits*	*Demerits*
Coulomb Counting	Easy to compute. SoC can be calculated directly. Useful for short term estimation.	Accurate initial SoC is needed. Current value should be very accurate.
Open circuit voltage method	Very efficient if accurate OCV is known. Easy to be implemented.	The battery should be at rest for long time. Small error in OCV causes large error in SoC measurement.
Electrochemical Impedance Spectroscopy method	It achieves good accuracy and can operate online if the value of impedance is updated.	EIS results are difficult to reproduce in non-steady state condition. The equipment is expensive.
Model based method	Very accurate for online SoC estimation. Captures the internal battery performance. Low time required. Initial SoC is not required.	Precise estimation of model parameters is necessary. High Computational efforts.
ANN-based method	Do not need the data of internal structure of battery. Self- learning algorithm. Capable to work in non-linear conditions.	Many training samples are required. More neurons are needed to improve accuracy, which in turn overloads the system.

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

Methods	*Merits*	*Demerits*
Filter based Methods	States can be estimated very accurately in spite of the external disturbances. Also, can predict the non-linear dynamic states.	Needs large computing capacity. Requires highly complex mathematical calculations.

a) Filter based method

These methods result in highly accurate estimation reading, even when it is affected by external disturbances or sensor noises. Various filters have been proposed by researchers to get the accurate estimation results. Such as Estimation using adaptive kalman filter (KF), unscented KF (UKF) [50] and extended KF (EKF) [51]. Particle filtering method is proposed in ref. [52] to suppress the measurement noises. These methods have high precision and are very robust.

However, the battery model has to be very accurate in order to get the perfect parameters in case of adaptive KF [53]. These parameters are changing with the temperature and aging effect and hence have to be accurately calculated from time to time.

b) Neural network-based methods

Machine learning techniques such as back propagation neural network (BPNN) and wavelet neural network (WNN) are applied to estimate SoE. BPNN is used to capture the nonlinear properties of batteries. In ref. [54] a method has been proposed on the BPNN model, in which the voltage, current and temperature of battery are given as input and SoE as output. Similarly, the wavelet-NN model is also used to simulate the battery electrodynamics [55], considering effect of temperature. In ref. [56] a NN model was developed to explain the voltage response of LIBs at various current and temperature excitations, using a Monte Carlo sampling technique as a Bayesian probability learning scheme to predict the SoE.

The biggest disadvantage of the NN methods is that a lot of data is required to describe the battery dynamics and to train the system.

c) Prediction-based methods

In these methods the SoE is predicted using historical data and the past performance of the battery is considered. Such as in ref. [57] where the SoE was calculated depending on the future voltage sequence and in ref [58], the future temperature sequence was used. A combined Markov and Gaussian transition model were analyzed to predict the future temperature in ref. [59].

The forecast errors may increase when the future conditions vary significantly. In addition, the next sequence must be repeated each time and requires many calculations.

These the above explained methods have been tabulated with the advantages and disadvantages in Table 4.

VI. CONCLUSION

Owing to the advantages of the Li-ion batteries, it has been welcomed by researchers as well as the industry to be used in the EVs. With the increased usage of LIBs, it becomes necessary to maintain its efficient operation and ensure its safe operation. Hence for this purpose the BMS is used to measure the metrics that define the fitness of the battery. The metrics that define the fitness are SoC and SoE and hence its estimation is a necessity.

This study explains the estimation methods for both the metrics as well as discusses the various estimation techniques used till date with its drawbacks. It would help the future researchers in the form of guidance for their research work.

Table 4: Merits and Demerits of Different SoE Estimation Methods

Methods	*Merits*	*Demerits*
Power integration approach	Low computation burden.	Errors are accumulated due to imperfect measurements and sensor noises.
Joint estimation-based method	Has high accuracy and robustness	It requires accurate SoC as an input. Error in SoC value will lead to inaccurate SoE estimation.
Filter based method	Have high precision and robustness	Battery model has to be highly accurate to reflect the temperature changes and aging.
Neural network-based methods	Capable of simulating battery electrical dynamics considering the temperature change and discharge rate.	Too much data needed to train the model.
Prediction-based methods	Input as SoC is not required. Accurate Equivalent circuit model is not required.	Large number of calculations are conducted. Prediction errors increase when the future conditions change drastically.

