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Battery modelling and state of charge estimation methods for Energy Management in Electric Vehicle-A review

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Abstract. To reduce global warming, the Electric Vehicles (EV) are more attracting Worldwide for replacement of conventional IC engine vehicle but the main problem is driving range and the cost of EV is very high compared to a conventional vehicle. The driving range is mainly depending on the type of battery and size of the battery pack used in EV, for long driving range more number of batteries are required which automatically increase the weight and cost of EV. An effective battery management system will increase battery life and driving range of the EV with less number of batteries. In battery management system of EV the battery is major component but battery is costly and managing power of the battery is very much essential in EV technology. Majority of the issues can be solved by developing advanced battery management system (BMS) in EV such as, Battery modelling, accurate battery state of charge and state of health estimation, which can provide an exact driving range of EV and charging/discharging strategies work more effectively. This review paper mainly focuses on different battery modelling techniques and existing battery SOC estimation methods, issues and challenges.

1. Introduction

The BMS manage the electric energy storage system in EV. BMS is used to monitor and protect each cell in battery pack continuously and it's often interfaced with other devices in EV. The main function of the BMS is to provide the over voltage and under voltage protection, over current protection, state of charge (SOC) and state of health (SOH) estimation in each cell of battery, fault detection, cell balancing and thermal management. The secondary function of BMS is to current limit calculations, digital or analog interfaces with application, cell health monitoring, isolation fault monitoring.

BMS will improve the lifespan battery by providing over charge and over discharge protection to each cell in battery pack. Driving range and cost of EV mainly depends on the battery capacity. The capacity of the battery is depending on the battery chemistry, ambient temperature, aging effects, control algorithm used in the BMS and maintenance. The control algorithms are mainly used for estimate the SOC, SOH and thermal management. There are different control algorithms are proposed in the literature for battery parameters estimation, mainly they are classified as electrochemical battery impedance spectroscopy (ESI), Equivalent circuit models (ECM) and electrochemical model (EM),



each technique have its own advantages and disadvantages which are clearly explained in the following chapters.

For Different types of batteries anode and cathode materials have different property and Every battery have its own electrochemical and dynamic characteristics. Most of equivalent circuit model hysteresis effect of the battery was not consider. So, it's very difficult to model the equivalent circuit of it. It is necessary to design suitable model of the battery which can work with any load conditions.

In literature different battery models are there, they can classify as a thermal, physical, electrochemical, equivalent circuit model and so on. From that equivalent circuit model (ECM) is more using for estimation of SOC due to its simple structure.

2. EV Battery modelling

Now a days mostly the Lithium-ion batteries (LIB) are using in EV applications due its energy density, charging and low self-discharging characteristics. The Different LIB model-based methods are explained in the literature.

2.1. Rint ECM

The Rint ECM, as shown in the figure 1, it is simple model for practical implementation but output equation leads to uncertainties in state estimation. The equation 1 is the output voltage (V_L) is the sum of the open circuit voltage V_{oc} and internal resistance R_0 , where V_{oc} and R_0 are the function of SOC, SOH and temperature. The I_L is load current which is positive during discharging and negative during discharging of the cell.

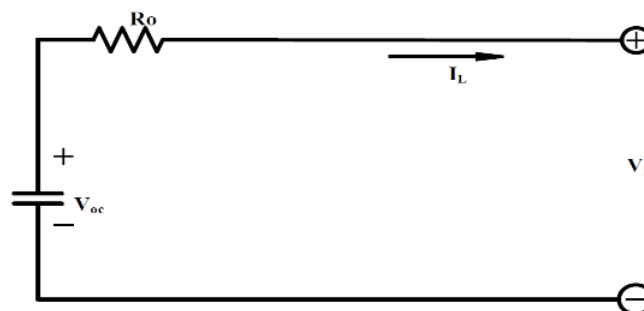


Figure 1. The Rint ECM.

$$V_L = V_{OC} - I_L R_0 \quad (1)$$

2.2. Thevenin ECM

Thevenin ECM is shown in figure 2. It is an Improved model of R_{int} with Parallel RC network in series. It Most used in practical applications but it has accuracy problem during charging and Discharging process. The internal resistance of this model includes R_0 and R_{th} namely called as ohmic and polarization resistances. The C_{Th} describes the transient response of the ECM. The behavior of the output voltage is shown in equation 2 and equation 3.

