State-of-Charge Estimation Methods for Li-ion Batteries in Electric Vehicles

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Abstract*: In recent years, due to zero caron emission Electric Vehicles (EVs) are considered as a best alternative choice for gasoline and diesel based vehicles in automotive industries. Despite the fact that, Li-ion batteries are preferred choice for EVs they have few drawbacks such as temperature dependent, slow charging and battery aging which degrade performance and operational efficiency of EVs. In real-cars, estimation of accurate battery State of Charge (SOC) is considered as most essential task to be performed by Battery Management System (BMS) because of the nonlinear battery characteristics and unpredictable operating conditions. The main objective of this paper is to comprehensively present common methods currently adapted by researchers in estimating battery SOC by analyzing their pros and cons. This investigation also highlights various issues and challenges associated to SOC estimation with possible recommendations to overcome them. All recommended insights can be amended into advanced BMS with accurate SOC estimation in next-generation EVs.

***Index Terms*: Electric Vehicle, State of Charge, Battery Management System, SOC Estimation, Li-ion battery**

I. INTRODUCTION

In recent years, many countries motivated to address environmental pollution and global warming issues. Gasoline and diesel based vehicles are considered as one of the main source for environmental pollution by emitting CO_2 gas. This laid a path for automotive industries to adapt Electric Vehicle (EVs) as a best alternative for gasoline and diesel based vehicles. There are various kinds of energy storage systems used by different EVs which includes fuel cell, ultra-capacitors and Batteries[1]. In general, battery based energy storage system is a recommended choice for many EVs. Table-1 describes some of the importantproperties of different categories of batteries[2]. From Table-1 It is evident, Lithium-ion batteries are most commonly accepted by EVs because of its environmental friendliness, long service life, high efficiency and less self-discharge rate[3].

In EVs, the energy storage system is managed by a separate module called Battery Management Systems(BMS). A highly efficient BMS assure safety, increase reliability, efficient operation of battery pack under most critical and energy demanding condition. The main functions of BMS includes ensuring safe operation of battery, controls charging and discharging of battery, cell balancing, over temperature protection, estimating SOC by measuring Voltage(V), Current(I) and Temperature(T). Figure-1 indicates list of operations carried out by BMS in an EVs.

Battery SOC is similar to fuel gauge which indicates remaining useful power in battery to operate a vehicle. Accurate SOC estimation is most vital and difficult operation carried out by BMS due to the fact that Li-ion batteries are most complex electrochemical devices with in-consistent cell characteristics under different internal and external operating conditions. In addition to this, performance of Li-ion batteries is alsoaffected by ageing, charge-discharge cycles and temperature variation [4].Inaccurate SOC estimation may lead to operate the battery pack in an inefficient mannerwhich reduces battery life cycle, operationaloutput power capabilityand energy storage capacity.

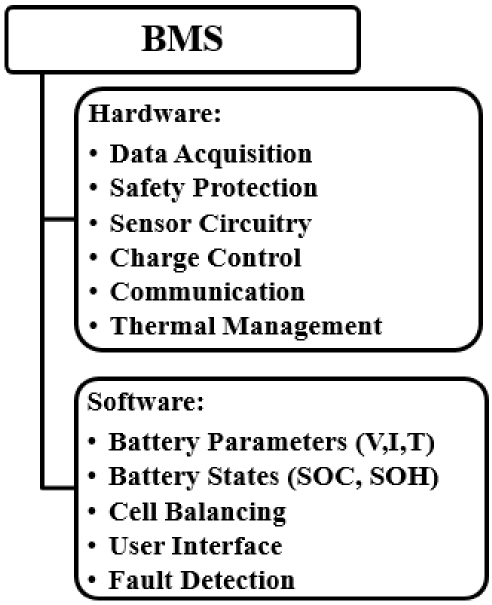

Fig. 1 Functions of Battery Management Systems

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Table-1 Important properties of differentkinds of batteries

Battery type	Service life /cycle	Nominal voltage/V	Energy density /(W·h·kg^{-1})	Power density /(W·kg^{-1})	Charging efficiency/%	Self-discharge rate /(%·month^{-1})	Charging temperature/°C	Discharging temperature/°C
Li-ion battery	600–3000	3.2–3.7	100–270	250–680	80–90	3–10	0 to 45	–20 to 60
Lead acid battery	200–300	2.0	30–50	180	50–95	5	–20 to 50	–20 to 50
NiCd battery	1000	1.2	50–80	150	70–90	20	0 to 45	–20 to 65
NiMH battery	300–600	1.2	60–120	250–1000	65	30	0 to 45	–20 to 65

The main objective of this paper is to investigate various types of SOC estimation techniques in an exhaustive manner based on their strength and weakness, also highlights some of the issues and challenges associated to SOC estimation with possible recommendations to overcome them. This paper is organized as, Section-II discusses different types of SOC estimation methods, Section-III indicates some of the issues and challenges with few recommendations to increase the accuracy of SOC estimation and inferences in final section.

