

Recent Progress and Future Trends on the State of Charge Estimation Methods to Improve Battery-storage Efficiency: A Review

Md Ohirul Qays, Yonis Buswig, Md Liton Hossain, *Student Member, IEEE*,
and Ahmed Abu-Siada, *Senior Member, IEEE*

Abstract—Battery storage systems are subject to frequent charging/discharging cycles, which reduce the operational life of the battery and reduce system reliability in the long run. As such, several Battery Management Systems (BMS) have been developed to maintain system reliability and extend the battery's operative life. Accurate estimation of the battery's State of Charge (SOC) is a key challenge in the BMS due to its non-linear characteristics. This paper presents a comprehensive review on the most recent classifications and mathematical models for SOC estimation. Future trends for SOC estimation methods are also presented.

Index Terms—Battery Management System (BMS), battery modeling, battery storage efficiency, state of charge (SOC).

I. INTRODUCTION

WITH the global trend to replace fossil fuel-based electricity generation by renewable energy sources, developing reliable energy storage systems have been prioritized in the agenda of worldwide utilities, manufacturers and researchers. Among various storage systems, battery technology has seen a revolution during the last decade due to its low greenhouse effect, high power density and low self-discharging rate [1], [2]. Reference [3] proposed a water and battery storage system for 100% renewable energy generation in Saudi Arabia by the year 2040. The Li-Ion battery (LIB) has supplanted other types such as lead-acid, Ni-MH, Ni-Cd batteries because of its superior technical advantages in the face of energy density factors. While the LIB features high power capacity and extended life cycle, a reliable battery energy management system (EMS) is essential to maintain its efficiency and reliability along with its entire operational life [4]–[6].

Manuscript received November 26, 2019; revised January 20, 2020, accepted May 23, 2020. Date of online publication July 06, 2020; date of current version October 16, 2021. This work was supported by research and innovation management center (RIMC) UNIMAS through Fundamental Research Grant Scheme FRGS/1/2017/TK10/UNIMAS/03/1, Ministry of Higher Education, Malaysia.

M. O. Qays (corresponding author, e-mail: 18020101@siswa.unimas.my), Y. Buswig are with Department of Electrical and Electrical Engineering, Faculty of Engineering, Universiti Malaysia Sarawak, Kota Samarahan, Sarawak, Malaysia.

M. L. Hossain and A. Abu-Siada are with Department of Electrical and Computer Engineering, Curtin University, Kent Street, Bentley, Perth 6102, WA, Australia.

DOI: 10.17775/CSEEJPES.2019.03060

Reference [7] presented a review on an EMS for the applications of LIB in electrical vehicles (EV). In an EMS, state of charge (SOC) of the battery is a key parameter that identifies the entire operational life of the battery. Reference [8] reviewed various methods of the SOC estimation for EV applications. The BMS observes the state of the battery cells and employs several algorithms to precisely normalize the charging-discharging process. References [9] and [10] presented various SOC estimation techniques for LIB and suggested some guidance for future research. SOC estimation can identify the maximum charging-discharging process to maintain the consistency and extend the effective life of the battery along with improving the State of Health (SOH), State of Function (SOF) and body-temperature [11].

II. BATTERY MODELING

A linear discrete-time state-space procedure is necessary to estimate the SOC of the battery as shown in Fig. 1(a) and the below equations:

$$x_{p+1} = A_p x_p + B_p u_p + w_p \quad (1)$$

$$y_p = C_p x_p + D_p u_p + v_p \quad (2)$$

where $x_p \in \text{real number } R^n$ is the system state vector at discrete-time index p , $u_p \in R^n$ is the system input, $w_p \in R^n$ is unmeasured stochastic “process noise” which distresses the system state, $y_p \in R^n$ is the system output as well as $v_p \in R^n$ is the measurement noise that affects the model output. A_p, B_p, C_p, D_p represents the dynamics of the system that depend on specific time-varying battery models.

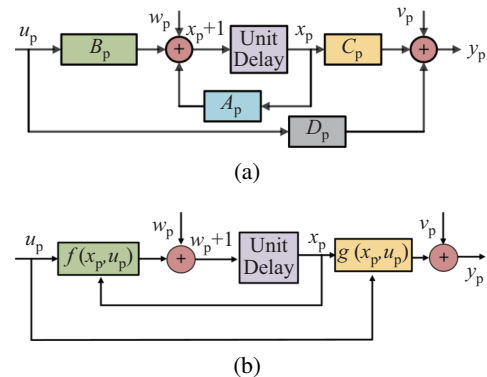


Fig. 1. (a) Linear discrete-time system; (b) Nonlinear discrete-time system.

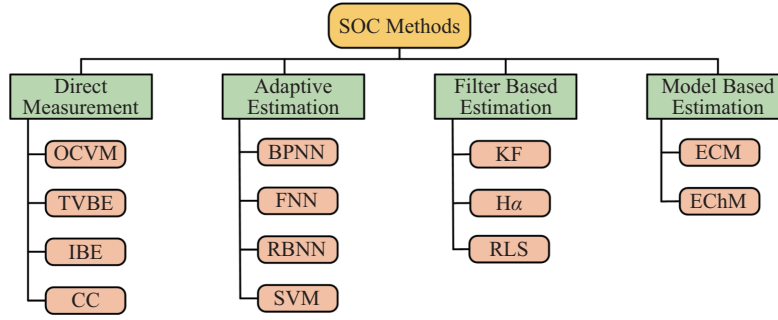


Fig. 2. Classification of SOC estimation methodologies.

In the case of the nonlinear discrete-time system as shown in Fig. 1b, the model is represented by (3) and (4).

$$x_{p+1} = f(x_p, u_p) + w_p \quad (3)$$

$$y_p = g(x_p, u_p) + v_p \quad (4)$$

where $f(x_p, u_p)$ and $g(x_p, u_p)$ are nonlinear functions that describe the individual battery models. The above equations can be reorganized as well according to the requirements of the system [11], [12].

III. OVERVIEW OF THE SOC ESTIMATION

Classification of the SOC estimation methods can be grouped into four main categories as shown in Fig. 2 and further described below.

A. Direct Measurement

In this method, various physical parameters such as voltage, current, temperature, impedance are used to estimate the SOC [13], [14]. Among various methods presented under this category, four methods are considered.

1) Open Circuit Voltage Method (OCVM)

The Open Circuit Voltage (OCV)-SOC method shown in the Thevenin battery model in Fig. 3 can be expressed by [15], [16],

$$\dot{V}_P = \frac{i}{C_P} - \frac{V_P}{R_P C_P} \quad (5)$$

$$e_0 = V_{OC} - iR_S - V_P \quad (6)$$

$$V_{OC}(t) = a_0 + a_1 * S + a_2 * S^2 + \dots + a_{m-1} * S^{m-1} \quad (7)$$

where $V_{OC}(t)$ is the Open Circuit Voltage (OCV) of the battery model at time t , $S(t)$ is the SOC capability of the Battery; e_0 is the terminal voltage of the battery at SOC = 0%, a_m ($m = 0, 1, 2, \dots, m-1$) are the parameters that fit the relationship for OCV-SOC. R_P is the Polarization resistance, C_P is the Polarization capacitance, V_P is the Polarization voltage across R_P and C_P , R_S is the Series resistance, i is the Current of which a positive value indicates discharging mode and a negative value indicates charging mode.

Reference [16] investigated the SOC estimation through two tests namely, the Incremental OCV test and Low-current OCV test. Reference [17] applied the Controlled Auto-Regressive and Moving Average model on the EV-BMS using the Back-Propagation Neural Network (BPNN) algorithm.

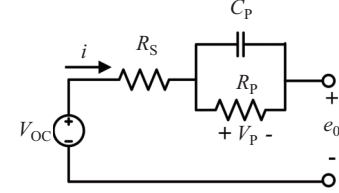


Fig. 3. Thevenin battery model structure.