Acknowledgements

This study was assisted by the Visvesvaraya National Institute of Technology, Nagpur, India and Tata Elxsi Ltd.

REFERENCES:

[1] X. Chen, W. Shen, T. T. Vo, Z. Cao, and A. Kapoor, “An overview of lithium-ion batteries for electric vehicles,” *2012 10th International Power & Energy Conference (IPEC)*, 2012.

[2] M. Shen and Q. Gao, “A review on Battery Management System from the modelling efforts to its multi-application and integration,” *International Journal of Energy Research*, vol. 43, no. 10, pp. 5042–5075, 2019.

[3] X. Lai, C. Jin, W. Yi, X. Han, X. Feng, Y. Zheng, and M. Ouyang, “Mechanism, modelling, detection, and prevention of the internal short circuit in lithium-ion batteries: Recent advances and perspectives,” *Energy Storage Materials*, vol. 35, pp. 470–499, 2021.

[4] R. Hickey and T. M. Jahns, “Direct comparison of state-of-charge and state-of-energy metrics for Li-Ion Battery Energy Storage,” *2019 IEEE Energy Conversion Congress and Exposition (ECCE)*, 2019.

[5] S. Zhang, X. Guo, X. Dou, and X. Zhang, “A data-driven Coulomb counting method for state of charge calibration and estimation of lithium-ion battery,” *Sustainable Energy Technologies and Assessments*, vol. 40, p. 100752, 2020.

[6] S. Zhang and X. Zhang, “Joint Estimation Method for maximum available energy and state-of-energy of lithium-ion battery under various temperatures,” *Journal of Power Sources*, vol. 506, p. 230132, 2021.

[7] X. Hu, F. Feng, K. Liu, L. Zhang, J. Xie, and B. Liu, “State Estimation for Advanced Battery Management: Key Challenges and future trends,” *Renewable and Sustainable Energy Reviews*, vol. 114, p. 109334, 2019.

[8] L. Ma, C. Hu, and F. Cheng, “State of charge and state of energy estimation for lithium-ion batteries based on a long short-term memory neural network,” *Journal of Energy Storage*, vol. 37, p. 102440, 2021.

[9] S. Lin, W. Song, J. Lv, Z. Feng, Y. Zhang, and Y. Li, “An SOE estimation model considering electro thermal effect for LiFePO4/C Battery,” *International Journal of Energy Research*, vol. 41, no. 14, pp. 2413–2420, 2017.

[10] Y. Zheng, C. Wang, S. Sang, and S. Yu, “Estimation of remaining energy and available power for Li-ion battery packs considering energy consumption by heat convection,” *Journal of Power Electronics*, vol. 23, no. 1, pp. 139–148, 2022.

[11] J. Jiang and C. Zhang, “Fundamentals and applications of lithium-ion batteries in electric drive vehicles,” 2015.

[12] R. Guo and W. Shen, “An enhanced multi-constraint state of power estimation algorithm for lithium-ion batteries in electric vehicles,” *Journal of Energy Storage*, vol. 50, p. 104628, 2022.

[13] J. G. Qu, Z. Y. Jiang, and J. F. Zhang, “Investigation on lithium-ion battery degradation induced by combined effect of current rate and operating temperature during fast charging,” *Journal of Energy Storage*, vol. 52, p. 104811, 2022.

[14] Y. Xing, W. He, M. Pecht, and K. L. Tsui, “State of charge estimation of lithium-ion batteries using the open-circuit voltage at various ambient temperatures,” *Applied Energy*, vol. 113, pp. 106–115, 2014.

[15] S. Piller, M. Perrin, and A. Jossen, “Methods for state-of-charge determination and their applications,” *Journal of Power Sources*, vol. 96, no. 1, pp. 113–120, 2001.

