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Research paper

Review of Lithium-Ion Battery State of Charge Estimation Methodologies for Electric Vehicle Application

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Abstract

With the ever-rising concerns over energy conservation, global warming, and climate change issues, extensive research on electric vehicles (EVs) is being actively performed. EVs are considered to be the most promising replacement of gasoline-based vehicles in reducing CO_2 emissions in recent decades. The number of EV run by rechargeable batteries has been increased significantly due to enhanced performances and efficiencies. The lithium-ion battery has some advantageous features such as lightweight, long lifespan, low self-discharge, high voltage, high energy density, and low memory effect. However, EVs using lithium-ion batteries have drawbacks with regard to short mileage, slow charging, and high cost. Moreover, load variation, temperature variations, and battery aging can degrade EV performance and efficiency. Therefore, there is an urgent necessity to develop an efficient energy storage management system that can evaluate the charging state and health condition of lithium-ion batteries. The state of charge (SOC) is an essential parameter of EV which determines the remaining charge of lithium-ion batteries. Also, SOC provides information about the charging/discharging approach and thus protects the battery from being overcharged/over discharged. This paper comprehensively reviews the different estimation methodologies to evaluate SOC. The estimation approaches of SOC are discussed in detail on their algorithm, mathematical model, strength, weakness and error rate. Finally, the review delivers some important proposals for the future development of SOC estimation in EV application.

Keywords: *state of charge (SOC); Electric vehicle; lithium-ion battery; charging and discharging; the intelligent algorithm*

1. Introduction

Electric vehicle (EV) not only has improved cost and efficiency but also has been considered as the most promising replacement of petrol based vehicles in order to mitigate carbon emissions problems [1], [2]. Nevertheless, the stability of EV is dependent on reliability, safety, and operation of energy storage devices. The lithium-ion battery exhibits a long life cycle, high voltage, high energy density, high efficiency, and environmental friendliness, therefore it is highly recommended in EV application [3]. The research on lithium-ion battery based EV is explored to improve the power management and charge control system, extend the driving range, decrease the charging duration and examine the critical health parameters such as state of charge (SOC) and state of charge (SOC) and reaming useful life (RUL) [4], [5].

SOC is a critical and important feature in EV which have been investigated extensively in modern decades. SOC specifies the residual energy that is required to power a vehicle [6]. A safe, reliable and stable operation of EV is highly dependent on the establishment of an improved SOC evaluation model. However, battery SOC estimation could be affected by non-linear, electrochemical reactions, and time-varying characteristics of lithium-ion battery [7]. Furthermore, aging cycles, temperature variation, hysteresis, charge-discharge current rates have a serious influence on SOC accuracy [8].

This paper reviews the SOC estimation methodologies for lithium-ion battery in EV technologies. The SOC estimation methods with its mathematical model, algorithm, strength, weakness and estimated error are briefly elaborated. The review also proposes some suggestions for further technological improvements of SOC estimation methods. The results of this review will deliver information about SOC evaluation criteria to the automobile engineers. Therefore, this critical review will be beneficial to the EV automotive industry.

2. SOC estimation methods

The most conventional technique to examine SOC is the integration of charging/discharging current with respect to interval divided by the maximum stored capacity [9], as shown in (1).

$$SOC = SOC_0 - \frac{\int i\eta dat}{C_n} \qquad (1)$$

Where SOC_0 denotes the initial SOC value, i signifies the charging/discharging current; C_n indicates the nominal capacity; t is interval and η represents the columbic efficiency. This review classifies the SOC evaluation approaches into the three groups as shown in Fig. 1.

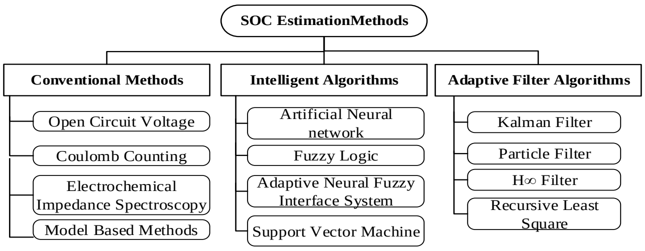

Fig 1: Classification of SOC estimation methodologies

2.1. Conventional methods

The conventional SOC estimation methods use discharge current, voltage, resistance, and impedance. The conventional methods have some advantageous features such as low power consumption and simple execution and small power consumption. Nonetheless, conventional methods fail to deliver acceptable results due to various uncertainties such as aging, material degradation, noise, temperature differences.

