DOI: https://doi.org/10.46354/i3m.2019.imaaca.013

AN OVERVIEW OF STATE OF CHARGE(SOC) AND STATE OF HEALTH(SOH) ESTIMATION METHODS OF LI-ION BATTERIES

K. Saqli[(a)], H. Bouchareb[(b)], M. Oudghiri[(c)], N.K. M'sirdi[(d)]

[(a),(b),(c)]Sidi Mohamed Ben Abdellah University - National School of Applied Sciences, Fez, Morocco
[(d)]LIS - Informatics and Systems Laboratory (LIS CNRS 7020), Aix Marseille University, CNRS,13397 Marseille Cedex, France

[(a)]saqli.khadijah@gmail.com, [(b)]houda.bouchareb.seii@gmail.com, [(c)]oudghiri.ensafes@gmail.com
[(d)] Kouider-Nacer.Msirdi@lis-lab.fr

ABSTRACT

Battery Management System (BMS) is an essential component for lithium-ion battery-based devices. It provides a variety of functionalities that help improve the overall lifespan of the battery, including states estimation algorithms. An accurate estimation of the battery State Of Health (SOH) and State Of Charge (SOC) is a crucial task that an advanced battery management system should perform.

This paper aims to outline the most relevant battery model types that were used in literature for Electric Vehicle (EV) applications. An overview of the estimation algorithms that estimate the battery state of charge and state of health are presented and simulations of some methods are also illustrated in order to test their accuracy.

Keywords: Battery management system, State Of Health, State Of Charge, Lithium-ion.

1. INTRODUCTION

The global need for a clean and renewable energy sources that can replace fossil energy is essential to create a more sustainable planet. This global shift favours the use of electric vehicles as a safe and clean alternative of fossil fuels in transportation to help reduce air pollution. Due to their high power and energy density, Li-ion batteries are widely used to power electric cars. However, to ensure a long-life cycle and avoid any risk of explosion, a Battery Management System (BMS) is needed to boost the efficiency and guarantee a safe usage of the battery.

A smart battery management system uses the required data to estimate the battery states, whether it's the battery state of charge (SOC), state of health (SOH), or any other battery state that can help improve the performance.

The ability to predict the instantaneous battery state and conditions is a crucial task a BMS should perform with accuracy. The SOC indicates the battery available capacity to help avoid overcharging/discharging the battery pack. An accurate SOC can be achieved using the proper battery model and estimation algorithm.

Different estimation approaches were introduced in literature in the aim of predicting this parameter, Wen-Yeau Chang (2013) presented a classification of the different mathematical methods that were used in literature to predict the battery SOC. However, this variable only is not enough for proper utilization of the battery, since the battery is subject to different ageing mechanisms, it's important to track of the battery health. The battery ageing results in an increment in internal resistance and a decrease in capacity, which affects the performance and the ability to provide the same energy decreases. Therefore, estimation of the battery SOH can be achieved by tracking the change of one of these two metrics. This battery state was the subject of research of different authors who used different estimation algorithms with different battery models to provide an accurate estimation. (Ungurean, Cârstoiu, & Groza, 2016), presented a detailed review of the most relevant models, algorithms and commercial devices that were used in literature to estimate the battery Remaining Useful Life (RUL) and SOH.

This paper outlines the most relevant methods that were used in literature to estimate the battery SOC and SOH. First, we present the battery model categories that were used for EV applications. Then an overview of battery state of health and state of charge estimation algorithms, in particular, the coulomb counting method, internal resistance method, voltage-based method, Kalman filtering based methods, sliding mode observer, fuzzy logic and least squares-based method are presented. an equivalent circuit model with 2 RC networks is used to test the accuracy of some methods to determine the battery SOC and internal resistance.

2. BATTERY MODELING FOR EVS

Building a proper battery model that suits better the target application is a crucial task during BMS design; it helps capture the battery electric and thermal behaviors under different operating conditions, to ensure safe and fast charging for optimal utilization and secure discharging of the battery (Kailong, Kang, Qiao, & Cheng, 2019).