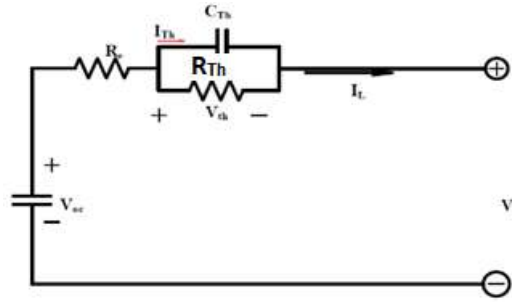


Figure 2. Thevenin ECM.

$$\dot{V}_{Th} = -\frac{V_{Th}}{R_{Th}C_{Th}} + \frac{I_L}{C_{Th}} \quad (2)$$

$$V_L = V_{OC} - V_{Th} - I_L R_0 \quad (3)$$

2.3. Dual polarization ECM

Dual polarization ECM is shown in the figure 3. It is an improved model of the Thevenin's model. It has more accurate during charging and discharging. The output voltage equation is shown in 4 to 6.

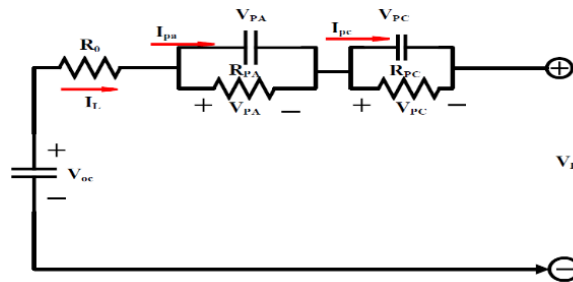


Figure 3. Dual polarization ECM.

$$\dot{V}_{pa} = -\frac{V_{pa}}{R_{pa}C_{pa}} + \frac{I_L}{C_{pa}} \quad (4)$$

$$\dot{V}_{pc} = -\frac{V_{pc}}{R_{pc}C_{pc}} + \frac{I_L}{C_{pc}} \quad (5)$$

$$V_L = V_{OC} - V_{pa} - V_{pc} - I_L R_0 \quad (6)$$

2.4. PNGV (partnership for new generation of vehicle) ECM

PNGV ECM is shown in the figure 4. It is an improved model of the Thevenin model by adding a capacitor in series with the source voltage of the Thevenin model. Data saturation and accumulation over time of load current problem can be overcome using PNGV model. Equation 7 to 9 describe the output voltage the model.

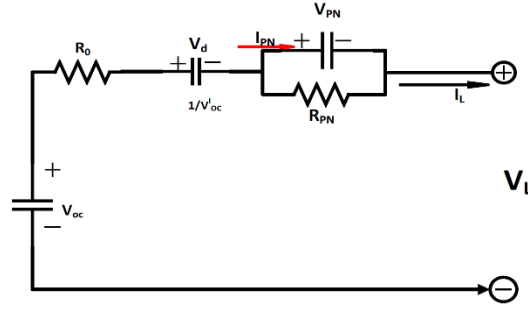


Figure 4. PNGV ECM.

$$\dot{V}_d = V'_{oc} I_L \quad (7)$$

$$\dot{V}_{pn} = -\frac{V_{pn}}{R_{pn}C_{pn}} + \frac{I_L}{C_{pn}} \quad (8)$$

$$V_L = V_{oc} - V_d - V_{pn} - I_L R_0 \quad (9)$$

2.5. GNL (General non-linear) ECM

GNL ECM is shown in the figure 5. It is combination model of the PNGV and Dual polarization with additional parallel source resistance R_S . This model is used in non-linear battery modelling due its less self-discharging features. The equation 10 to 13 describe the output voltage of model.