2.1.1 Coulomb counting (CC)

CC method is a straightforward approach which uses the current integration to examine SOC while the battery is charging or discharging. The method is popular due to its ease of implementation and low power consumption. Nevertheless, the method could be affected by current fluctuation, temperature variations, and noise. Besides, the cumulative effect could arise due to inaccuracy in determining the initial value of SOC [10]. In [11], CC based smart SOC estimation model is proposed. The proposed model has an estimation error of 1% and can be implemented in EV and portable devices for practical use.

2.1.2 Open circuit voltage (OCV)

SOC estimation using OCV is used in common and exhibits strong points of having high accuracy. However, OCV has some shortcomings such as it cannot operate online and requires a long interval for achieving a stable state [12]. Besides, the hysteresis characteristics have an influence on OCV measurements [13]. Also, the estimation method depends on material and capacity of the battery since the linear relationship between SOC and OCV changes with battery type [14]. The OCV characteristics of C/$LiFePO_4$ battery is shown in Fig. 2. SOC estimation based on the OCV method provides a sufficiently accurate result with root means square error (RMSE) under 5%.

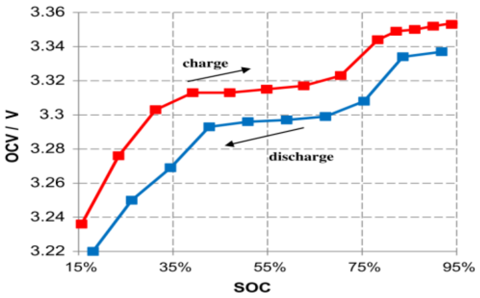

Fig. 2: charging and discharging profile of C/$LiFePO_4$ battery experimented at 25°C

2.1.3. Electrochemical impedance spectroscopy (EIS)

EIS based SOC estimation uses an appropriate electrochemical model and employs inductances, capacitances in the different frequency spectrum. A work in [15] uses impedance, terminal voltage, and discharge current to estimate battery Electromotive Force (EMF) voltage. The normalized impedance value achieves good SOC accuracy with low cost. However, battery aging and temperature variations could reduce accuracy. In [16], an inductive arc and two capacitive arcs based equivalent circuit are developed to estimate the model impedances at different charging values. In [17], an extended Kalman filter (EKF) with an equivalent circuit model and based SOC is examined. The model is evaluated using different charge-discharge rates and achieves an error under 3%.

2.1.4 Model-based estimation

Battery model can be characterized by two models; Equivalent Circuit Model (ECM) and Electrochemical Model (EM). ECM is frequently used for SOC estimation while the EM uses electrodynamics, chemical thermodynamics effects, and many internal materials. The schematic figure of ECM is shown in Fig. 3.

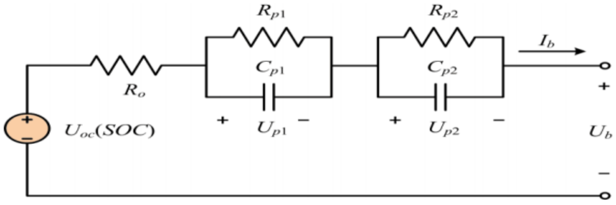

Fig. 3: Second-order ECM battery model

The electrical characteristics of ECM shown in Figure 3 can be mathematically expressed as,

$$\begin{cases} \dot{U}_{p1} = -\frac{1}{R_{p1}C_{p1}}U_{p1} + \frac{1}{C_{p1}}I_b \\ \dot{U}_{p2} = -\frac{1}{R_{p2}C_{p2}}U_{p2} + \frac{1}{C_{p2}}I_b \\ S\dot{O}C = -\frac{1}{C_n}I_b \end{cases} \quad (2)$$

$$U_b = U_{OCV}\left(SOC\right) - U_{p1} - U_{p2} - R_0 I_b \quad (3)$$

Where U_{p1} and U_{p2} represent the terminal voltage of C_{p1} and C_{p2}, respectively U_b and I_b denote the terminal voltage and current, respectively. U_{OCV} represents OCV which is a function of SOC.