II. SOC ESTIMATION METHODOLOGY

Battery SOC of a EVis generally represented in terms of percentage as shown in eq. (1)

$$SOC=Q_{res}/Q_{max} * 100\% \qquad (1)$$

where Q_{res} represents the remaining capacity and $Q_{max}$is the maximumcapacity [6]. Accurate and reliable estimation of SOC of a battery in a EVs is a major challenge due their dynamic battery characteristics and unpredictable battery operating conditions [7]. Several researchers suggested their effective approaches to improvise SOC accuracy in EVs. There are many SOC estimation algorithms are existing in many literatures and they are categorized into various types such as Direct methods, Book-keeping method, model based methods, Adaptive filtering methods, data driven approaches. Figure-2 summaries different types SOC estimating methods.

A. Direct Method

The direct measurement method is based on predefined relationship between SOC and measured battery variables. Some of the battery variables includes battery operating Temperature (T), battery Voltage (V), voltage relaxation time (τ) and battery impedance (Z). Figure-3 shows basic principle of Direct method to estimate SOC [8]. The function f_T^d is the relationship between SOC and measured battery variable, d denotes direct method and T indicates temperature dependency. Direct methods are most reliable SOC estimation method since battery's physical parameters are directly measured. Though this method is easy to implement, it is highly sensitive to measured voltage, temperature and current which directly affects the accuracy of the SOC. Some of the commonly used direct measurement methods are OCV method, Resistance method, EMF method and Electrochemical Impedance Spectroscopy (EIS).

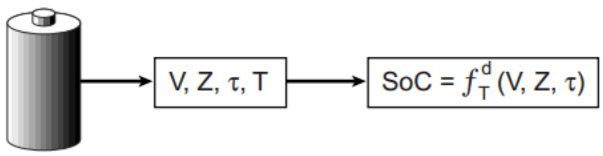

Fig. 3 – SOC Estimation byDirect method

a. Open Circuit Voltage(OCV) Method

In OCV method, value ofSOC is obtained by directly measuring battery's open-circuit voltage and mapping corresponding SOC with OCV-SOC relationship curve. Figure-4 illustrates SOC- OCV relationship of LiFePO4 cell [9]. The Eq. (2) express the OCV-SOC relationship.

$$SOC = f(OCV) \qquad (2)$$

The strength of the OCV method is, very simple and it deliver high accuracy on SOC estimation. But this method can't be used directly for real-time applications such as EVs, since it requires sufficient amount of rest time for equilibrium. Also, OCV-SOV relationship curve is not same for all type of Li-ion battery, it differs from one battery chemistry to another. However, OCV method helps to improve the SOC accuracy by combining with other SOC estimation techniques such as Coulomb Counting, Adaptive filtering etc.,

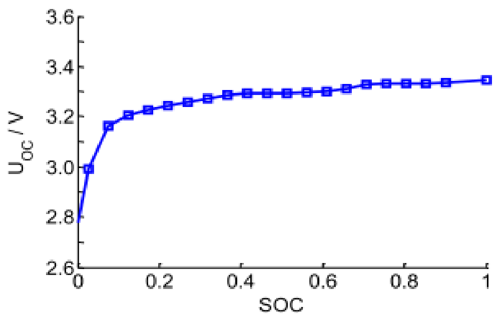

Fig. 4 - OCV vs SOC curves of LiFePO4 cell

b. DC Resistance Method

DC resistance has a close relationship with SOC, by representing the battery capacity. This method measures the battery'sDC resistance by using battery current and voltage. Battery voltage will be measured by altering the current for a short period of time (less than 10ms).