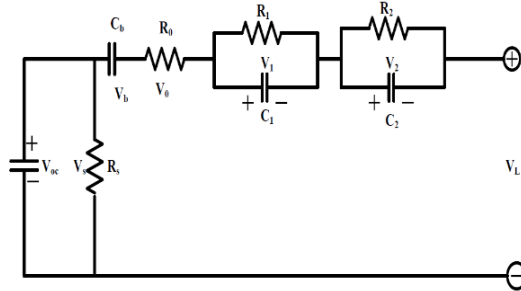


Figure 5. GNL ECM.

$$\dot{V}_b = V'_{oc} \quad (10)$$

$$\dot{V}_1 = \frac{1}{C_1} - \frac{V_b}{C_1 R_S} \left(\frac{V_1}{C_1 R_S} + \frac{V_1}{C_1 R_1} \right) - \frac{V_2}{C_1 R_S} + \frac{V_{oc}}{C_1 R_S} \quad (11)$$

$$\dot{V}_2 = \frac{1}{C_2} - \frac{V_b}{C_2 R_S} \left(\frac{V_2}{C_1 R_S} + \frac{V_2}{C_2 R_2} \right) - \frac{V_1}{C_2 R_S} + \frac{V_{oc}}{C_2 R_S} \quad (12)$$

$$V_L = V_{oc} - V_b - V_1 - V_2 - I_L R_0 \quad (13)$$

2.6. RC Equivalent model

The RC equivalent model is shown in the figure 6. It will give the dynamic voltage performance of the battery. Equation 14 and 15 describe the output voltage of the model.

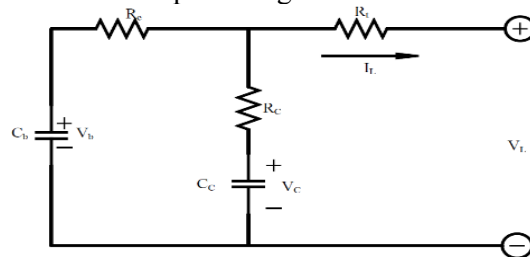


Figure 6. RC Equivalent model.

$$\begin{bmatrix} \dot{V}_b \\ \dot{V}_c \end{bmatrix} = \begin{bmatrix} \frac{-1}{C_b(R_e+R_c)} & \frac{1}{C_b(R_e+R_c)} \\ \frac{1}{C_c(R_e+R_c)} & \frac{-1}{C_c(R_e+R_c)} \end{bmatrix} \begin{bmatrix} V_b \\ V_c \end{bmatrix} + \begin{bmatrix} \frac{-R_c}{C_b(R_e+R_c)} \\ \frac{-R_e}{C_c(R_e+R_c)} \end{bmatrix} [I_L] \quad (14)$$

$$[V_L] = \begin{bmatrix} \frac{R_c}{(R_e+R_c)} & \frac{R_e}{(R_e+R_c)} \end{bmatrix} \begin{bmatrix} V_b \\ V_c \end{bmatrix} + \begin{bmatrix} -R_t & -\frac{R_e R_c}{(R_e+R_c)} \end{bmatrix} [I_L] \quad (15)$$

2.7. Fractional order ECM

The fractional order ECM is shown in the figure 7. It is used to reduce the computational complexity and to improve the efficiency of outdated existing ECMs faults for assurance of optimal trend off among ECMs. The equations 16 to 18 describe output voltage of the model.