[16] J. H. Aylor, A. Thieme, and B. W. Johnso, “A battery state-of-charge indicator for electric wheelchairs,” *IEEE Transactions on Industrial Electronics*, vol. 39, no. 5, pp. 398–409, 1992.

[17] T.-H. Liu, D.-F. Chen, and C.-C. Fang, “Design and implementation of a battery charger with a state-of-charge estimator,” *International Journal of Electronics*, vol. 87, no. 2, pp. 211–226, 2000.

[18] J. Meng, M. Ricco, G. Luo, M. Swierczynski, D.-I. Stroe, A.-I. Stroe, and R. Teodorescu, “An overview and comparison of online implementable SOC estimation methods for Lithium-Ion Battery,” *IEEE Transactions on Industry Applications*, vol. 54, no. 2, pp. 1583–1591, 2018.

[19] Y.Shen, “Adaptive online state-of-charge determination based on neuro-controller and Neural Network,” *Energy Conversion and Management*, vol. 51, no. 5, pp. 1093–1098, 2010.

[20] A. J. Salkind, C. Fennie, P. Singh, T. Atwater, and D. E. Reisner, “Determination of state-of-charge and state-of-health of batteries by Fuzzy Logic Methodology,” *Journal of Power Sources*, vol. 80, no. 1-2, pp. 293–300, 1999.

[21] Q.-S. Shi, C.-H. Zhang, and N.-X. Cui, “Estimation of battery state-of-charge using ν-support vector regression algorithm,” *International Journal of Automotive Technology*, vol. 9, no. 6, pp. 759–764, 2008.

[22] “Universal battery parameterization to yield a nonlinear equivalent circuit valid for battery simulation at Arbitrary Load,” *Fuel and Energy Abstracts*, vol. 41, no. 4, p. 218, 2000.

[23] N. Watrin, H. Ostermann, B. Blunier, and A. Miraoui, “Multiphysical lithium-based battery model for use in state-of-charge determination,” *IEEE Transactions on Vehicular Technology*, vol. 61, no. 8, pp. 3420–3429, 2012.

[24] H. He, R. Xiong, and J. Fan, “Evaluation of lithium-ion battery equivalent circuit models for state of charge estimation by an experimental approach,” *Energies*, vol. 4, no. 4, pp. 582–598, 2011.

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

[25] W. B. Gu and C. Y. Wang, "Thermal-electrochemical modeling of Battery Systems," *Journal of The Electrochemical Society*, vol. 147, no. 8, p. 2910, 2000.

[26] D. Di Domenico, G. Fiengo, and A. Stefanopoulou, "Lithium-Ion Battery State of charge estimation with a Kalman filter based on a electrochemical model," *2008 IEEE International Conference on Control Applications*, 2008.

[27] D. Di Domenico, A. Stefanopoulou, and G. Fiengo, "Lithium-ion battery state of charge and critical surface charge estimation using an electrochemical model-based extended Kalman filter," *Journal of Dynamic Systems, Measurement, and Control*, vol. 132, no. 6, 2010.

[28] X. Tang, B. Liu, and F. Gao, "State of charge estimation of Lifepo 4 battery based on a gain-classifier observer," *Energy Procedia*, vol. 105, pp. 2071–2076, 2017.

[29] C. Chen, R. Xiong, and W. Shen, "A lithium-ion battery-in-the-loop approach to test and validate multiscale dual H Infinity Filters for state-of-charge and capacity estimation," *IEEE Transactions on Power Electronics*, vol. 33, no. 1, pp. 332–342, 2018.

[30] M. Li, "Li-Ion Dynamics and state of charge estimation," *Renewable Energy*, vol. 100, pp. 44–52, 2017.

[31] A. Densmore and M. Hanif, "Determining battery SOC using electrochemical impedance spectroscopy and the Extreme Learning Machine," *2015 IEEE 2nd International Future Energy Electronics Conference (IFEEC)*, 2015.

[32] D. N. How, M. A. Hannan, M. S. Hossain Lipu, and P. J. Ker, "State of charge estimation for lithium-ion batteries using model-based and data-driven methods: A Review," *IEEE Access*, vol. 7, pp. 136116–136136, 2019.