Hu et al. [18] did a comparative analysis of twelve frequently used EMS with two kinds of lithium-ion cells in different temperature conditions. The results prove that that one-state hysteresis based RC model achieves the highest accuracy. Domenico et al. [19] considered electrolyte concentration, microscopic current density, and material concentration effects in the EM model to compute SOC. However, the model is not suitable for a specific battery due to lack of explanation of electrochemical reactions. In addition, the model is found difficult and complex to be practical for all types of the battery. Du et al. [20] developed a SOC estimation model using EM to characterize the electrical and thermal characteristics and battery fault diagnosis. In [21], An ECM model with nRC network based OCV method is suggested to estimate SOC for $LiFePO_4$ cell. Urban Dynamometer Driving Schedule (UDDS) cycles are used to validate the model robustness and accuracy. The model accuracy is improved with an error under 5 %.

2.2 Intelligent algorithms

The intelligent algorithms need lots of computation and a huge amount of training data to evaluate SOC. Intelligent algorithms have the rich computational capability to address the issues like measurement noises, temperature variation, and battery aging. Nonetheless, complex training computation, slow convergence speed, and large memory unit for storing data make the algorithm very hard to implement.

2.2.1 Artificial Neural network (ANN)

The complexity of a battery non-linear system can be addressed using the ANN algorithm. The benefits of NN is that it can avoid the need to estimate battery parameters and it does not depend on any mathematical relationship [22]. Also, there is no need for prior knowledge about battery physics, chemistry, and initial SOC. Nevertheless, BMS with the ANN method is overloaded with a large amount of training data, hence decreases the SOC estimation speed. In [23], a BPNN based Particle Swarm Optimization (PSO) with the Principle Component Analysis (PCA) feature extraction model is developed for $LiNiMnCoO_2$ cells to evaluate SOC. The proposed model reduces the SOC estimation error drastically and archives RMSE of 0.58%, 0.72%, and 0.47% in Beijing Dynamic Stress Test (BJDST), FUDS and US06 cycle, respectively. In [24], Radial Basis Function Neural Network (RBFNN) model is presented to monitor SOC. The model robustness is checked with aging cycles and temperatures. The UDDS and Economic Commission of Europe (ECE) load profiles are utilized to validate the model robustness. RBFNN obtains better accuracy than conventional methods with Mean Squared Error (MSE) of 0.16%.

2.2.2 Fuzzy logic (FL)

FL uses appropriate training dataset for characterizing a complex, non-linear model. However, FL has some weak points such as complex computations, a large memory unit, and an expensive processing unit. In [26], a Merged Fuzzy Neural Network (FNN) with genetic algorithm (RGA) based SOC estimation is established for a lithium-ion battery. The proposed model is suitable for assessing any suitable degree of accuracy. In [27], A Fuzzy logic model based SOC is developed for a lithium-ion battery. A continuous 1.4 A current discharge profile with 10 A pulse interruption is used to construct a load profile under different temperature conditions. The model is executed in a Motorola MC 68HC12 microcontroller and has an average SOC error of ±2%.

2.2.3 Adaptive neuro-fuzzy inference system (ANFIS)

ANFIS model is a combination of FL and ANN as shown in Fig. 4. ANFIS model consists of five layers including fuzzification, product, normalized, defuzzification, and an output layer. ANFIS model is designed using a first-order Sugeno model based on two fuzzy if-then rules

$$Rule\ 1: if\ \ (x\ is\ A_1)\ and\ \ (y\ is\ B_1)\ then\ (z_1 = p_1x + q_1y + r_1)$$
$$Rule\ 1: if\ \ (x\ is\ A_2)\ and\ \ (y\ is\ B_2)\ then\ (z_2 = p_2x + q_2y + r_2)$$

Where x and y denote the input variables, A_i and B_i represent the fuzzy sets, z_i signifies the outputs and defined by the fuzzy rule within boundary limit, p_i,q_i and r_i represent the parameters to be obtained by training method. A work in [28] explored an ANFIS algorithm based on SOC- OCV relationship at different operating temperatures. The model effectiveness is compared with coulomb counting method and results confirm the superiority of ANFIS technique with high accuracy. In [29], ANFIS with constant and random discharging current based SOC is suggested to measure the remaining capacity for a lithium-ion battery. The proposed model provides good results and obtains SOC error below 1%. In [30], SOC estimation model is developed using ANFIS algorithm. The model is verified using various discharge current profiles. The model obtains average error under 1%.