Literature has presented numerous battery models with different complexity and fidelity scales. For EV applications the battery model needs to be simple, computationally efficient and suitable for high discharge rates. Therefore, two main groups of EV battery models were presented: Equivalent Circuit Models (ECM) and Reduced Order Models (ROM) (A., J., K., & Longo S. and Wild, 2016).

2.1. Equivalent Circuit battery Model

Equivalent circuit models on the other hand are widely used when developing a BMS for EV application thanks to their speed, simplicity and reasonable accuracy (Rincon-Mora, 2006).

The model uses a combination of resistors, capacitors and voltage sources, to describe the battery behavior under load. Starting by the most basic model that represents the battery as an ideal voltage source mounted on series with internal resistance to describe the voltage polarization, researchers have include different electrical components, in the interest of building improved versions which take into account the dependence of the battery cell on state of charge, temperature, and other characteristics (Kempera, Li, & Kum, 2015).

Figure 2 illustrates a typical ECM that was widely used in literature for battery states estimation. The resistor-capacitor networks are used to describe the battery charge transfer or diffusion processes (Kailong, Kang, Qiao, & Cheng, 2019).

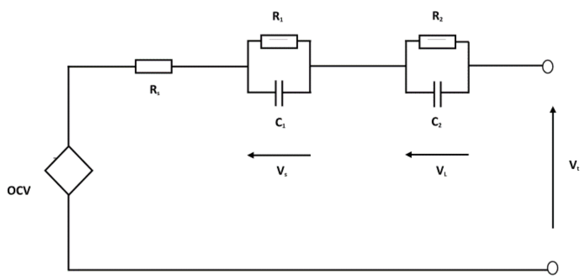

Figure 2 : Second order equivalent circuit model

2.2. Reduced-Order battery Model

Reduced-order models are simplified version of electrochemical battery model (A., B., & M., 2016) . The governing Partial Differential Equations (PDE) equations that describe the electrochemical reactions inside the battery are approximated into low order systems of ODEs equations using a set of Model Order Reduction (MOR) techniques (Fan & Canova, 2017).

The most basic electrochemical model is known as Single Particle Model (SPM) (Figure 1), it represents each electrode of the battery by a single spherical particle ignoring thermal effects, approximating spatial and time characteristics at the separator region to 0 and assuming all unknown states to be scalar and uniform Figure 1. SPM are simple and they can be adopted for real time applications, however, they lack accuracy at high C-rate.

To overcome this limitation an extended version of these model that incorporates the electrolyte dynamics has been developed and they were proved to maintain a high accuracy prediction even at high C-rates conditions (Moura, Argomedo, Klein, & Krstic, 2016).

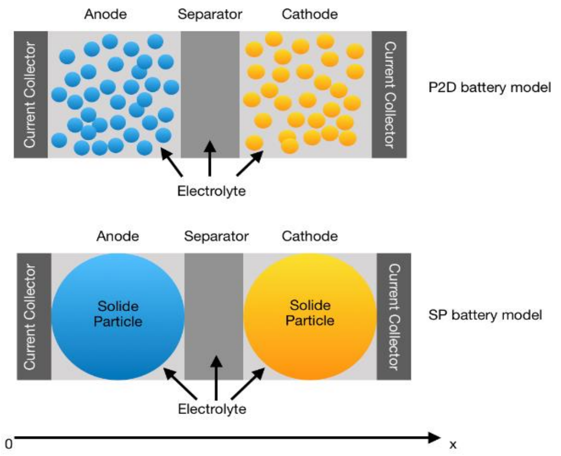

Figure 1: P2D and single particle battery model

Another version that aims to reduce the computational burden of the P2D model was presented in the literature as the Simplified P2D model (SP2D), it describes the dynamic concentration profiles derived from the P2D model to help improve the accuracy of the BMS (G., X., & M., 2018).

Once the battery model has been decided, it can be used as an input for the states estimation algorithms whether it is the SOC, SOH or any other state.