[33] S. Cho, H. Jeong, C. Han, S. Jin, J. H. Lim, and J. Oh, "State-of-charge estimation for lithium-ion batteries under various operating conditions using an equivalent circuit model," *Computers & Chemical Engineering*, vol. 41, pp. 1–9, 2012.

[34] M. A. Rahman, S. Anwar, and A. Izadian, "Electrochemical model parameter identification of a lithium-ion battery using particle swarm optimization method," *Journal of Power Sources*, vol. 307, pp. 86–97, 2016.

[35] X. Hu, S. Li, and H. Peng, "A comparative study of equivalent circuit models for Li-Ion Batteries," *Journal of Power Sources*, vol. 198, pp. 359–367, 2012.

[36] C. Zou, X. Hu, S. Dey, L. Zhang, and X. Tang, "Nonlinear fractional-order estimator with guaranteed robustness and stability for lithium-ion batteries," *IEEE Transactions on Industrial Electronics*, pp. 1–1, 2017.

[37] A. Zenati, P. Desprez, and H. Razik, "Estimation of the SOC and the soh of li-ion batteries, by combining impedance measurements with the fuzzy logic inference," *IECON 2010 - 36th Annual Conference on IEEE Industrial Electronics Society*, 2010.

[38] M. S. Chitnis, S. P. Pandit, and M. N. Shaikh, "Electric vehicle Li-Ion Battery State of charge estimation using Artificial Neural Network," *2018 International Conference on Inventive Research in Computing Applications (ICIRCA)*, 2018.

[39] C. Hu, B. D. Youn, and J. Chung, "A multiscale framework with extended Kalman filter for lithium-ion battery SOC and capacity estimation," *Applied Energy*, vol. 92, pp. 694–704, 2012.

[40] R. Xiong, X. Gong, C. C. Mi, and F. Sun, "A robust state-of-charge estimator for multiple types of lithium-ion batteries using adaptive extended Kalman filter," *Journal of Power Sources*, vol. 243, pp. 805–816, 2013.

[41] P.-cheng Li, N. Chen, J.-song Chen, and N. Zhang, "A state-of-charge estimation method based on an adaptive proportional-integral observer," *2016 IEEE Vehicle Power and Propulsion Conference (VPPC)*, 2016.

[42] X. Tang, Y. Wang, and Z. Chen, "A method for state-of-charge estimation of LiFePO4 batteries based on a dual-circuit state observer," *Journal of Power Sources*, vol. 296, pp. 23–29, 2015.

[43] U. Amir, L. Tao, X. Zhang, M. Saeed, and M. Hussain, "A novel SOC estimation method for lithium-ion battery based on improved Adaptive Pi Observer," *2018 IEEE International Conference on Electrical Systems for Aircraft, Railway, Ship Propulsion and Road Vehicles & International Transportation Electrification Conference (ESARS-ITEC)*, 2018.

[44] X. Sui, S. He, D.-I. Stroe, X. Huang, J. Meng, and R. Teodorescu, "A review of sliding mode observers based on equivalent circuit model for Battery SOC estimation," *2019 IEEE 28th International Symposium on Industrial Electronics (ISIE)*, 2019.

[45] J. Xie, J. Ma, and J. Chen, "Available power prediction limited by multiple constraints for lifepo4 batteries based on Central Difference Kalman filter," *International Journal of Energy Research*, vol. 42, no. 15, pp. 4730–4745, 2018.

[46] A. Barai, K. Uddin, W. D. Widanalage, A. McGordon, and P. Jennings, "The effect of average cycling current on total energy of lithium-ion batteries for electric vehicles," *Journal of Power Sources*, vol. 303, pp. 81–85, 2016.

[47] K. Mamadou, E. Lemaire, A. Delaille, D. Riu, S. E. Hing, and Y. Bultel, "Definition of a state-of-energy indicator (SOE) for electrochemical storage devices: Application for energetic availability forecasting," *Journal of The Electrochemical Society*, vol. 159, no. 8, 2012.