Reference [18] presented a simplified method for the SOC estimation. A $\pm 2\%$ error rate was attained by the Dynamic Stress Test (DST) scheme as a consequence of the noise sensitivity instrumental faults. Aging effect is observed even due to a slight change of temperature and humidity [19], [20]. Reference [21] conducted aging tests for LIB under standard temperature and (25 ± 2 °C), humidity ($65 \pm 20\%$ RH) and atmospheric pressure ($86 \sim 106$ kPa). To characterize the OCV-SOC relationship, the Polynomial model showed high accuracy compared to the Exponential and Gaussian models.

2) Terminal Voltage Based Estimation (TVBE)

A linear relationship can be found between the Electromotive Force (EMF) and the SOC of a battery. At discharging mode, terminal voltage of a battery depends on the voltage of the internal impedances. Therefore the terminal voltage of a battery is also in a linear proportion relationship with the State of Charge [22]. For this method, the SOC can be calculated as:

$$\frac{ds}{dt} = \frac{i}{36Q_a} \quad (8)$$

$$Q_a = Q_{a0} - Q_f \quad (9)$$

where S is SOC of the cell that can be achieved by using the integration formula in (8), η is the Faraday efficiency, Q_a is the actual capacity of the battery, Q_{a0} is the Initial capacity of the battery, Q_f is the Capacity fading due to aging effect. Reference [23] conducted experimental testing on LIB by employing the Extended Kalman Filter (EKF) algorithm where the DC/DC converter was used to allocate energy from one battery cell to another. Reference [24] carried out a trial on a single cell of the Li-ion battery through simulation analysis. Reported results indicated that the estimated SOC is 0.8 whereas the actual SOC is 0.8121 which was satisfactory. However, these results have not been experimentally validated.

3) Impedance Based Estimation (IBE)

In this method, the battery impedance is restrained from the AC frequencies where the voltage and current are memorized properly at charging and discharging moments [25], [26]. However, the dependency of the battery impedance parameters on its lifecycle sensitive factors is the main drawback of this model [27]. From Fig. 4, resistance R_s and inductor L designate the battery behavior at high frequency. The frequency section is demonstrated by a Constant Phase Element (CPE) with a parallel resistance R_p and fractional coefficient Qs^α . The impedance of the CPE (Z_{CPE}) and entire model (Z_{Model}) can be expressed as:

$$Z_{CPE}(s) = \frac{1}{Qs^\alpha} \quad (10)$$

$$Z_{model}(s) = Ls + R_s + \frac{R_p}{1 + R_p Qs^\alpha} \quad (11)$$

$$V_{OC}(t) = i * Z_{model}(s) + e_0 \quad (12)$$

$$SOC = f^{-1}(V_{OC}(t)) \quad (13)$$

where $V_{OC}(t)$ is the Open Circuit Voltage, e_0 is the terminal voltage and i is the flowing current of the battery at time t .

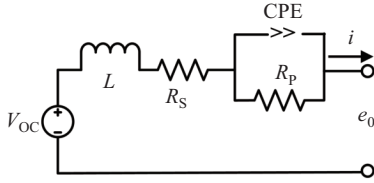


Fig. 4. Battery impedance equivalent circuit model.

Reference [28] presented a circuit model for the $\text{LiNi}_{0.80}\text{Co}_{0.15}\text{Al}_{0.05}\text{O}_2$ battery where the Odd Random Phase-Electrochemical Impedance Spectroscopy and the symmetric cell tactic were appropriately implemented. Reference [29] applied the impedance spectroscopy method for three several types of Lithium-ion pouch cells considering the SOC and temperature from 10% to 90% and -10°C to $+40^\circ\text{C}$ respectively. The authors concluded that SOC upturns by decreasing impedance rating with the incremental temperature. Reference [30] employed a 15.4 Ah NCM/graphite LIB for SOC estimation where the Warburg impedance percentage was applied to evaluate the ability of the battery performance.

4) Coulomb Counting (CC)

The Coulomb Counting (CC) method is also known as the ampere-hour (Ah) method. Mathematically, the SOC can be calculated from,

$$SOC(t) = SOC(t_0) + \frac{1}{C_n} \int_{t_0}^{t_0+t} I_{bat}(d\tau) \quad (14)$$

where $SOC(t_0)$ is the preliminary SOC of the battery, C_n is the nominal capacity of the battery, i_{bat} is the charging/discharging current of the battery. Since several factors, such as temperature, discharging current, battery cycle life, and aging effect on the accuracy of the CC method, a modified CC method is anticipated to improve the conventional

method [31], [32]. The corrected current $I_c(t)$ is in a quadratic relationship with the conventional current $I(t)$ as in (15).

$$I_c(t) = m_2 I(t)^2 + m_1 I(t) + m_0 \quad (15)$$

where m_2 , m_1 and m_0 are constant values which can be obtained from the practiced investigational statistics. Reference [33] studied the CC-SOC estimation by the combination of Peukert's Law and the coulombic efficiency algorithm. Reference [34] implemented an experimental combination of the Adaptive Neuro-Fuzzy Inference System (ANFIS) and CC method (Fig. 5). From this investigation, the mean and maximum errors were obtained at 4% and 7% respectively.

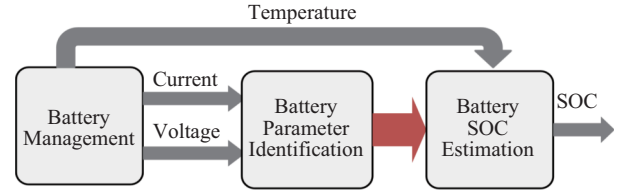


Fig. 5. Procedure of SOC estimation technique.

Reference [35] considered LIB from CGR 18650D Panasonic for the OCV-CC SOC estimation where only 1% error was reported. However, temperature increases drastically when the discharging rate increases more than 0.8C. Reference [36] estimated the SOC through CC method with the help of calibrating SOH for 2.3 Ah LIB. Battery charge status was controlled via the Constant Current-Constant Voltage (CC-CV) scheme. The estimation error was below 1.905% owing to the involvement of the SOH factor.

B. Adaptive Based Estimation

The adaptive systems are self-processing methods that can be determined to fulfill its targeted value [37], [38]. BPNN, Fuzzy Neural Network (FNN), Radial Basis Neural Network (RBNN) and Support Vector Machine (SVM) are employed for SOC estimation. The adaptive methods offer better emulation to the batteries chemical effect and nonlinear charge characteristics [39].

1) Back Propagation Neural Network (BPNN)

BPNN is widely used to estimate the SOC because of its self-learning and nonlinear characteristics. Due to the nonlinear nature of the SOC estimation, artificial neural network can forecast the up-to-date SOC by means of updating the voltage, current and battery temperature. The BPNN comprises an input layer, an output layer and a hidden layer [40], [41]. In the case of the SOC estimation procedure, the layers contained three input neurons (Battery-cell: voltage, current and temperature), one output neuron (SOC) and n number of hidden neurons as shown in Fig. 6 [42].

Total input of a hidden layer neuron or overall output of the input layer neuron can be calculated by:

$$neti_n = \sum_{i=1}^3 x_i w_{in} + b_n \quad (16)$$

where $neti_n$ is the total input of hidden layer neurons n , x_i is the input to the hidden layer, w_{in} is the weight between

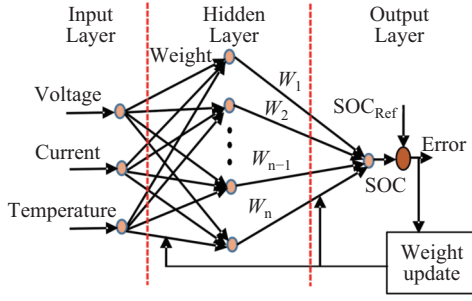


Fig. 6. Structural design of the BPNN based SOC estimation scheme.

input layer neuron i and hidden layer neuron n , b_n is a bias of the hidden layer neuron n . In the hidden layer neuron, the applied activation function is the tangent function which can be calculated as:

$$h_n = f(neti_n) = \frac{1 - \exp(-2neti_n)}{1 + \exp(-2neti_n)} \quad (17)$$

The total input of the output layer neuron o can be calculated as:

$$neto = \sum_{i=1}^n h_i w_i + k \quad (18)$$

where $neto$ is the total input of the output layer neuron o , h_i is the value of the hidden layer to output layer neuron i , w_i is the weight between the hidden layer neuron i and output layer neuron o , k is a bias of the output layer neuron o , n is the number of hidden layer neurons. In the output layer neuron, the applied activation function is a sigmoid function which can be calculated as:

$$h_n = f(neto) = \frac{1}{1 + \exp(-neto)} \quad (19)$$

Reference [43] presented the Backtracking Search Algorithm (BSA) based BPNN SOC estimation for the LIB. The DST and Federal Urban Driving Schedule (FUDS) drive profiles were investigated at three different temperatures (0, 25 and 45° C). The research ensured the reduction of the Root Mean Square Error (RMSE) for the BPNN-BSA model at 25° C compared to RBNN-BSA, Generalized Regression Neural Network-BSA and Extreme Learning Machine-BSA models. Reference [44] considered the Particle Swarm Optimization (PSO) algorithm for the SOC estimation of LIB. The achieved RMSE of several tests, such as the Beijing Dynamic Stress Test (0.58%), FUDS (0.72%) and US06 (0.47%) showed better results compared to RBNN. Reference [45] used the Lead-acid battery for devising the optimum employment with the BPNN algorithm.