3. BATTERY SOC AND SOH ESTIMATION

3.1. Coulomb Counting

Coulomb counting, also known as Ampere-hour method is one of the most common techniques that were used to estimate the battery states and especially the battery state of charge. As the name suggests, this method calculates the accumulated current that flows in or out during the charge-discharge process to determine the battery state of charge (equation 1) (Fleischer, W., Z., & D.U., 2013) or state of health (equation 2) (Ungurean, Cârstoiu, & Groza, 2016).

$$SOC(t) = SOC(t_0) - \frac{1}{Q_{rated}} \int_{t_0}^{t} \eta(t) I_{bat} dt \qquad (1)$$

Where $SOC(t_0)$ represents the initial SOC, Q_{rated} is the rated capacity and I_{bat} is the battery current.

$$SOH(t) = \frac{1}{Q_{rated}} \int_{t_0}^{t} I(t)dt \qquad (2)$$

Where I is the discharge current.

Coulomb counting method requires an accurate estimation of the initial SOC and a precise measurement of the battery current to be able to estimate the battery states as correctly as possible. However, in reality, the measured current includes sensor noise, and it doesn't take into consideration the self-discharge current and current losses during charging and discharging, which makes the measured current different from the true cell current.

To overcome those limitations, several researchers have proposed modified versions of the coulomb counting method. For example, in (Berecibar, et al., 2016) The initial value of the state charge was first estimated using a SOC-OCV mapping function, and then a periodic re-calibration of the capacity was performed. The measured results have shown a reliable estimation.

3.2. Direct Resistance Estimation Algorithm

The life evolution of Li-ion battery cells is affected by different degradation mechanisms that can be represented by two measurable quantities: Capacity loss and increment of internal resistance. Consequently, we can estimate the battery state of health by observing the changes of these two parameters.

By observing the step change in the voltage curve during the discharge process, the battery internal resistance can be approximated using the following equation (Yu, et al., 2017):

$$R = \frac{\Delta U}{\Delta I} \qquad (3)$$

Where ΔI represents the current step-change and ΔU is the corresponding voltage to the same step-change.
The estimation of the battery internal resistance using the DRE algorithm gives noisy results due to noise in the measurement reading. Therefore, Lievre et al. (2016) have used an Exponentially Weighted Moving Average (EWMA)(equation 4) filter to reduce the noise while maintaining the efficiency of the algorithm.

$$EWMA_k = \lambda \times R_s + (1 - \lambda) \times EWMA_{k-1} \qquad (4)$$

Where, $EWMA_k$ represents the current filtered resistance estimate, λ is a tunable constant that represents the depth of memory, $EWMA_{k-1}$ is the previous value of the filtered resistance estimate and R_s is the raw ohmic resistance.

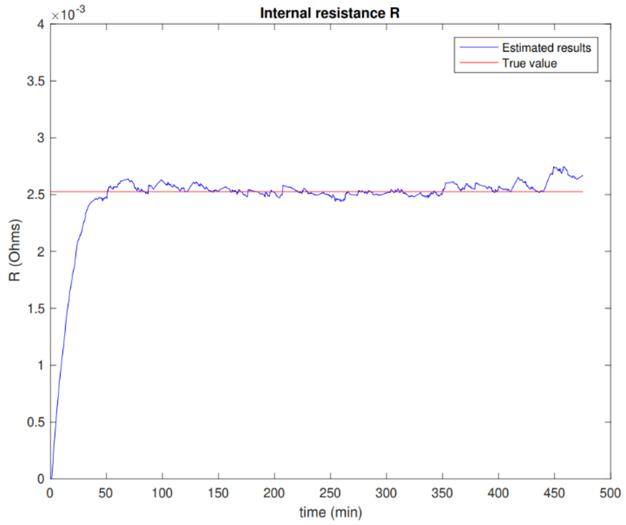

Figure 3 : Internal resistance estimation using DRE approach

Figure 3 shows the implementation of this approach using the same battery model as 3. The estimated results slightly converge to the true value of the battery internal resistance. The implementation of this method requires a smaller memory space since no training data or initial battery characterization are needed. Also, it does not require complex matrix calculation, which makes it suitable for an embedded system (Mathew, Janhunen, Rashid, Long, & Fowler, 2018).