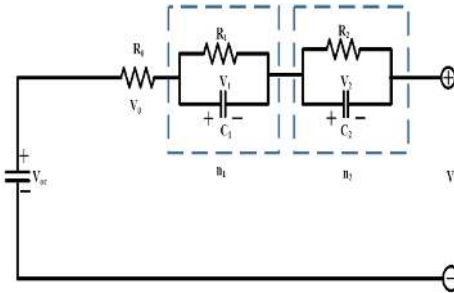


Figure 7. Fractional order ECM

$$D^{n_1} \dot{V}_1 = \frac{1}{C_1} - \frac{V_1}{C_1 R_1} \quad (16)$$

$$D^{n_2} \dot{V}_2 = \frac{1}{C_2} - \frac{V_2}{C_2 R_2} \quad (17)$$

$$V_t = V_{oc} - V_1 - V_2 - IR_0 \quad (18)$$

We can conclude that the dual polarization model has best dynamic performance and less losses compare to other model-based method.

3. STATE OF CHARGE ESTIMATION METHODS.

The SOC estimation is main challenge in EV batteries, we can't measure the SOC of the battery directly, a specific algorithm required for it, which describe the remaining capacity of it. The accurate SOC estimation is paly major role in the battery life and performance improvement. This estimation algorithms continuously monitor all internal parameters of the battery and provide the protection from battery from over charging and over discharging. The SOC and SOH of battery is defined as equation 19 and 20. The exiting SOC and SOH estimation methods are reviewed in the following sections.

$$\text{State of Charge} = \frac{\text{remaining capacity of the battery}}{\text{Total capacity of the battery}} \quad (19)$$

$$\text{State of Health} = \frac{\text{Maximum charging capacity of the battery}}{\text{Rated capacity of the battery}} \quad (20)$$

The evolution of the SOC estimation methods is shown in the figure 8. There are various methods available in the literature for battery SOC Estimation. Each method having some merits and demerits. Mainly the SOC estimation methods are classified into Conventional Methods, Adaptive filter based, artificial intelligent based algorithms, Non-linear Observer algorithms, Hybrid methods. each method is further classified into sub method which are explained as follows.

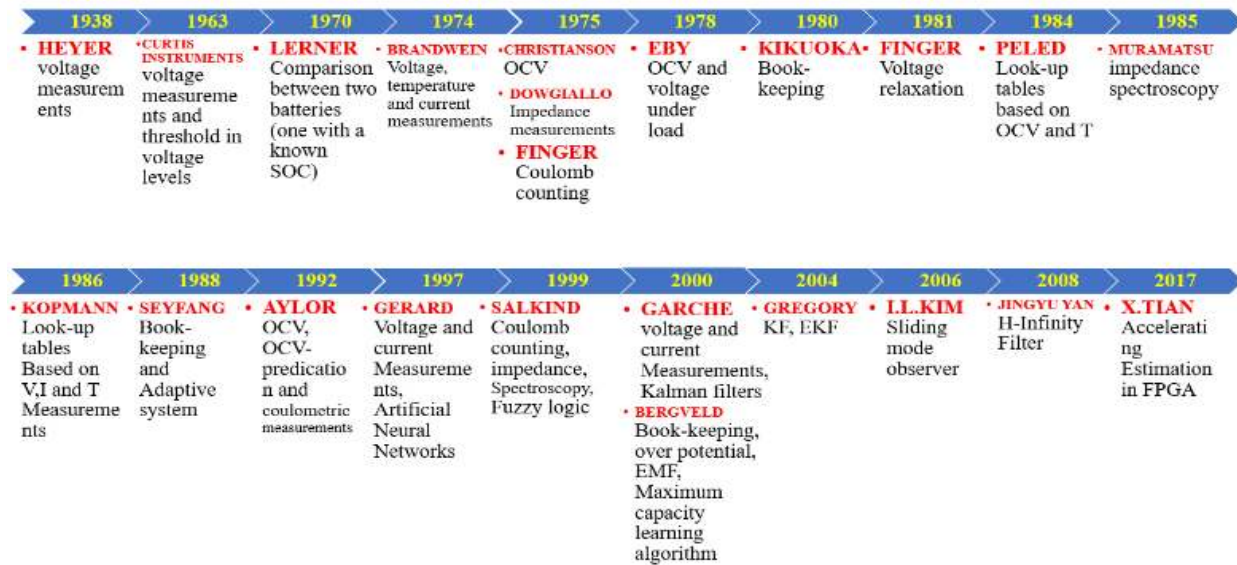


Figure 8. Battery SOC estimation methods evolution.