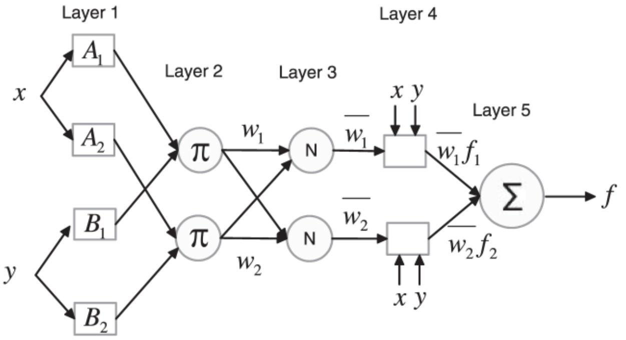

Fig. 4: ANFIS architecture for SOC estimation

2.2.4 Support vector machine (SVM)

SVM uses regression algorithm and kernel function to convert a non-linear model to a linear model. SVM has some strong points such as high accuracy and fast convergence. In [30], support vector regression (SVR) algorithm based SOC is proposed. The validation reports confirm the high accuracy of SOC. In [31], adaptive unscented Kalman filters (AUKF) and least square support vector machines (LSSVM) based SOC is established to examine SOC for a lithium-ion battery. The proposed model offers high robustness and achieves absolute error under 2% and mean absolute error (MAE) under 5%.

2.3 Adaptive filter algorithms

The adaptive filter algorithms use different battery models and equations in a non-linear system. The methods exhibit fast convergence speed and high time efficiency. Nevertheless, the methods suffer from a lot of mathematical equations and poor robustness.

2.3.1 Kalman filter (KF)

KF can describe the dynamic behaviors of battery and is capable of suppressing large extent of current and noise. KF algorithm estimates SOC through the prediction and correction of states repeatedly. The prediction state is called a time update in which the algorithm projects the state ahead and error covariance. The correction state is known as measurement update in which KF revises the state and error covariance based on Kalman gain. The equations are arranged in discrete time and state space form. KF uses linear optimal filtering to achieve a recursive solution. The equations of the KF algorithm are presented in Fig. 5.

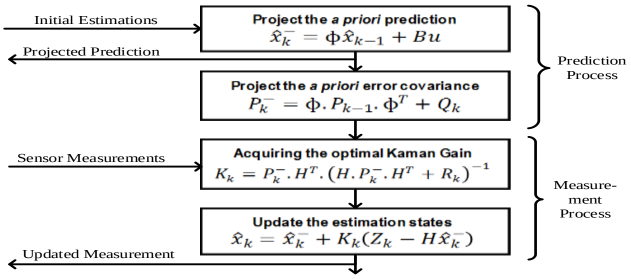

Fig 5: Block diagram of the KF algorithm

The KF method has some advantages such as it can estimate SOC with high accuracy considering the effect of external disturbances. Nevertheless, KF cannot perform state estimation in a nonlinear system. Also, KF cannot deliver a reasonable result due to temperature variations and inappropriate battery model. SOC estimation with non-linear system requires a revised version of KF which is shown in Fig. 6.

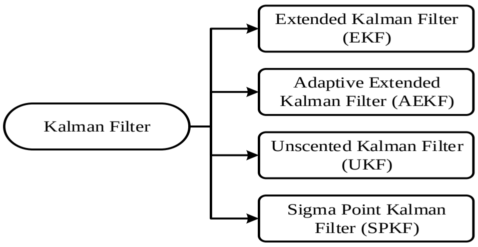

Fig. 6: Extension version of KF used for SOC model development

Extended Kalman Filter (EKF) algorithm performs linearization of state space model based on partial derivatives and first-order Taylor series. However, EKF cannot achieve the desired accuracy and could provide linearization error in the highly non-linear system. Mastali et al. [31] used zero state hysteresis and hysteresis state models to monitor SOC of $LiFePO_4$ cells based on EKF. The validation reports verify the SOC accuracy and model obtains the maximum error of 4%. In [32], the EKF algorithm with OCV based SOC estimation is proposed. EKF reduces the measurement noise and obtains good accuracy with unknown initial SOC.