3.3. Open Circuit Voltage (OCV)

Another simplistic approach to estimate the battery states is by measuring the open circuit voltage (OCV) of the cell. Literature has proven a strong dependence between OCV and SOC of the battery cell. This voltage-based method gives the equivalent SOC value of the given voltage value using the OCV vs. SOC discharge curve of the battery.

Based on a simplified electrical model we can define the battery OCV as follow:

$$U_{OCV}\big(SOC(t)\big) = U(t) - R_0 I(t) \qquad (5)$$

Where U_{OCV} is the battery OCV, $U(t)$ is the battery terminal voltage, R_0 is the internal resistance and I(t) is the battery current.

Using the same equivalent circuit model previously discussed, we can implement this method in MATLAB. The estimated SOC was filtered using the EWMA approach to reduce noises (see Figure 4).

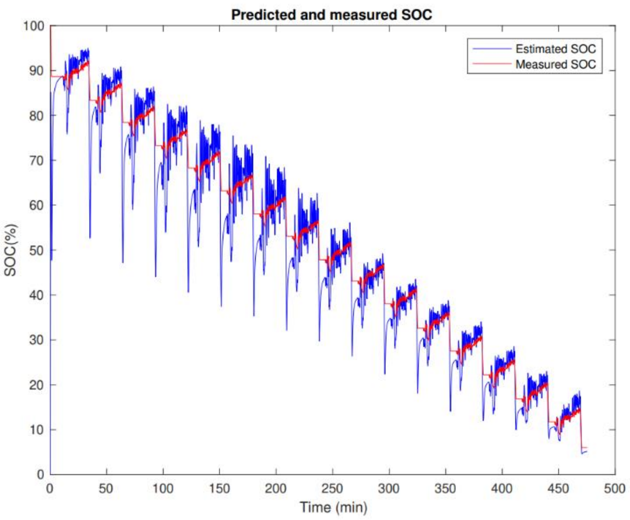

Figure 4 : SOC estimation using OCV

Figure 4 illustrates the estimate and the true SOC curve of the Li-ion battery cell, and by observing these curves we notice that the predicted values are noisy and that can be explained by the fact that this voltage-based method doesn't take into consideration the diffusion voltage and the hysteresis.

OCV has been used also to estimate the battery SOH. By knowing the SOC/OCV relation the estimation of the internal resistance can be easily conducted. (Mathew, Janhunen, Rashid, Long, & Fowler, 2018) used a combination of OCV and Coulomb counting approach to estimate the battery SOH. However, others considered this voltage-based method unsuitable for estimating SOH, (A., et al., 2016) present some disadvantages of using this method and tried to eliminate the OCV from the equations to simplify the computation of the battery SOH.

3.4. Kalman filtering

Kalman filter is a model-based algorithm that uses the mathematical representation of a linear system to determine its states. The literature defines this approach as a sturdy algorithm that operates in two fundamental steps (Ungurean, Cârstoiu, & Groza, 2016):

- Prediction phase: the system state is estimated using the following equations:

$$\hat{x}_{(t|t-1)} = F_t \hat{x}_{(t-1|t-1)} + B_t u_t \tag{6}$$

$$P_{(t|t-1)} = F_t P_{(t-1|t-1)} + Q_t \tag{7}$$

- Update phase: the algorithm updates the prediction based on the system errors as follow:

$$\hat{x}_{(t|t)} = \hat{x}_{(t|t-1)} + K_t(y_t - H\hat{x}_{(t|t-1)}) \tag{8}$$

$$K_t = P_{(t|t-1)} H_t^T \left(H_t P_{(t|t-1)} H_t^T + R_t\right)^{-1} \tag{9}$$

$$P_{(t|t)} = P_{(t|t-1)} - K_t H_t P_{(t|t-1)} \tag{10}$$

Where $\hat{x}$ is the estimated state, F is the state transition matrix, B is the control matrix, u is the input vector, P and Q are respectively the state and the process variance matrix, y is the output measurement, K is the Kalman gain, H is the measurement matrix and R is the measurement variance matrix.

Since the Kalman filter is limited for linear systems and has proven a reliable estimation of the states of a process, researchers have developed different extensions of this model-based algorithm to adapt it for nonlinear systems.