2) Fuzzy Neural Network (FNN)

The adaptive neuro-fuzzy inference system (ANFIS) and the local linear model tree are the foremost two types of classification for Fuzzy logic Neural Network based SOC estimation methods. ANFIS comprises Fuzzy and Neural Network compensations [46], [47].

Reference [48] applied a power prediction scheme on the Li-Ion cell and adopted the ANFIS system to estimate the SOC by the EKF algorithm. Reference [49] applied the Neuro-Fuzzy

algorithm with the MANHATTAN driving cycle where the Maximum absolute error for the SOC estimation was less than 0.1%. Reference [50] tested PLF08150240 LIB using the fuzzy logic control-neural network procedure through the Urban Dynamometer Driving Schedule (UDDS) test for Hybrid EV (HEV). Reference [51] presented the SOC estimation method with the help of Stochastic FNN (SFNN) as shown in Fig. 7. Here, x_j^l are inputs of the SFNN model, y_j^l is SOC, τ_j^l is the activation function, w_j^l is weight and ψ_j^l is the integration function.

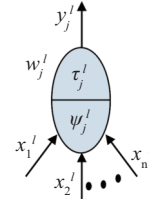


Fig. 7. Nodal structure of SFNN.

3) Radial Basis Neural Network (RBNN)

In case of inadequate statistics of a system, RBNN (shown in Fig. 8) is the most useful methodology to estimate SOC [52].

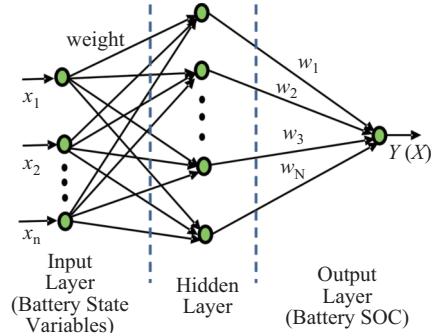


Fig. 8. Structural design of the RBNN SOC estimation scheme.

In case of the Radial Basis Function based SOC estimation technique, output $Y(X)$ is the combination of the hidden layer neurons with the synaptic weights w_i which is calculated as:

$$Y(X) = \sum_{i=1}^N w_i \varphi_i(X, C_i) \quad (20)$$

$$\varphi_i(X, C_i) = \varphi(\|X - C_i\|) \quad (21)$$

where N is the number of hidden layer neurons and $\varphi_i(X, C_i)$ is a radial basis function that is the difference between the input vector $X = (x_1, x_2, \dots, x_n)$ and center $C(C_i \in R^n)$. Reference [53] presented a Robust Sliding Mode Observer (RSMO) method and applied the Forgetting Factor Recursive Least Square algorithm of a Battery Equivalent Circuit Model (ECM) for the SOC estimation. Reference [54] presented some results for a twelve series-connected LIB cell. The RBNN based uncertainty quantification algorithm was used to construct a Response Surface Approximate Model (RSAM). Reference [55] conducted a test for the RBNN SOC

estimation (Fig. 8) with the amalgamation of the Orthogonal Least-Squares (OLS) and Adaptive Genetic Algorithm (AGA) where the Maximum Absolute Percentage Error was 1.82%.

4) Support Vector Machine (SVM)

The SVM technique is applied for nonlinear estimation problems owing to its insensitiveness to system minor variations [56]. If x is the input vector containing battery parameters, μ is a real number coefficient, σ is the deviation and $\mathcal{O}(x)$ is the diagramming from the original to the targeted space, the target function and the regression R of the SVM can be obtained from,

$$f(x) = \mu \mathcal{O}(x) + \sigma, \mu \in R^n, \sigma \in R \quad (22)$$

$$R[\vec{w}, b, \beta] = \frac{1}{2} \|\vec{w}\|^2 + \mathfrak{C} \sum_{j=1}^L (\beta_j^+, \beta_j^-) \quad (23)$$

In (23), $\frac{1}{2} \|\vec{w}\|^2$ is the flatness function and the regulation constant $\mathfrak{C}$ is used as a trade-off between the margin and the magnitude of the slack variables β_j^+ and β_j^- . Reference [57] utilized eight types of cyclic situations and seven battery parameters for the Support Vector Regression (SVR) based SOC estimation by the double search procedure. Reference [58] tested the LiFePO₄ by the Cross validation algorithm. Reference [59] presented the SVM SOC estimation on the LiFeMnPO₄ with the cross validation technique.

C. Filter Based Estimation

In case of filter based estimation, the feedback technique is applied to modify the output by following its input. It is a self-designing system that can routinely regulate the output [60]. Among all the types of methodologies, three types are described below:

1) Kalman Filter (KF)

The battery SOC estimation determined by a real-time quantity is problematic and costly to precisely measure [61]. From [62], the Thevenin model was preferred to design the battery configuration (shown in Fig. 9). From this model,

$$V_p = -\frac{V_p}{C_p R_p} + \frac{I_L}{C_p} \quad (24)$$

$$V_t = V_{OC} - V_p - I_L R_s \quad (25)$$

$$x_{p+1} = A_p x_p + B_p u_p + G_p \quad (26)$$

$$y_p = g(x_p, u_p) + \delta_p \quad (27)$$

$$A_p = \begin{bmatrix} \exp(-\Delta t / \gamma) & 0 \\ 0 & 1 \end{bmatrix} \quad (28)$$

Let x_p be the State vector, y_p is the output vector, u_p is the Input vector, A_p is the Plant matrix, B_p is the Input matrix, C_p is the output matrix, S_p is the SOC of p_{th} sample time. $\gamma = C_p * R_p$ is the time constant, G_p is the Gaussian white noise with zero mean and the covariance P_p , δ_p is the Gaussian white noise with zero mean and the covariance S_p . $y_p = g(x_p, u_p)$ is known as the nonlinear output function. The detailed iteration diagram of the KF algorithm is shown in Fig. 10. Reference [63] conducted tests on Series HEV LiFePO₄ using the Unscented Kalman Filter (UKF) procedure

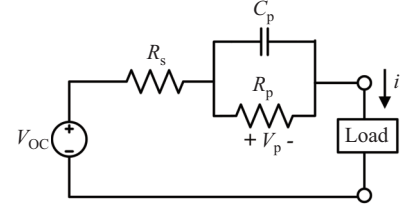


Fig. 9. Thevenin model to describe KF method.