3.1. Conventional Methods

3.1.1. Ampere-Hour Counting Method (AHM) / Coulomb Counting (CC) Estimation Method.

The ampere-hour counting method is most commonly used conventional method for SOC estimation of batteries. It is accurate method for short term calculations and the main advantage is it is very simple, concise method it can be implement easily in practice. This method is using in the applications of industries, Portable Electronics and EVs. In [1] J. Rivera-Barrera *et al* proposed the ampere-hour counting method (AHM) / coulomb counting (CC) SOC Estimation method. It will measure the charging and discharging current over a time of period to estimate the remaining capacity of the battery. Mathematically that can be define as equation 21.

$$SOC = SOC(t_0) + \frac{1}{C_n} \int_{t_0}^{t_0+t} I_{bat} (dT) \times 100 \quad (21)$$

Where SOC(t₀) is the Initial SOC, I_{bat} is the Charging or Discharging Current and C_n is the Nominal Capacity.

However, this CC method is suffering from cumulative error due to its initial value estimation problem. So, to implement this method initial vales must be Known.

3.1.2. Modified Coulomb Counting Method

In [2] I. Baccouche *et al* from the piecewise relationship of SOC-OCV(open circuit voltage), an improved coulomb counting algorithm is proposed, which can increase the accuracy of the SOC estimation in LIB compare to coulomb counting algorithm. In [3] Venkatesh Prasad K. S *et al* proposed a modified coulomb counting (CC) method by using a peukert mathematical model to overcome inaccuracy problem in CC method. The modified CC SOC estimation equation is given by equation 22.

$$SOC_t = \left(1 - \frac{1}{Q_\tau} \int_0^\tau \eta_d i_\tau dT\right) \times 100 \quad (22)$$

Where SOC_t is corrected SOC, η_d is coefficient of efficiency.

3.1.3. The open circuit voltage method

The OCV algorithm is to require less number of computations for SOC estimation. However, the SOC estimation time increasing along with the age of the battery and estimation time is changing along with temperature change. This OCV method is not suitable for online SOC estimation because the battery required long resting time to reach balance condition and to get accurate SOC. This method is not possible in practical because its measuring OCV that means estimation of battery SOC is not available while Battery is Charging and Discharging. Direct OCV method can be useful for low power consumption application, it will provide the Comparatively high Accuracy. In [4] M.A.Hannan *et al* proposed a EMF method for SOC and capacity of the battery at time by OCV relaxation process to reduce the SOC estimation time of the battery and to eliminate the effect of the over voltage.

3.1.4. Electrochemical Method

In electrochemical battery we can directly calculate the SOC from its positive and negative Electrodes. Theoretically this method can give the accurate values of the SOC and it is suitable for battery offline parameters analysis only. However, this method consisting of partial difference equations of multi parameters. So, it is very complex process and difficult to solve the online SOC estimation and it has very poor accuracy in real time application because of poor parameters fitting. In [5] Nima Lotfi *et al* proposed a reduced-order electrochemical model based on the Luenberger and recursive least square algorithms, without any partial differential equations and with less mathematical complexity. it is observed that the algorithm reaches their actual values within 1min. In [6] Rui Xiong *et al* proposed electrochemical genetic algorithm for SOC estimation of lithium-ion battery, which is also estimate the SOH battery based on battery degradation characteristics.

3.1.5. Model Based Method

The model-based method widely adopted for SOC estimation of the batteries in the BMS of EV, for accurate online SOC Estimation in batteries first we need to develop the battery equivalent model, which can describe the actual dynamic behaviour of the battery. There are different model-based methods available for battery modelling like electrochemical or white box model. The most commonly used other model is Linear equivalent circuit model [7-9]. However, some of the characteristics of the battery cannot be designed in the simulation like hysteresis and Warburg effects. To overcome that problem Mathematical model with Hysteresis is used in simulation for better SOC estimation.