The extended Kalman Filter is one of the enhanced versions that deals with non-linear systems such as battery state estimation. This model-based approach was widely used to estimate the battery SOC. The process of estimation starts by choosing the battery model that describes its response in discrete-time, then the algorithm is applied to estimate the state. The state description of the battery model has to include the wanted unknown quantities that should be determined. For this paper, a second-order ECM (Figure 2) will be used to test the performance of this approach to estimate the battery state of charge.

(E. Kamal, 2015) and (Sepasi, Ghorbani, & Liaw, 2014) used the same battery model to estimate the battery SOC. The nonlinear system is first represented using equations 11 and 12, to represent respectively the system dynamics expressed in state equations and the output equation of the system (O., P., S., & Molinas, 2017).

$$x_{k+1} = f(x_k, u_k) + w_k \tag{11}$$

$$y_{k+1} = g(x_k, u_k) + v_k \tag{12}$$

Where $f(x_k, u_k)$ represents the nonlinear transition function, $g(x_k, u_k)$ represents the nonlinear measurement function, w_k and v_k denote respectively the process and the measurement noise.

To apply the EKF $f(x_k, u_k)$ and $g(x_k, u_k)$ are linearized at each time step using the first order of Taylor-series. 13 and equation 14 can be rewritten as follows (E. Kamal, 2015):

$$x_{k+1} = A_k x_k + B_k I_{L,k} + w_k \tag{13}$$

$$y_k = C_k x_k + D_k I_{L,k} + v_k \tag{14}$$

Where $A_k = \left.\frac{\partial f(x_k,u_k)}{\partial x_k}\right|_{x_k,u_k}$, $B_k = \left.\frac{\partial f(x_k,u_k)}{\partial u_k}\right|_{x_k,u_k}$, $C_k = \left.\frac{\partial g(x_k,u_k)}{\partial x_k}\right|_{x_k,u_k}$ and $D_k = \left.\frac{\partial g(x_k,u_k)}{\partial u_k}\right|_{x_k,u_k}$.

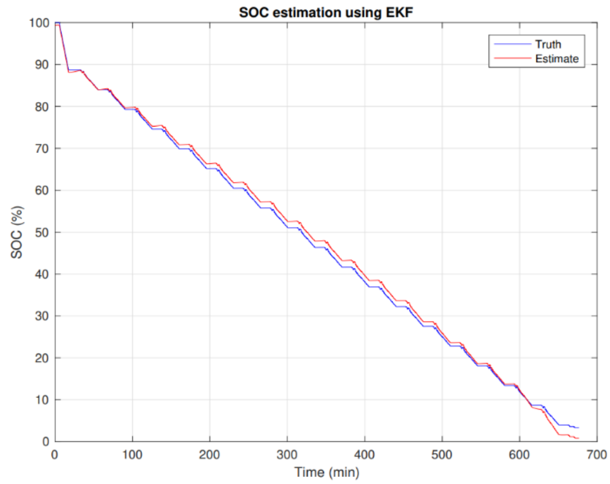

Figure 5 : SOC estimation using EKF

EKF was proven to give accurate results even with noisy input data, the algorithm is much lighter and can be implemented for real-time application. However, when the system is highly non-linear, linearization error would lead to highly unstable filters because of uncertainties in the first order Taylor series (Sun, Hu, Zou, & Li, 2011).

Many authors have used dual extended Kalman filter to provide an online estimation of both battery SOH and SOC. As the name suggested, this approach uses two extended Kalman filters to predict the battery states and update its parameters to give more reliable results. In (Wassiliadisa, et al., 2018) the authors provide an outstanding investigation of the DEKF performance for SOC and SOH estimation under different dynamics and degradation stages. Compared to a simple EKF, the DEKF was proven to improve the accuracy of the SOC over battery lifetime, while the battery internal resistance and capacity become inaccurate with advanced degradation.

3.5. Sliding Mode Observer

Another model-based approach that was used to estimate the internal states of the battery is known as the sliding-mode observer (SMO). This algorithm has the advantage of compensating the modelling errors caused by parameters variation of circuit model and can help overcome some drawbacks that other model-based methods present. Introduced by Emel'yanov (1959) the SMO algorithm was adopted to estimate the battery SOC. A combination of an improved ECM and a SMO were used by different authors to provide an accurate estimation of the battery SOC (Chen, X., Z., & A., 2012) (Nacer, Ahmed, & Naamane, 2012).