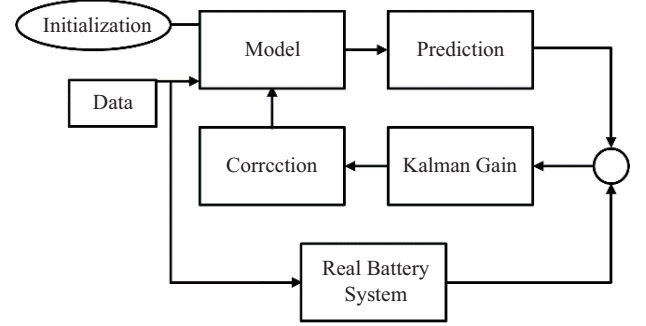


Fig. 10. Iteration diagram for Kalman Filter method.

to diminish the sampling noise with the enhancement of SOC perfection.

$$B_p = \begin{bmatrix} [1 - \exp(-\Delta t / \gamma)] R_{pr} \\ -\Delta t / C \end{bmatrix} \quad (29)$$

$$C_p = \begin{bmatrix} -1 & \frac{dV_{OC,p}}{dS_p} \end{bmatrix} \quad (30)$$

$$g(x_p, u_p) = V_{OC,p} - I_{L,p} R_s - V_{p,p} \quad (31)$$

The estimation error and the reduction of fuel depletion was 1.5% and 5% respectively. Reference [64] used the Differential Voltage (DV) exploration on the LIB for the combination of Extended KF (EKF) and Particle Filter SOC estimation. Reference [65] applied the combination of the UKF and EKF algorithm on the LiNMC battery with the first order RC ECM. Reference [66] presented a comparison between [67] and [68] with the execution of the EKF algorithm. Reference [69] presented the Adaptive UKF with a noise statistics estimator to precisely establish the SOC of the Battery Energy Storage System (BESS).

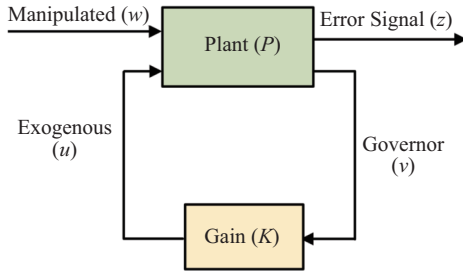
2) H infinitive (H_∞)

To limit the influence of disturbances on the SOC estimation, the H infinitive (H_∞) method has been adopted in [70]. The measurement inaccuracy and system noise can be restricted under a fixed attenuation level by the H infinitive method (Fig. 11), by which the SOC estimation accuracy can be precisely improved. To implement H_∞ , the following equations are used,

$$\begin{pmatrix} z \\ v \end{pmatrix} = P(s) \begin{pmatrix} w \\ u \end{pmatrix} \quad (32)$$

$$P(s) = \begin{bmatrix} P_{11}(S) & P_{12}(S) \\ P_{21}(S) & P_{22}(S) \end{bmatrix} \quad (33)$$

where P is a plant matrix, u and w are the exogenous and manipulated inputs respectively. Two outputs are obtained

Fig. 11. General structure of the H_∞ method.

from the plant matrix, first is the error signal z which has to be minimized and the other one is v which is used to govern the system. The purpose of this method is to find the gain value K of the controller for which model error $F_t(P, K)$ is reduced.

$$u = K(s).v \quad (34)$$

$$z = F_t(P, K).w \quad (35)$$

$$F_t = P_{11} + P_{12} K(I + P_{22} K)^{-1} P_{21} \quad (36)$$

Reference [71] implemented the H Infinity-EKF on 3,200 Lithium-ion cells by the New European Driving Cycle (NEDC). Reference [72] presented one order ECM of the LIB with the help of the Variable Forgetting Factor Recursive Extended Least Squares (VFFRELS) to identify the battery parameters. Results show improved Adaptive H-Infinity Filter (AHIF) performance which was superior to the estimate by SOC through regulating the noise covariance. Reference [73] implemented the H infinity filter (HIF) for the OCV-SOC estimation method to lessen the time and cost of the LiFePO4 battery. Reference [74] proposed a joint algorithm called the HIF-UKF method and compared this method with the PSO-UKF based SOC estimation by the DST test and UDDS test. Though this method is fast, its accuracy is still questionable.

3) Recursive Least Squares (RLS)

Recursive Least Square (RLS) is based on the adaptive filter scheme where the coefficients are found recursively and the least square cost function is minimized according to its input signals. Though the RLS algorithm is a speedy pattern compared to others, errors can occur due to the computational complexity [75]. In Fig. 12, $\mathcal{L}$ is the cost function that has to be minimized by the forgetting factor μ . If $\partial(n)$ is the looked-for signal and $e(n)$ is the error signal with the filter coefficients ω_n , the cost function can be calculated as:

$$\mathcal{L}(\omega_n) = \sum_{j=1}^n \mu^{n-j} e^2(j); \quad 0 < \mu < 1 \quad (37)$$

$$e(n) = \partial(n) - \hat{\partial}(n) \quad (38)$$

Reference [76] studied the resistor and capacitor model of the Battery ECM by the Decoupled Weighted Recursive Least

Square (DWRLS) method and presented a comparison with the Least Square method. Reference [77] conducted tests on a 2.2 Ah LIB where the Multiplies, Divides, and Square Roots were utilized to estimate the model accuracy. Reference [78] obtained less than 2.8% absolute error by applying the Multiple Adaptive Forgetting Factor-RLS algorithm on the EV

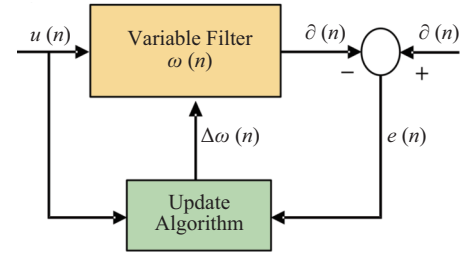


Fig. 12. Fundamental structure of the RLS method.

for LiFePO4. Results were compared with the unadventurous Single Fixed Forgetting Factor-RLS technique.

D. Model Based Estimation

In this method, a battery model is set up with an advanced algorithm to establish the status of a battery from its measuring factors; voltage, current and temperature [79]. The electrical and electrochemical model based SOC estimations are reviewed below [80].

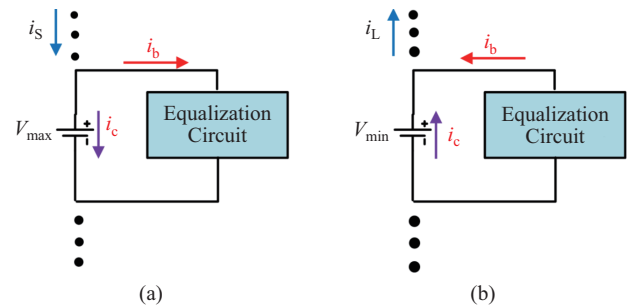
1) Electrical Circuit Model (ECM)

In the case of the Electrical circuit based SOC estimation method, the battery model is primarily considered [81]. A general calculation of the battery model is determined by (39) and (40):

$$V_{OCV} = f(SOC) \quad (39)$$

$$SOC(k) = SOC(k-1) + I(k-1) * \frac{T_s}{3600C_n} \quad (40)$$

where V_{OCV} is OCV, C_n is the capacity and T_s is the charging/discharging time of the battery-cell. Reference [82] designed an electrical sub-model and a thermal sub-model where several temperatures were applied to assess the internal heat generation of the SOC estimation. The EKF algorithm was applied to the LiFePO4 battery with 2.31% estimated RMSE. Reference [83] calculated the battery pack voltage and cell voltage separately (shown in Fig. 13) and applied the dynamic voltage difference method for the ten series connected Li(NiCoMn)O₂ battery. Reference [84] applied EKF-Ah algorithm for three different LIB models.

Fig. 13. (a) V_{max} in charging procedure; (b) V_{min} in discharging procedure.

2) Electrochemical Model (EChM)

In the case of the SOC estimation by the Electrochemical model (EChM), diffusion, intercalation, electrochemical kinetics of a battery concerning equations are utilized [85].