3.2. Adaptive filter algorithm methods

Adaptive filtering algorithms are used to estimate the SOC of battery by reducing noise influence on the battery model and these algorithms also improve the accuracy and robustness of the battery.

3.2.1. Kalman filter

This algorithm is used as state estimation tool in linear systems, it is also used as dynamic state of charge estimator in batteries. This computational method is useful to predict the past, present and future states of parameters [10]. The main drawback of the Kalman filter is it requires large computing capacity, suitable battery model and problem of determining initial parameters [11].

3.2.2. Extended Kalman filter

The EKF can overcome the non-linear estimation problem by linearizing the state equations [12]. In [13] Ruifeng Zhang *et al* the partial derivatives and first order Taylor series expansion are used in EKF to linearize the battery model. The state-space model is linearized at every time instance, which compares the estimated value with its measured batteries terminal voltage to correct the estimation parameters for SOC. However, if the system is highly non-linear, linearization error may occur due to the lack of accuracy in the first order Taylor series under a highly non-linear condition [14]. In [15] Jia, J *et al* Proposed multi-rate strong tracking EKF, this algorithm was improving the battery parameters tracking stability and SOC estimation accuracy 55.34% compare to EKF algorithm.

3.2.3. Fading Kalman Filter

In [16] KaiChin Lim *et al* proposed a Fading Kalman filter (FKF) to estimate the OCV and SOC. FKF algorithm uses a fading factor due to that factor its can capable to compensate for any modelling error. FKF algorithm can avoid the large SOC estimation errors in batteries, which may occur with a conventional KF. This algorithm implementation is easy and SOC estimation accuracy is more in the real time applications compare to KF and EKF. In [17] Yunfei Zhao *et al* proposed an Adaptive fading EKF algorithm, it is combination of the EKF and FKF algorithm, which can reduce the noise problems and improve the convergent speed and provide more accurate SOC estimation results of the battery.

3.2.4. Unscented Kalman filtering

The Unscented Kalman filter (UKF) is extended version of the EKF. The performance of the EKF is not poor for more than second order model. This problem can be overcome by using UKF. The UKF is designed by using state space model for higher order nonlinear applications, which can also reduce the sampling noise [18].

3.2.5. Sigma-Point Kalman Filter

Sigma-point Kalman filter (SPKF) algorithm is subjected to numeric approximation and algorithm selects the sets of sigma points, which is completely similar to the value of mean and covariance of the model being developed. The advantages of using SPKF are that it has an identical calculation complexity to EKF without considering Jacobian matrices [19-20]. The SPKF can proved more accurate with less memory and less computational calculations [21].

3.2.6. H_∞ Filter

This model is simple in design and which high robust under certain conditions. The accuracy of SOC estimation will reduce due to the thermal and aging effects. In order to improve the accuracy and robustness in [22] cheng chen *et al* proposed a multiscale dual H infinity filter, the results are shown that it have more accurate SOC estimation and robustness compare to KF algorithms.

However, these KF family algorithms are not suitable for high complexity system because of its high mathematical computational cost. These methods consist of complex matrix operations which can make the numerical instability. The SOC estimation sensor accuracy and battery model are the major concerns for SOC estimation. For the performance analysis KF's variants are mainly depends on measurement noise covariance and required Prior knowledge of the model.

3.3. Adaptive Learning Algorithm

3.3.1. Artificial Neural Network (ANN) based algorithms

In [23] F. Zhao, Y *et al* proposed a recursive NN algorithm to estimate the SOC of the lithium-ion battery, the multi-channel extended convolution NN is used to extract the battery parameters. The accuracy of this algorithm is 11.3% more compared to ampere hour count method. In [24] Jian Chen *et al* proposed a radial basis function NN algorithm along with nonlinear observer for online SOC estimate of the battery.