In (Ning, Xu, Cao, Wang, & Xu, 2016), the authors used SMO to estimate the battery SOC based on a parameter adaptive battery model to reduce the systematic errors. The estimation result shows a rapid convergence of SOC curve with an estimation error of less than 2%, which reflects the robustness of the algorithm.

3.6. Fuzzy Logic

Fuzzy logic is a useful mathematical concept that allows modelling non-linear and complex systems using the appropriate training dataset. It's a non-monotonic logic that uses crisp sets to categorize the measured data. The relationship between a member of a set and its degree of membership is defined using a membership function. In the case of SOH, the membership function outputs can be set as healthy, tolerable and not healthy.

Jonghoon Kim (2014), used a fuzzy logic-controlled methodology to predict the battery SOH, first the cell resistance and maximum capacity were determined based on voltage, current, temperature and time, then fuzzy logic approach was applied to estimate the battery SOH using the resistance and the maximum capacity values.

Burgos et al. proposed a novel fuzzy logic algorithm to predict the battery SOC. A fuzzy model that characterizes the relationship between the battery open-circuit voltage, SOC and the discharge current was used in combination with an EKF to predict the battery SOC (Burgos, Saez, Orchard, & Cardenas, 2015).

3.7. Least squares

The least square algorithm is a widely used approach that identifies the best fit function that minimizes the sum of quadratic errors between measured output and system response.

In (L, 2011), Gregory L.Pett proposed an enhanced version of the LS algorithm called Weighted Total Least square to estimate the battery capacity. Since the standard least square approach doesn't consider the uncertainties that the input measurement includes, the author used the WTLS algorithm that takes into account the noises of the accumulated ampere-hour measurements and the battery SOC. The estimation results are more accurate than a standard least squares approach, and the algorithm can be used for real-time applications.

4. CONCLUSION

SOC and SOH estimation is of a great importance when developing a battery management system, they provide an overview of the short- and long-term state of the battery.

The main goal of this paper is to provide a basic understanding of the different algorithms, the advantages and shortcomings of each to help build an advanced BMS for EV application. The review shows that there is no perfect approach to estimate the battery states, and the choice should be made based on the complexity of the system and the target application.

The battery model types that are used for EV applications are first presented. Then the most relevant estimation algorithms that were used in literature to predict the battery SOC and SOH are outlined. Certain algorithms were tested using a second order equivalent circuit battery model to test out their accuracy.

5. REFERENCES

A., F., J., A. D., K., P., & Longo S. and Wild, M. (2016). A review on electric vehicle battery modelling: From Lithium-ion toward Lithium–Sulphur. *Renewable and Sustainable Energy Reviews, 56,* 1008-1021.

A., J., B., R., & M., D. M. (2016). Review of simplified Pseudo-two-Dimensional models of lithium-ion batteries. *Journal of Power Sources, 327,* 44–55.

A., L., A., S., Venet, P., A., H., M., O.-B., & S., P. (2016). Practical online estimation of lithium-ion battery apparent series resistance for mild hybrid vehicles. *IEEE Transactions on Vehicular Technology, 65*, 4505–4511.

Berecibar, M., Gandiaga, I., Villarreal, I., Omar, N., Mierlo, J. V., & Bossche., P. V. (2016). Critical review of state of health estimation methods of Li-ion batteries for real applications. *Renewable and Sustainable Energy Reviews, 56* , 572-587.

Burgos, C., Saez, D., Orchard, M. E., & Cardenas, R. (2015). Fuzzy modelling for the state-of-charge estimation of lead-acid batteries. *Journal of Power Sources* , 355-366.

Chang, W.-Y. (2013). The State of Charge Estimating Methods for Battery: A Review. *International Scholarly Research Notices*, 7.

Chen, X., X., S. W., Z., C., & A., K. (2012). Sliding Mode Observer for State of Charge Estimation Based on Battery Equivalent Circuit in Electric Vehicles. *Australian Journal of Electrical and Electronics Engineering*, 225–234.