TABLE I
SUMMARY OF SOC ESTIMATION TECHNIQUES

Method	Advantage	Limitation
OCVM [17], [18]	Easy for application. Precision is high.	Long time resting is necessary to reach the equilibrium condition. Only applicable when the battery is not charging or discharging.
TVBE [22], [24]	Terminal Voltage is approximately linear proportional to SOC. At different temperature and discharging current, the method is suitable.	The estimated error is high. At the end of battery discharge, terminal voltage drops down suddenly.
IBE [25], [26]	High accuracy is achieved when impedance is normalized.	Result is affected by following the temperature and age factor.
CC [34], [35]	Low cost. Easily applicable. Power distortion is low.	Suitable only for charging condition with the AC frequency. Initial SOC is mandatory to estimate current SOC.
BPNN [40], [41]	Capable of preparing the input output nonlinear relationship. Easy to implement.	Cumulative error is high due to the undefined disturbances. Data training is necessary before implementing. More neuron is required to improve the accuracy.
FNN [49], [51]	Performs well in non-linear dynamic system. Effective at any degree of consideration.	Computational complexity and processing scheme is costly. Aging effect can't be considered.
RBNN [52], [55]	The operation speed and estimation speed can meet the expected demand.	Costly and processing complexity. Large sized memory is needed to train the data.
SVM [56], [59]	SOC estimation accuracy is faster and accurate. In high dimensional and non-linear model, it performs well.	To modify the model parameters, trial and error processing is necessary. Processing complexity.
KF [64], [65]	Good accuracy in non-linear dynamic states.	Robustness becomes limited for highly non-linear states. Diverge the accuracy for calculation complexity.
H α [71], [72]	High accuracy and low computational cost.	Hysteresis and age affect the accuracy.
RLS [76], [77]	Accuracy is high. Noise is eliminated from the measured signal.	Computation is heavy. Operation becomes unstable due to the inappropriate forgetting factor.
ECM [81], [82]	Suitable for the new batteries.	Time consuming and costly. Aging effect is high.
EChM [85], [86]	Good precision owing to battery internal chemical involvement.	Error is high owing to the chemical complexity.

Reference [86] considered three different observers, namely the EKF, Kalman smoother and particle filter where the dual-nonlinear observer was utilized to estimate the SOC and reduce the forfeiture of cycling time with a proper electrochemical model (shown in Fig. 14). Reference [87] presented the Electrochemical based SOC estimation for an LMO battery and verified its robustness using the Lyapunov stability method. The actual cell current (i_c) of the cell voltage (V) was primarily determined by following the charging (i_s), discharging (i_L) and balancing (i_b) current. Reference [88] used the Partial Differential Equation as a key function where the EKF was applied on the LIB.

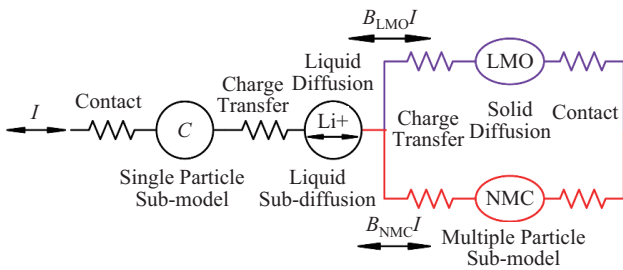


Fig. 14. Schematic structure of the electrochemical mode.

IV. FUTURE CHALLENGES AND DISCUSSION

The accuracy of the SOC estimation methods has become important due to the storage applications of a Electric Vehicle (EV) and Renewable Energy (RE). The accuracy of SOC estimation is necessary to monitor the medium level battery storage section along with the giant system. Recently, researchers have employed several types of SOC estimation

methods for BMS and so the estimation potentiality is greatly enhanced. Two main challenges can be summarized from using the SOC estimation field: (1) improvement of the SOC estimation efficiency, (2) cost effective implementation of the proposed method [89], [90]. Thus a trade-off between the SOC estimation accuracy and the computational complexity of the system should be evaluated. Table I summarizes various types of SOC estimating methodologies from different aspects..

V. CONCLUSION

This paper presents SOC estimation techniques for only single battery cells. The previous technique will be helpful for SOC estimation with respect to cell strings and battery packs. The main conclusions of this comprehensive review can be summarized in the following bullet points:

- In the case of the direct method, the SOC estimation error increases with the incremental temperature and its aging effect. Moreover, it results in delays when further estimating the current SOC.
- The adaptive methods are more accurate due to their feedback schemes. Among the classification of the adaptive system methods, more accuracy and less-complexity are obtained from the BPNN technique compared to others. However, this method should be experimented using a practical environment.
- Among the various filter based SOC estimation methods, KF is more popular compared to the others. Nevertheless, the cell inconsistency and the temperature effect the accuracy of the SOC estimation method.
- The electrical circuit based SOC estimation method implements the OCV for the model-based estimation.

The charging/discharging cycles and the measurement accuracy affect the wide implementation of this method. The electrochemical-based estimation is related to the chemical reaction within the battery.

- Developing a suitable battery model is vital for the SOC estimation procedure that redirects the impact of the battery parameters i.e. internal resistance and capacity fading.