In [21], Extended Kalman Filter (AEKF) is used to examine SOC using different EV drive cycles. A comparative analysis between offline and online terminal voltage is performed. The proposed model can decrease the SOC error by 4%. In [33], AEKF algorithm uses a Thevenin model along with SOC-OCV look-up table to measure SOC. UDDS test is used to validate the model adaptability and robustness. The model obtains SOC error under 2%.

Unscented Kalman Filter (UKF) has an advanced filter algorithm that can work efficiently in a highly nonlinear system. UKF based SOC does not require Jacobian matrix and Gaussian noise. However, the method cannot deliver accurate results due to inappropriate battery model and disturbances. In [39], an Adaptive Unscented Kalman Filter (AUKF) with extreme learning machine (ELM) based SOC is proposed. The ELM algorithm reduces the computation load, thus increases the time efficiency of the model. The evaluation reports confirm that AEKF and AUKF have high convergence speed while AUKF achieves high accuracy.

Sigma-Point Kalman Filter (SPKF) algorithm uses a set of sigma points to evaluate the non-linear system. SPKF has some benefits such as it does not consider the Jacobian matrices, derivatives and has the similar computation complexity as EKF, thus provides stability in computation and increases the estimation speed. In [40], SPKF, EKF, and Luenberger observer models are employed for SOC assessment of the $LiFePO_4$ battery. The experimental results prove that SPKF is dominant to than other models in terms of accuracy and robustness.

2.3.2 Particle filter (PF)

PF has random particles and employs the Monte Carlo simulation technique to approximate the probability density function. A stochastic model-based PF is suggested in [36] to monitor SOC. The proposed algorithm is constructed by Monte Carlo simulation tool which can measure SOC accurately with hysteresis effect can be avoided. EV load cycles are used for model validation and the model achieves high accuracy under different aging states. In [37], a new model is established based on Unscented Particle Filter (UPF) for high-power lithium-ion batteries with the effect of different charge/discharge rate, temperature variations and drift noise. The model robustness is checked with EKF and UKF algorithms and results confirm that UPF is dominant to EKF and UKF algorithms in reducing Root Mean Squared Error (RMSE). In [40], a SOC estimation model is established using PF for lithium-ion battery at -10◦C to 45◦C under constant and dynamic load profiles. The model obtains MAE and RMSE of 0.57% and 0.24% respectively in constant and dynamic current profiles.

Table 1: Comparative analysis of SOC estimation methods

Method	Ref.	Test Battery	Temperature	Validation Profile	Estimated Error
CC	[11]	Panasonic 2.35 Ah CGR 18650D	Room temperature of 25 °C.	Constant Charging and discharging rate (0.1C to 1C)	SOC error 1%
OCV	[34]	18650 cylindrical type 1.1 Ah lithium-ion cells ($LiFePO_4$)	0 °C to 50 °C	Federal Urban Driving Schedule (FUDS)	RMSE < 5%
EIS	[17]	Commercial $LixC_6$-$Li_yMn_2O_4$ battery, which consists of a negative electrode (Li_xC_6), a separator, and a positive electrode ($Li_yMn_2O_4$)	25°C	Discharged at five constant rates (0.1C, 1C, 2C, 4C and 8C)	SOC error < 3%
ECM	[21]	3 Ah $LiFePO_4$ cell	25°C	Urban Dynamometer Driving Schedule (UDDS)	SOC error < 5% in different RC networks
FL	[27]	Sanyo 18650 cells in a 4 series × 3 parallel arrangement	Three different temperatures (0, 20 and 40 ◦C)	A continuous 1.4 A current discharge profile with 10 A pulse interruption	Average SOC error ±2
ANN	[6]	2 Ah 18650 $LiNiMnCoO_2$/NMC	0°C, 25°C and 45°C	Dynamic Stress Test (DST)	MAE 0.32%~0.76% RMSE 0.48% ~1.47%
ANFIS	[28]	40 Ah Lithium-Ion cells	Temperature range from -30 °C to 55 °C	Charging and discharging currents (i) 57 A, (ii) 68 A	MSE 3.4% in 57 A MSE 5.6% in 68A
SVM	[35]	Kokam 70 Ah lithium polymer battery	25°C to 42°C	(i) -224 A to 396 A (ii) -110 A to 430 A	MAE < 5% SOC absolute error <2%
KF	[31]	20 AH A123 cylindrical 26650 Li-ion batteries	25°C (ambient temperature)	US06 drive cycle	SOC error <4%
PF	[36]	9.5 Ah IFP1865140-type lithium-ion batteries	-10◦C to 45◦C	Constant and dynamic load profiles	MAE 1.06 % (Constant current) RMSE 0.57% (Constant current) MAE 0.79 % (Dynamic current) RMSE 0.24%(Dynamic current)
$H\infty$ filter	[37]	1.2 Ah lithium-ion battery	Room temperature	Pulse charging and discharging	RMSE under 2.5%
RLS	[38]	100 Ah Cobalt Manganese Nickel Oxide Lithium-ion polymer	Varying temperature conditions	ECE15 test cycle	Maximum relative error 1.0.32%