E. Kamal, A. E. (2015). State of charge estimation based on extended Kalman filter algorithm for Lithium-Ion battery. *23rd Mediterranean Conference on Control and Automation (MED).*

Fan, G., & Canova, X. L. (2017). A Reduced-Order Electrochemical Model of Li-Ion Batteries for Control and Estimation Applications. *IEEE Transactions on Vehicular Technology, 67*(1), 76-91.

Fleischer, C., W., W., Z., B., & D.U., S. (2013). Adaptive on-line state of available power prediction of lithium-ion batteries. *Journal Power Electron, 13,* 516–527.

G., F., X., L., & M., C. (2018). A Reduced-Order Electrochemical Model of Li-Ion Batteries for Control and Estimation Applications. *IEEE Transactions on Vehicular Technology, 67*(1), 76–91.

Kailong, L., Kang, L., Qiao, P., & Cheng, Z. (2019). A brief review on key technologies in the battery management system of electric vehicles. *Frontiers of Mechanical Engineering, 14*(1), 47-64.

Kempera, P., Li, S. E., & Kum, D. (2015). Simplification of pseudo two dimensional battery model using dynamic profile of lithium concentration. *Journal of Power Sources, 286,* 510-525.

Kim, J. (2014). Fuzzy Logic-Controlled Online State-of-Health (SOH) Prediction in Large Format LiMn2O4 Cell for Energy Storage System (ESS) Applications.

L, P. G. (2011). Recursive approximate weighted total least squares estimation of battery cell total capacity. *Journal of Power Sources*, 2319–2331.

Mathew, M., Janhunen, S., Rashid, M., Long, F., & Fowler, M. (2018). Comparative Analysis of Lithium-Ion Battery Resistance Estimation Techniques for Battery Management Systems. *Energies, 11*, 1490.

Moura, S. J., Argomedo, F. B., Klein, R., & Krstic, A. M. (2016). Battery State Estimation for a Single Particle Model With Electrolyte Dynamics. *IEEE Transactions on Control Systems Technology, 25*(2), 453–468.

Nacer, M., Ahmed, B., & Naamane, A. (2012). Battery Models for Estimation of State of Charge by Sliding Mode Observer. *Journal of Smart Innovation, Systems and Technologies*, 133-149.

Ning, B., Xu, J., Cao, B., Wang, B., & Xu, G. (2016). A Sliding Mode Observer SOC Estimation Method Based on Parameter Adaptive Battery Model. *Energy Procedia*, 619 – 626.

O., G., P., V., S., J., & Molinas, M. (2017). Battery modeling and Kalman filter-based State-of-Charge estimation for a race car application. *IEEE 14th International Conference on Networking, Sensing and Control (ICNSC).* .

Rincon-Mora, E. C. (2006). Accurate electrical battery model capable of predicting runtime and I-V performance. *IEEE Transactions on Energy Conversion, 21*(2), 504-511.

Sepasi, S., Ghorbani, R., & Liaw, B. Y. (2014). Improved extended Kalman filterfor state of charge estimation of battery pack. *Journal of Power Sources* , 368-376.

Sun, F., Hu, X., Zou, Y., & Li, S. (2011). Adaptive unscented Kalman filtering for state of charge estimation of a lithium-ion battery for electric vehicles. *Energy, 36*, 3531-3540.

Ungurean, L., Cârstoiu, G., & Groza, M. V. (2016). Battery state of health estimation: a structured review of models, methods and commercial devices. *International Journal of Energy Research, 41*(2), 151-181.

Wassiliadisa, N., Adermanna, J., Frericksb, A., Pakb, M., Reitera, C., Lohmannb, B., & Lienkampa., M. (2018). Revisiting the dual extended Kalman filter for battery state-of-charge and state-of-health estimation: A use-case life cycle analysis. *Journal of Energy Storage*, 73-87.

Yu, J., Mo, B., Tang, D., Yang, J., Wan, J., & Liu, J. (2017). Indirect State-of-Health Estimation for Lithium-Ion Batteries under Randomized Use. *Energies*.