REFERENCES

- [1] H. Branco, R. Castro, and A. Setas Lopes, "Battery energy storage systems as a way to integrate renewable energy in small isolated power systems," *Energy for Sustainable Development*, vol. 43, pp. 90–99, Apr. 2018.
- [2] E. Hossain, M. Zawad, K. H. Rakibul Islam, and Q. Akash, "Design a novel controller for stability analysis of microgrid by managing controllable load using load shaving and load shifting techniques; and optimizing cost analysis for energy storage system," *International Journal of Renewable Energy Research*, vol. 6, no. 3, pp. 772–786, Jan. 2016.
- [3] U. Caldera and C. Breyer, "The role that battery and water storage play in Saudi Arabia's transition to an integrated 100% renewable energy power system," *Journal of Energy Storage*, vol. 17, pp. 299–310, Jun. 2018.
- [4] M. Partovibakhsh and G. J. Liu, "An adaptive unscented kalman filtering approach for online estimation of model parameters and state-of-charge of lithium-ion batteries for autonomous mobile robots," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 1, pp. 357–363, Jan. 2015.
- [5] J. S. Lee, S. T. Kim, R. G. Cao, N. S. Choi, M. L. Liu, K. T. Lee, and J. Cho, "Metal-air batteries with high energy density: Li-air versus Zn-air," *Advanced Energy Materials*, vol. 1, no. 1, pp. 34–50, Jan. 2011.
- [6] J. Balach, J. Linnemann, T. Jaumann, and L. Giebeler, "Metal-based nanostructured materials for advanced lithium-sulfur batteries," *Journal of Materials Chemistry A*, vol. 6, no. 46, pp. 23127–23168, Nov. 2018.
- [7] M. A. Hannan, M. Hoque, A. Hussain, Y. Yusof, and P. J. Ker, "State-of-the-art and energy management system of lithium-ion batteries in electric vehicle applications: Issues and recommendations," *IEEE Access*, vol. 6, pp. 19362–19378, Mar. 2018.
- [8] R. Xiong, J. Y. Cao, Q. Q. Yu, H. W. He, and F. C. Sun, "Critical review on the battery state of charge estimation methods for electric vehicles," *IEEE Access*, vol. 6, pp. 1832–1843, Dec. 2017.
- [9] J. P. Rivera-Barrera, N. Muñoz-Galeano, and H. O. Sarmiento-Maldonado, "SoC estimation for lithium-ion batteries: Review and future challenges," *Electronics*, vol. 6, no. 4, pp. 102, Dec. 2017.
- [10] W. Y. Chang, "The state of charge estimating methods for battery: A review," *International Scholarly Research Notices*, vol. 2013, pp. 953792, Jul. 2013.
- [11] A. B. Ahmad, C. A. Ooi, D. Ishak, and J. Teh, "State-of-charge balancing control for ON/OFF-line internal cells using hybrid modular multi-level converter and parallel modular dual I-bridge in a grid-scale battery energy storage system," *IEEE Access*, vol. 7, pp. 131–147, Dec. 2018.
- [12] Y. Q. Yang, S. Bremner, C. Menictas, and M. Kay, "Battery energy storage system size determination in renewable energy systems: A review," *Renewable and Sustainable Energy Reviews*, vol. 91, pp. 109–125, Aug. 2018.
- [13] Y. J. Zheng, X. B. Han, L. G. Lu, J. Q. Li, and M. G. Ouyang, "Lithium ion battery pack power fade fault identification based on Shannon entropy in electric vehicles," *Journal of Power Sources*, vol. 223, pp. 136–146, Feb. 2013.
- [14] R. Ahmed, M. El Sayed, I. Arasaratnam, J. Tjong, and S. Habibi, "Reduced-order electrochemical model parameters identification and state of charge estimation for healthy and aged li-ion batteries—part II: Aged battery model and state of charge estimation," *IEEE Journal of Emerging and Selected Topics in Power Electronics*, vol. 2, no. 3, pp. 678–690, Sep. 2014.
- [15] Z. Y. Zou, J. Xu, C. Mi, B. G. Cao, and Z. Chen, "Evaluation of model based state of charge estimation methods for lithium-ion batteries," *Energies*, vol. 7, no. 8, pp. 5065–5082, Aug. 2014.
- [16] C. Lin, L. Q. Q. Yu, R. Xiong, and L. Y. Wang, "A study on the impact of open circuit voltage tests on state of charge estimation for lithium-ion batteries," *Applied Energy*, vol. 205, pp. 892–902, Nov. 2017.
- [17] X. J. Dang, L. Yan, H. Jiang, X. R. Wu, and H. X. Sun, "Open-circuit voltage-based state of charge estimation of lithium-ion power battery by combining controlled auto-regressive and moving average modeling with feedforward-feedback compensation method," *International Journal of Electrical Power & Energy Systems*, vol. 90, pp. 27–36, Sep. 2017.
- [18] G. Z. Dong, J. W. Wei, C. B. Zhang, and Z. H. Chen, "Online state of charge estimation and open circuit voltage hysteresis modeling of LiFePO₄ battery using invariant imbedding method," *Applied Energy*, vol. 162, pp. 163–171, Jan. 2016.
- [19] R. E. Tudoroiu, M. Zaheeruddin, S. M. Radu, and N. Tudoroiu, "Estimation techniques for state of charge in battery management systems on board of hybrid electric vehicles implemented in a real-time MATLAB/SIMULINK environment," in *New Trends in Electrical Vehicle Powertrains*, L. R. Martinez, Ed. London: IntechOpen, 2019, pp. 13.
- [20] T. Blank, C. Lipps, W. Ott, P. Hoffmann, and M. Weber, "Influence of environmental conditions on the sensing accuracy of Li-Ion battery management systems with passive charge balancing," in *Proceedings of the 2015 17th Europea Conference on Power Electronics and Applications*, 2015, pp. 1–9.
- [21] R. F. Zhang, B. Z. Xia, B. H. Li, L. B. Cao, Y. Z. Lai, W. W. Zheng, H. W. Wang, W. Wang, and M. W. Wang, "A study on the open circuit voltage and state of charge characterization of high capacity lithium-ion battery under different temperature," *Energies*, vol. 11, no. 9, pp. 2408, Sep. 2018.
- [22] M. Coleman, C. K. Lee, C. B. Zhu, and W. G. Hurley, "State-of-charge determination from EMF voltage estimation?: Using impedance, terminal voltage, and current for lead-acid and lithium-ion batteries," *IEEE Transactions on Industrial Electronics*, vol. 54, no. 5, pp. 2550–2557, Oct. 2007.
- [23] H. B. Ren, Y. Z. Zhao, S. Z. Chen, and T. P. Wang, "Design and implementation of a battery management system with active charge balance based on the SOC and SOH online estimation," *Energy*, vol. 166, pp. 908–917, Jan. 2019.
- [24] L. Y. Wang, M. P. Polis, G. G. Yin, W. Chen, Y. H. Fu, and C. C. Mi, "Battery cell identification and soc estimation using string terminal voltage measurements," *IEEE Transactions on Vehicular Technology*, vol. 61, no. 7, pp. 2925–2935, Sep. 2012.
- [25] H. F. Dai, B. Jiang, and X. Z. Wei, "Impedance characterization and modeling of lithium-ion batteries considering the internal temperature gradient," *Energies*, vol. 11, no. 1, pp. 220, Jan. 2018.
- [26] B. G. Carkhuff, P. A. Demirev, and R. Srinivasan, "impedance-based battery management system for safety monitoring of lithium-ion batteries," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 8, pp. 6497–6504, Aug. 2018.
- [27] W. Waag, S. Käbitz, and D. U. Sauer, "Experimental investigation of the lithium-ion battery impedance characteristic at various conditions and aging states and its influence on the application," *Applied Energy*, vol. 102, pp. 885–897, Feb. 2013.
- [28] X. H. Zhu, L. Fernández Macía, J. Jaguemont, J. de Hoog, A. Nikolian, N. Omar, and A. Hubin, "Electrochemical impedance study of commercial LiNi_{0.80}Co_{0.15}Al_{0.05}O₂ electrodes as a function of state of charge and aging," *Electrochimica Acta*, vol. 287, pp. 10–20, Oct. 2018.
- [29] S. Skoog and S. David, "Parameterization of linear equivalent circuit models over wide temperature and SOC spans for automotive lithium-ion cells using electrochemical impedance spectroscopy," *Journal of Energy Storage*, vol. 14, pp. 39–48, Dec. 2017.
- [30] Q. A. Huang, Y. Shen, Y. H. Huang, L. Zhang, and J. J. Zhang, "Impedance characteristics and diagnoses of automotive lithium-ion batteries at 7.5% to 93.0% state of charge," *Electrochimica Acta*, vol. 219, pp. 751–765, Nov. 2016.
- [31] M. W. Cheng, Y. S. Lee, M. Liu, and C. C. Sun, "State-of-charge estimation with aging effect and correction for lithium-ion battery," *IET Electrical Systems in Transportation*, vol. 5, no. 2, pp. 70–76, Jun. 2015.
- [32] K. W. E. Cheng, B. P. Divakar, H. J. Wu, K. Ding, and H. F. Ho, "Battery-management system (BMS) and SOC development for electrical vehicles," *IEEE Transactions on Vehicular Technology*, vol. 60, no. 1, pp. 76–88, Jan. 2011.
- [33] J. L. Xie, J. C. Ma, and K. Bai, "Enhanced coulomb counting method for state-of-charge estimation of lithium-ion batteries based on peukert's law and coulombic efficiency," *Journal of Power Electronics*, vol. 18, no. 3, pp. 910–922, May 2018.
- [34] A. Fotouhi, D. J. Auger, K. Propp, and S. Longo, "Lithium-sulfur battery state-of-charge observability analysis and estimation," *IEEE Transactions on Power Electronics*, vol. 33, no. 7, pp. 5847–5859, Jul. 2018.