2.3.3 H∞ filter

H∞ Filter has the strong robustness to operate in a time-varying system without characterizing the process noise and the measurement noise. Nevertheless, the model achieves inaccurate results due to aging, hysteresis, and temperature variation. In [37]**,** H∞ algorithm based SOC evaluation model is suggested. UDDS cycles are used to verify the model accuracy. The validation results demonstrate SOC error of 2.49%.

2.3.4 Recursive least square (RLS)

RLS algorithm uses the forgetting factor to adjust battery model parameters. In [42], recurrent neural network (RNN) with RLS based SOC estimation model is developed. The proposed model has the capability to suppress SOC error and measurement noise. The developed model obtains a maximum error of 1.032%. Table 1 illustrates the comparative analysis of various SOC estimation approaches. The benefits, drawbacks of conventional, intelligent and adaptive filter methods are shown in Table 2.

Table 2: Characteristics of SOC estimation methods

Method	Benefits	Drawbacks
Conventional	• Less power consumption • Easy to implement	• Coulomb counting causes cumulative effect due to an error in estimating initial SOC. • Open circuit voltage cannot operate online. Needs a long interval to reach an equilibrium condition.
Intelligent algorithm	• Satisfactory performance in non-linear and high dimension models. • Quick and accurate estimation.	• Requires large storage device • Needs expensive device for data processing.
Adaptive Filter	• Dynamic and accurate • Less computation time.	• Requires highly complex mathematical computation. • Aging, hysteresis and temperature effects could decrease accuracy.

3. Proposed suggestions for SOC accuracy improvement

Each SOC estimation algorithm has some issues and challenges which need to be investigated properly. This review has provided some selective recommendations for the future advancement of SOC assessment, such as:

i. Further research should be conducted on enhancing lithium-ion battery material in EV applications.
ii. An improved battery management system (BMS) with sensors, controller, and actuators need to be established.
iii. Further attention should be made to monitor SOC with battery model under various disturbances and uncertainties.
iv. Further investigation is required to design an appropriate controller to improve the robustness of the nonlinear system.
v. Further study is needed on the development of novel artificial intelligence methods and the improvement of training algorithms.
vi. Further attention should be made to select the optimal parameters of the battery model and artificial intelligence methods.

4. Conclusion

A detail investigation of various SOC estimation approaches and algorithms for a lithium-ion battery is carried out. Each SOC estimation method is highlighted with an explanation of benefits, drawbacks and error rates. This review has divided the SOC estimation approaches into three classes, such as a conventional, intelligent and adaptive filter. The conventional method is simple and has easy execution, but are highly vulnerable to temperature variations and noises. The adaptive filter algorithm has good precision but suffers from the heavy computation. The intelligent algorithms feature good adaptability, accuracy, and robustness. Nonetheless, intelligent algorithms have some negative points in terms of data training implementation. The review also gives some selective suggestion for future exploration. The explanation of various SOC estimation methodologies and their strength, weakness, and estimated error will deliver concrete outlines and directions to the automobile companies on the advancement of EV technologies.

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