3.3.2. Extreme Machine Learning (EML) based algorithms

To reduce the mathematical complex calculation and when we combine any two algorithms more complex and expensive in the implementation. In order to overcome that problem in [25] M. S. Hossain Lipu *et al* proposed an improved extreme learning machine algorithm for battery SOC estimation and gravitational search algorithm which improve the speed and reduce the computational complexity of the EML algorithm by finding the optimal value hidden layer neurons. This algorithm is robust and does not require the battery internal mathematical model and knowledge.

3.3.3. Support Vector Machine (SVM) based algorithms

In [26] Juan Carlos Álvarez Antón *et al*, proposed SVM algorithm for battery SOC estimation. The algorithm will extract the battery model parameters from its charging and discharging test cycles, cell thermal temperature, voltage and current as independent variables. This algorithm does not require any matrix inversion. So, which will reduce the mathematical computational complexity.

3.3.4. Genetic Algorithm (GA) based algorithms

In [27] Shen, Y *et al* proposed an improved chaos genetic algorithm for SOC estimation of the battery with less computational complexity and high initial stability, ampere hour approach and adaptive switch mechanism is advised to predict the available capacity of the battery. In [28] Jiahuan Lu *et al* proposed the online approach of GA-based estimation method that can improve the State of power (SOP) estimation accuracy. Compared with the traditional Taylor method the online approach of GA-based estimation method can improve the 7.2% more accuracy.

3.3.5. Fuzzy logic-based algorithms

In [29] Yan Ma *et al* proposed a two-stage bidirectional equalization model with fuzzy logic control scheme to improve the inconsistency of series connected batteries. Compared to mean difference algorithm, the fuzzy logic control scheme can be reducing the standard deviation of final SOC, equalization time by 18.5% and 23% respectively and can improve the energy efficiency 5.54%.

3.4. Non-Linear Observers

3.4.1. The Luenberger Observer

Online equivalent circuit model are used to estimate SOC and power capacity of battery, but due to the noise corruption accuracy will reduce, to overcome these problems [30] Z. Wei *et al* proposed online model identification method based on adaptive forgetting recursive total least squares to compensate the noise effect and combined this method with Luenberger observer to estimate the SOC of the battery, the simulation results are shown that the estimation accuracy was improved and robust in noise corruption. In [31] Hu. X *et al* proposed online SOC estimation method for Lithium-ion battery using Luenberger observer. This observer method will reduce difference between actual and estimated voltage error, the stochastic gradient method is used for adaptive adjustment of the observer gain.

3.4.2. Sliding mode observer

In order to increase stability by compensating non-linear dynamic uncertainties in the battery model, in [32] Kim I.L first introduced the SMO in battery SOC estimation in HEV. The SMO controls the convergence of high charging and discharging values by using Lyapunov inequality equations. The author shown that the test results with less than 3% SOC estimation error. In [33] Ning B *et al* proposed adaptive SMO for accurate online SOC estimation in the adaptive parameters-based battery model. This observer method will improve the accuracy of SOC estimation by using the dynamic self-adjusting switching gain in response to the tracking errors. The result shown that the error between actual and estimated SOC is less than 2%. In [34] Y. Feng *et al* proposed a three-terminal sliding-mode observer (TSMOs) for battery SOC and SOH estimation, each observer in the TSMOs will estimate one parameter in battery variables. This estimation algorithm doesn't contain any low pass filters, which will increase the accuracy and robustness, reduce cost.