- [35] K. S. Ng, C. S. Moo, Y. P. Chen, and Y. C. Hsieh, "Enhanced coulomb counting method for estimating state-of-charge and state-of-health of lithium-ion batteries," *Applied Energy*, vol. 86, no. 9, pp. 1506–1511, Sep. 2009.
- [36] T. H. Wu and C. S. Moo, "State-of-charge estimation with state-of-health calibration for lithium-ion batteries," *Energies*, vol. 10, no. 7, pp. 987, Jul. 2017.
- [37] M. S. H. Lipu, M. A. Hannan, A. Hussain, M. H. M. Saad, A. Ayob, and F. Blaabjerg, "State of charge estimation for lithium-ion battery using recurrent NARX neural network model based lightning search algorithm," *IEEE Access*, vol. 6, pp. 28150–28161, May 2018.
- [38] H. Chaoui and C. C. Ibe-Ekeocha, "State of charge and state of health estimation for lithium batteries using recurrent neural networks," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 10, pp. 8773–8783, Oct. 2017.
- [39] L. W. Kang, X. Zhao, and J. Ma, "A new neural network model for the state-of-charge estimation in the battery degradation process," *Applied Energy*, vol. 121, pp. 20–27, May 2014.
- [40] B. Q. Wang, L. J. Wang, Y. L. Yin, Y. L. Xu, W. T. Zhao, and Y. C. Tang, "An improved neural network with random weights using backtracking search algorithm," *Neural Processing Letters*, vol. 44, no. 1, pp. 37–52, Aug. 2016.
- [41] A. A. Hussein, "Capacity fade estimation in electric vehicle li-ion batteries using artificial neural networks," *IEEE Transactions on Industry Applications*, vol. 51, no. 3, pp. 2321–2330, May-Jun. 2015.
- [42] O. Qays, Y. Buswig, and M. Anyi, "Active cell balancing control method for series-connected lithium-ion battery," *International Journal of Innovative Technology and Exploring Engineering*, vol. 8, no. 9, pp. 2424–2430, Jul. 2019.
- [43] M. A. Hannan, M. S. H. Lipu, A. Hussain, M. H. Saad, and A. Ayob, "Neural network approach for estimating state of charge of lithium-ion battery using backtracking search algorithm," *IEEE Access*, vol. 6, pp. 10069–10079, Jan. 2018.
- [44] T. Leveringhaus and L. Hofmann, "Optimized voltage and reactive power adjustment in power grids using the least-squares-method: Optimization of highly utilized power grids with stochastic renewable energy-sources," in *Proceedings of 2011 International Conference on Power and Energy Systems*, 2011, pp. 1–6.
- [45] F. Husnayain, A. R. Utomo, and P. S. Priambodo, "State of charge estimation for a lead-acid battery using backpropagation neural network method," in *Proceedings of 2014 International Conference on Electrical Engineering and Computer Science*, 2014, pp. 274–278.
- [46] M. A. Awadallah and B. Venkatesh, "Accuracy improvement of SOC estimation in lithium-ion batteries," *Journal of Energy Storage*, vol. 6, pp. 95–104, May 2016.
- [47] H. F. Dai, P. J. Guo, X. Z. Wei, Z. C. Sun, and J. Y. Wang, "ANFIS (adaptive neuro-fuzzy inference system) based online SOC (State of Charge) correction considering cell divergence for the EV (electric vehicle) traction batteries," *Energy*, vol. 80, pp. 350–360, Feb. 2015.
- [48] C. Fleischer, W. Waag, Z. Bai, and D. U. Sauer, "Adaptive on-line state-of-available-power prediction of lithium-ion batteries," *Journal of Power Electronics*, vol. 13, no. 4, pp. 516–527, Jul. 2013.
- [49] T. Zahid, K. Xu, W. M. Li, C. M. Li, and H. Z. Li, "State of charge estimation for electric vehicle power battery using advanced machine learning algorithm under diversified drive cycles," *Energy*, vol. 162, pp. 871–882, Nov. 2018.
- [50] S. M. Zhang, L. Yang, X. W. Zhao, and J. X. Qiang, "A GA optimization for lithium-ion battery equalization based on SOC estimation by NN and FLC," *International Journal of Electrical Power & Energy Systems*, vol. 73, pp. 318–328, Dec. 2015.
- [51] L. Xu, J. P. Wang, and Q. S. Chen, "Kalman filtering state of charge estimation for battery management system based on a stochastic fuzzy neural network battery model," *Energy Conversion and Management*, vol. 53, no. 1, pp. 33–39, Jan. 2012.
- [52] L. Zhang, K. Li, and E. W. Bai, "A new extension of newton algorithm for nonlinear system modelling using RBF neural networks," *IEEE Transactions on Automatic Control*, vol. 58, no. 11, pp. 2929–2933, Nov. 2013.
- [53] X. P. Chen, W. X. Shen, M. X. Dai, Z. W. Cao, J. Jin, and A. Kapoor, "Robust adaptive sliding-mode observer using RBF neural network for lithium-ion battery state of charge estimation in electric vehicles," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 4, pp. 1936–1947, Apr. 2016.
- [54] F. C. Sun, R. Xiong, and H. W. He, "A systematic state-of-charge estimation framework for multi-cell battery pack in electric vehicles using bias correction technique," *Applied Energy*, vol. 162, pp. 1399–1409, Jan. 2016.
- [55] W. Y. Chang, "Estimation of the state of charge for a LFP battery using a hybrid method that combines a RBF neural network, an OLS algorithm and AGA," *International Journal of Electrical Power & Energy Systems*, vol. 53, pp. 603–611, Dec. 2013.
- [56] V. Surendar, V. Mohankumar, S. Anand, and V. D. Prasanna, "Estimation of state of charge of a lead acid battery using support vector regression," *Procedia Technology*, vol. 21, pp. 264–270, 2015.
- [57] J. N. Hu *et al.*, "State-of-charge estimation for battery management system using optimized support vector machine for regression," *J. Power Sources*, vol. 269, pp. 682–693, Nov. 2014.
- [58] J. C. Álvarez Antón, P. J. García Nieto, F. J. de Cos Juez, F. Sánchez Lasheras, M. González Vega, and M. N. Roqueñí Gutiérrez, "Battery state-of-charge estimator using the SVM technique," *Applied Mathematical Modelling*, vol. 37, no. 9, pp. 6244–6253, May 2013.
- [59] J. C. Alvarez Anton, P. J. Garcia Nieto, C. Blanco Viejo, and J. A. Vilan Vilan, "Support vector machines used to estimate the battery state of charge," *IEEE Transactions on Power Electronics*, vol. 28, no. 12, pp. 5919–5926, Dec. 2013.
- [60] M. Shehab El Din, M. F. Abdel-Hafez, and A. A. Hussein, "Enhancement in Li-Ion battery cell state-of-charge estimation under uncertain model statistics," *IEEE Transactions on Vehicular Technology*, vol. 65, no. 6, pp. 4608–4618, Jun. 2016.
- [61] Y. W. Li, C. Wang, and J. F. Gong, "A combination Kalman filter approach for State of Charge estimation of lithium-ion battery considering model uncertainty," *Energy*, vol. 109, pp. 933–946, Aug. 2016.
- [62] S. C. Yang, C. Deng, Y. L. Zhang, and Y. L. He, "State of charge estimation for lithium-ion battery with a temperature-compensated model," *Energies*, vol. 10, no. 10, pp. 1560, Oct. 2017.
- [63] W. D. Wang, X. T. Wang, C. L. Xiang, C. Wei, and Y. L. Zhao, "Unscented kalman filter-based battery SOC estimation and peak power prediction method for power distribution of hybrid electric vehicles," *IEEE Access*, vol. 6, pp. 35957–35965, Jun. 2018.
- [64] L. F. Zheng, J. G. Zhu, G. X. Wang, D. D. C. Lu, and T. T. He, "Differential voltage analysis based state of charge estimation methods for lithium-ion batteries using extended Kalman filter and particle filter," *Energy*, vol. 158, pp. 1028–1037, Sep. 2018.
- [65] C. Huang, Z. H. Wang, Z. H. Zhao, L. Wang, C. S. Lai, and D. Wang, "Robustness evaluation of extended and unscented kalman filter for battery state of charge estimation," *IEEE Access*, vol. 6, pp. 27617–27628, May 2018.
- [66] H. S. Ramadan, M. Becherif, and F. Claude, "Extended kalman filter for accurate state of charge estimation of lithium-based batteries: A comparative analysis," *International Journal of Hydrogen Energy*, vol. 42, no. 48, pp. 29033–29046, Nov. 2017.
- [67] B. Li, X. Q. Yuan, and L. Zhao, "Li-ion battery SOC estimation based on EKF algorithm," in *Proceedings of the 2015 IEEE International Conference on Cyber Technology in Automation, Control, and Intelligent Systems*, 2015, pp. 1584–1588.
- [68] N. Watrin, "Modélisation multi-physique des batteries à base lithium et application à l'estimation de l'état de charge," Ph. D. dissertation, Department Electrical Engineering, Belfort-Montbéliard University of Technology, Belfort, France, 2013.
- [69] S. M. Peng, C. Chen, H. B. Shi, and Z. L. Yao, "State of charge estimation of battery energy storage systems based on adaptive unscented Kalman filter with a noise statistics estimator," *IEEE Access*, vol. 5, pp. 13202–13212, Jul. 2017.
- [70] S. Muhammad, M. U. Rafique, S. Li, Z. L. Shao, Q. X. Wang, and N. Guan, "A robust algorithm for state-of-charge estimation with gain optimization," *IEEE Transactions on Industrial Informatics*, vol. 13, no. 6, pp. 2983–2994, Apr. 2017.
- [71] L. H. Zhao, Z. Y. Liu, and G. H. Ji, "Lithium-ion battery state of charge estimation with model parameters adaptation using H_∞ extended Kalman filter," *Control Engineering Practice*, vol. 81, pp. 114–128, Dec. 2018.
- [72] Z. Liu, X. J. Dang, and H. X. Sun, "Online state of charge estimation for lithium-ion battery by combining incremental autoregressive and moving average modeling with adaptive h-infinity filter," *Mathematical Problems in Engineering*, vol. 2018, pp. 7480602, Jul. 2018.
- [73] R. Xiong, Q. Q. Yu, L. Y. Wang, and C. Lin, "A novel method to obtain the open circuit voltage for the state of charge of lithium ion batteries in electric vehicles by using H infinity filter," *Applied Energy*, vol. 207, pp. 346–353, Dec. 2017.
- [74] Q. Q. Yu, R. Xiong, C. Lin, W. X. Shen, and J. J. Deng, "Lithium-ion battery parameters and state-of-charge joint estimation based on h-infinity and unscented kalman filters," *IEEE Transactions on Vehicular Technology*, vol. 66, no. 10, pp. 8693–8701, Oct. 2017.