[48] Y. Wang, C. Zhang, and Z. Chen, "A method for joint estimation of state-of-charge and available energy of Lifepo 4 Batteries," *Applied Energy*, vol. 135, pp. 81–

IFERP

ISSN (Online) 2395-2717

International Journal of Engineering Research in Electrical and Electronic Engineering (IJEREEE)

Vol 10, Issue 11, November 2023

87, 2014.

[49] L. Zheng, J. Zhu, G. Wang, T. He, and Y. Wei, "Novel methods for estimating lithium-ion battery state of Energy and maximum available energy," *Applied Energy*, vol. 178, pp. 1–8, 2016.

[50] W. Zhang, W. Shi, and Z. Ma, "Adaptive unscented Kalman filter based state of energy and Power Capability Estimation Approach for lithium-ion battery," *Journal of Power Sources*, vol. 289, pp. 50–62, 2015.

[51] Y. Wang, C. Zhang, and Z. Chen, "Model-based state-of-energy estimation of lithium-ion batteries in electric vehicles," *Energy Procedia*, vol. 88, pp. 998–1004, 2016.

[52] Y. Wang, C. Zhang, and Z. Chen, "Model-based state-of-energy estimation of lithium-ion batteries in electric vehicles," *Energy Procedia*, vol. 88, pp. 998–1004, 2016.

[53] H. W. He, Y. Z. Zhang, R. Xiong, and C. Wang, "A novel Gaussian model based Battery State Estimation Approach: State-of-energy," *Applied Energy*, vol. 151, pp. 41–48, 2015.

[54] X. Liu, J. Wu, C. Zhang, and Z. Chen, "A method for state of energy estimation of lithium-ion batteries at dynamic currents and temperatures," *Journal of Power Sources*, vol. 270, pp. 151–157, 2014.

[55] G. Dong, X. Zhang, C. Zhang, and Z. Chen, "A method for state of energy estimation of lithium-ion batteries based on neural network model," *Energy*, vol. 90, pp. 879–888, 2015.

[56] Y. Wang, D. Yang, X. Zhang, and Z. Chen, "Probability based remaining capacity estimation using data-driven and neural network model," *Journal of Power Sources*, vol. 315, pp. 199–208, 2016.

[57] G. Liu, M. Ouyang, L. Lu, J. Li, and J. Hua, "A highly accurate predictive-adaptive method for lithium-ion battery remaining discharge energy prediction in Electric Vehicle Applications," *Applied Energy*, vol. 149, pp. 297–314, 2015.

[58] D. Ren, L. Lu, P. Shen, X. Feng, X. Han, and M. Ouyang, "Battery remaining discharge energy estimation based on prediction of future operating conditions," *Journal of Energy Storage*, vol. 25, p. 100836, 2019.

[59] M. F. Niri, T. M. N. Bui, T. Q. Dinh, E. Hosseinzadeh, T. F. Yu, and J. Marco, "Remaining energy estimation for lithium-ion batteries via gaussian mixture and Markov models for future load prediction," *Journal of Energy Storage*, vol. 28, p. 101271, 2020.

AUTHORS PROFILE

Ms. Trupti Shende, Bachelor of Technology in Electrical Engineering from College of Engineering, Pune, Maharashtra, India. Master of Technology in Integrated Power Systems from Visvesvaraya National Institute of Technology, Nagpur, India. Pursued Internship in TATA Elxsi Ltd. and worked in the domain of Battery management system.

Dr. V S Kale, is Professor in Visvesvaraya national institute of Technology, Nagpur, Maharashtra, India**.** His research interest are power systems and artificial intelligence. He has published 26 international journal papers, 34 international conference papers and 6 national journal papers. Among these, 7 papers have received awards.

Mrs. Anjusha K B, Bachelor of Technology in Electrical and Electronics Engineering from College of Engineering, Trivandrum, Kerala, India. Master of Technology in Control Systems from College of Engineering, Trivandrum, Kerala, India. Has worked on design and development of Battery management system in EV and design of controllers for solar powered plant. Currently works as a specialist in TATA Elxsi ltd.