3.5. Hybrid methods

Based on the analysis of number of SOC estimation methods, each method or algorithm has its own merits and demerits. By combining these algorithms, we can get advantages both algorithms, which can improve the performance and accuracy as well as reduce cost. In [35] J. Wang *et al* proposed hybrid coulomb counting and Kalman filter algorithm, the main limitation of coulomb count counting method

is that, in order to estimate the battery SOC, the initial values of the battery parameters are needed, to solve this issue, the Kalman filter is used in this process, which can correct the initial values of the battery parameters and be used as input to the coulomb counting algorithm. In [36] Bizhong Xia et al have proposed the Levenberg-Marquardt hidden layer (LMMWNN) and PSO algorithm for SOC estimation of battery. The piecewise network and seven-point linear smoothing method are used to optimize the LMMWNN. The proposed LMMWNN method tested on New European Driving cycle and results showed that it has better robustness, noise performance compared to the Levenberg-Marquardt wavelet neural network algorithm. In [37] Chen, X et al, proposed a hybrid BPNN-EKF algorithm for SOC estimation method of thevenin equivalent model battery pack. The model bias and parameter uncertainties are considered as model uncertainties. In this hybrid model bias correction method was used to reduce model uncertainties, A BPNN based bias functioning method is used to reduce the polarization and temperature effects. Finally, the EKF is used for SOC estimation of the battery equivalent model. In [38] Yuejiu Zheng et al, has proposed a hybrid EKF method and PSO algorithm for SOC inconsistency estimation for RC second-order equivalent model. The POS algorithm is used to identify the battery parameters and EKF is used SOC estimation. In [39] Yanqing Shen, proposed a hybrid adaptive chaos GA(CGA) based on EKF for SOC estimation of LIBs. The EKF is used for local linear approximation and CGA is used for global optimization search for battery parameter estimation. This method quickly evaluates SOC estimation with high accuracy and it has high robustness without being affected by uncertain initial values. In [40] Ju wang et al, proposed recursive least square and adaptive H_∞ filter joint estimation framework. The proposed dual estimator setup analyzed with wide temperature range (-10°C to 25°C), results showed that the proposed hybrid method have better SOC estimation performance even at very low temperature i.e error is less than 3.5% at -10°C , and less than 2% at 0°C and 25°C . In [41] Shehab El Din et al, proposed adaptive equivalent circuit model with artificial neural network (ANN) controller with hybrid unscented Kalman filter (UKF) and Autocovariance least square (ALS) method. In the proposed hybrid method, ANN is used to identify the optimal parameters of battery model, UKF is used for fast covariance and ALS used to measure the noise covariance which improves the SOC estimation accuracy. In [42] Minghui Hu et al, proposed a mixed swarm based co-operative particle swarm optimization method, to improve the accuracy and better robustness with different driving range conditions for LIB. the proposed method can adequately coordinate the dynamic balance between local and global optimization for the optimal solution with fast accuracy. In [43] N. Guo et al Proposed fuzzy weighted algorithm, which is a combined model of genetic algorithm (GA) -back propagation neural network (BPNN) algorithm and ampere integration method (AIM) for battery SOC estimation. The weights of fuzzy controller are controlled by the GA-BPNN and AIM, for large voltage variation the weights of the fuzzy is propositional to the GA-BPNN and for small voltage variations proportional to the AIM. This algorithm can have advantage of both algorithms based on the situation and state of voltage and SOC levels. However, this algorithm will depend on battery working environmental conditions. In [44] F. Yang *et al*, proposed hybrid long-short-term memory (LSTM)- recurrent neural network (RNN) and (unscented Kalman filter) UKF algorithm. The battery current, voltage and temperature are taken as input Parameter to the LSTM-RNN and SOC estimation as output, the UKF is used as noise filter at output, the algorithm is model free and data driven, tested at different temperature from 0°C to 50°C and estimation error was less than 1%.

CONCLUSION

In this paper an over view of battery Equivalent circuit models, SOC and SOH estimation algorithms has been given. The major challenges and constrains in battery modeling, SOC and SOH estimation are discussed. Performance of different battery model, SOC and SOH estimation algorithms are compared in point of accuracy, speed and mathematical complexity. Our future work is focus on the development of new hydride estimation algorithms, which can provide more accurate and high-speed results with less complexity in development of smart BMS for EVs.

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