- [75] X. W. Guo, L. Y. Kang, Y. Yao, Z. Z. Huang, and W. B. Li, "Joint estimation of the electric vehicle power battery state of charge based on the least squares method and the Kalman filter algorithm," *Energies*, vol. 9, no. 2, pp. 100, Feb. 2016.
- [76] C. Zhang, W. Allafi, Q. Dinh, P. Ascencio, and J. Marco, "Online estimation of battery equivalent circuit model parameters and state of charge using decoupled least squares technique," *Energy*, vol. 142, pp. 678–688, Jan. 2018.
- [77] Z. B. Wei, C. F. Zou, F. Leng, B. H. Soong, and K. J. Tseng, "Online model identification and state-of-charge estimate for lithium-ion battery with a recursive total least squares-based observer," *IEEE Transactions on Industrial Electronics*, vol. 65, no. 2, pp. 1336–1346, Feb. 2018.
- [78] V. H. Duong, H. A. Bastawrous, K. C. Lim, K. W. See, P. Zhang, and S. X. Dou, "Online state of charge and model parameters estimation of the LiFePO₄ battery in electric vehicles using multiple adaptive forgetting factors recursive least-squares," *Journal of Power Sources*, vol. 296, pp. 215–224, Nov. 2015.
- [79] J. Kim, J. Shin, C. Chun, and B. H. Cho, "Stable configuration of a li-ion series battery pack based on a screening process for improved voltage/SOC balancing," *IEEE Transactions on Power Electronics*, vol. 27, no. 1, pp. 411–424, Jan. 2012.
- [80] R. Klein, N. A. Chaturvedi, J. Christensen, J. Ahmed, R. Findeisen, and A. Kojic, "Electrochemical model based observer design for a lithium-ion battery," *IEEE Transactions on Control Systems Technology*, vol. 21, no. 2, pp. 289–301, Mar. 2013.
- [81] R. Xiong, H. W. He, F. C. Sun, and K. Zhao, "Evaluation on State of Charge estimation of batteries with adaptive extended kalman filter by experiment approach," *IEEE Transactions on Vehicular Technology*, vol. 62, no. 1, pp. 108–117, Jan. 2013.
- [82] C. Zhang, K. Li, J. Deng, and S. Song, "Improved realtime state-of-charge estimation of LiFePO₄ battery based on a novel thermoelectric model," *IEEE Transactions on Industrial Electronics*, vol. 64, no. 1, pp. 654–663, Jan. 2017.
- [83] Z. L. Zhang, X. Cheng, Z. Y. Lu, and D. J. Gu, "SOC estimation of lithium-ion battery pack considering balancing current," *IEEE Transactions on Power Electronics*, vol. 33, no. 3, pp. 2216–2226, Mar. 2018.
- [84] Q. Q. Wang, J. Wang, P. J. Zhao, J. Q. Kang, F. Yan, and C. Q. Du, "Correlation between the model accuracy and model-based SOC estimation," *Electrochimica Acta*, vol. 228, pp. 146–159, Feb. 2017.
- [85] Y. Q. Shen, "Adaptive extended Kalman filter based state of charge determination for lithium-ion batteries," *Electrochimica Acta*, vol. 283, pp. 1432–1440, Sep. 2018.
- [86] A. Bartlett, J. Marcicki, S. Onori, G. Rizzoni, X. G. Yang, and T. Miller, "Model-based state of charge estimation and observability analysis of a composite electrode lithium-ion battery," in *Proceedings of the 52nd IEEE Conference on Decision and Control*, 2013, pp. 7791–7796.
- [87] K. A. Smith, C. D. Rahn, and C. Y. Wang, "Model-based electrochemical estimation and constraint management for pulse operation of lithium ion batteries," *IEEE Transactions on Control Systems Technology*, vol. 18, no. 3, pp. 654–663, May 2010.
- [88] M. Corno, N. Bhatt, S. M. Savaresi, and M. Verhaegen, "Electrochemical model-based state of charge estimation for Li-Ion cells," *IEEE Transactions on Control Systems Technology*, vol. 23, no. 1, pp. 117–127, Jan. 2015.
- [89] J. P. Tian, R. Xiong, and Q. Q. Yu, "Fractional-order model-based incremental capacity analysis for degradation state recognition of lithium-ion batteries," *IEEE Transactions on Industrial Electronics*, vol. 66, no. 2, pp. 1576–1584, Feb. 2019.
- [90] M. M. Hoque, M. A. Hannan, A. Mohamed, and A. Ayob, "Battery charge equalization controller in electric vehicle applications?: A review," *Renewable and Sustainable Energy Reviews*, vol. 75, pp. 1363–1385, Aug. 2017.



Systems and Control Systems.



Sarawak. He has authored and co-authored a number of well-recognized journals and conference papers and has been a regular reviewer for the IEEE, Wiley and other journals. His current research interests include the area of Power Electronics, Renewable energy technology, and Motor Drive Controls. He is a Member of the Board of Engineers Malaysia (BEM).



solar cells.



reviewer for various IEEE Transactions. He is the Vice Chair of the IEEE Computation Intelligence Society's WA Chapter.

Md Ohirul Qays received his Bachelor of Science in Electrical and Electronic Engineering in 2017 from Khulna University of Engineering & Technology (KUET), Bangladesh. Currently, he is working toward the M.S. degree in Electrical and Electronics Engineering at the Universiti Malaysia Sarawak (UNIMAS). He is a member of the International Association of Engineers (IAENG) as well as the Institute of Electrical & Electronics Engineers (IEEE), KUET Branch. His research interests include Renewable Energy, Power Electronics, Power

Yonis Buswig received the B.Eng. degree from Omar Al-Mukhtar University, Libya, in 2008, and the M.Sc. degree in electrical and Electronics engineering from Tun Hussein Onn University of Malaysia (UTHM), Batu Pahat, Johor, Malaysia, in 2011. In 2015, he was awarded the Ph.D. degree from the Department of Power Engineering, Faculty of Electrical Engineering, Tun Hussein Onn University of Malaysia (UTHM). Currently, he is a Lecturer in the Electrical and Electronic Engineering Department, Faculty of Engineering, Universiti Malaysia Sarawak. He has authored and co-authored a number of well-recognized journals and conference papers and has been a regular reviewer for the IEEE, Wiley and other journals. His current research interests include the area of Power Electronics, Renewable energy technology, and Motor Drive Controls. He is a Member of the Board of Engineers Malaysia (BEM).

Md. Liton Hossain received his Bachelor of Science in Electrical and Electronic Engineering in 2012 from Khulna University of Engineering & Technology, Bangladesh, and received his Master of Science in Electrical Engineering Degree from Universiti Teknikal Malaysia Melaka in 2016. Currently, he is working toward the Ph.D. degree at Curtin University, Australia. His current research interests include industrial internet of things, wind energy conversion systems, renewable energy, power Electronic converters, multilevel inverters, motor drives and

A. Abu-Siada received the B.S. and M.S. degrees from Ain Shams University, Cairo, Egypt, in 1998, and the Ph.D. degree from Curtin University, Perth, WA, Australia, in 2004, all in Electrical Engineering. He is currently an Associate Professor and discipline lead of the Electrical and Computer Engineering department at Curtin University. His current research interests include power system stability, condition monitoring, and power quality. Dr. Abu-Siada is the Editor-in-Chief of the International Journal of Electrical and Electronic Engineering and a regular