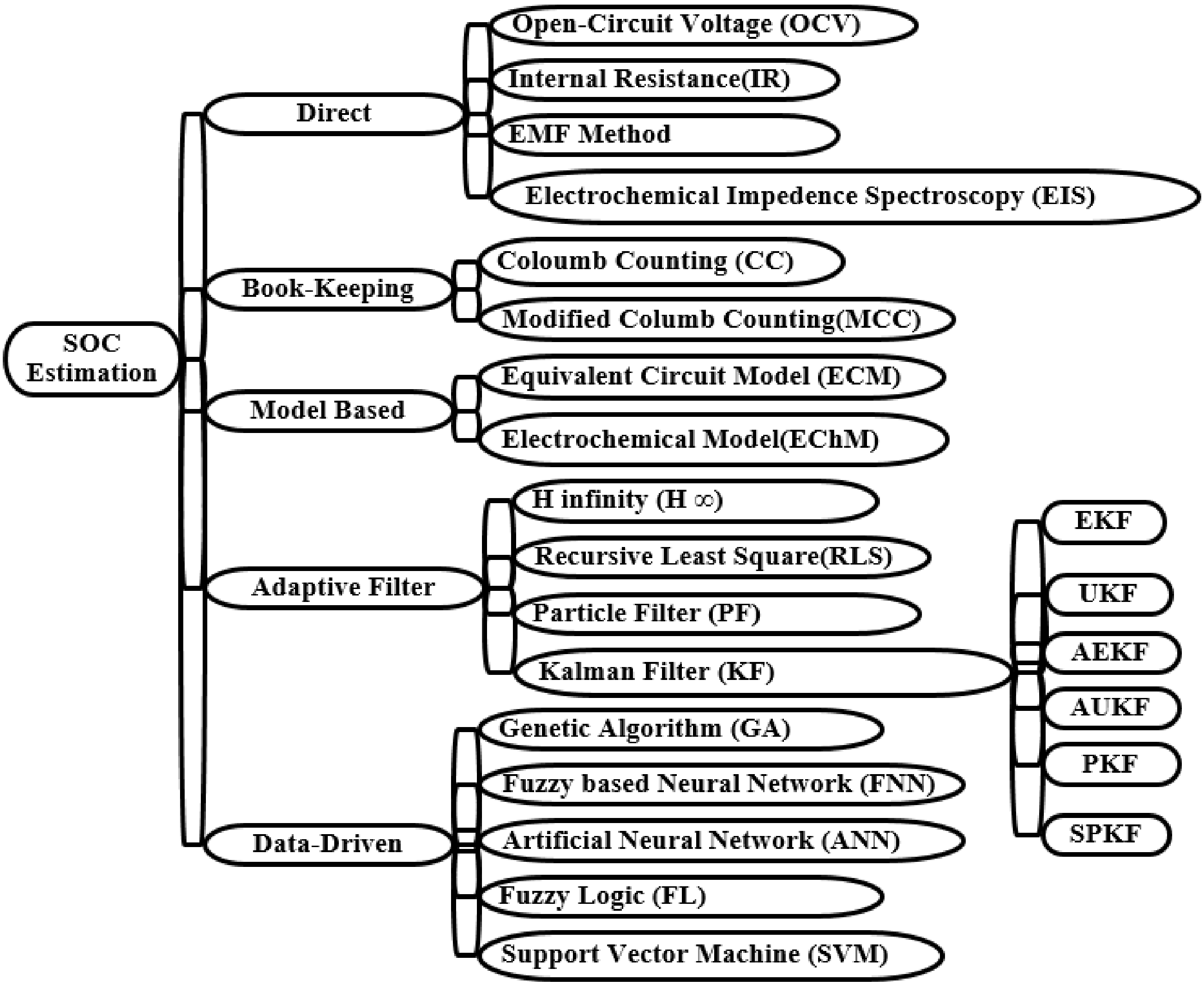

Fig.2 Various types of SOC estimating methods

The ratio of V & I difference result indicate battery capacity in DC resistance value [10]. This method is mainly affected by its calculation time. If longer time is allowed for calculating DC resistance will result in error and becomes complicated. Though, DC resistance method has high accuracy and good adaptability it is highly recommended to estimate the SOC only during final stage battery discharge condition [11]. Also, it is highly challenging to measure the small variation of DC resistance for extensive range of SOC as shown in Figure-5. Because of these drawbacks, DC resistance method is very rarely used in real cars.

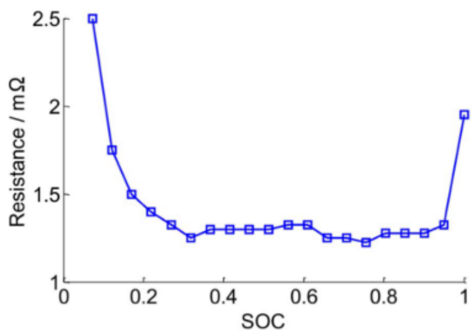

Fig.5 Internal DC Resistance vs SOC relationship

c. Electro-Motive Force (EMF) Method

Battery EMF can be measured by measuring OCV of the battery when specific amount of time is passed after the current interruption. In general, battery EMF can be obtained during the OCV relaxation time[12]. The EMF voltage is indicated by U_0[V] is sum of the equilibrium potential at battery electrodes. Figure-6 shows the relation between $U0$[V] and SOC for LiPoly and LiFePO4 batteries[13]. By using eq. (3) estimation of SOC is carried out for EMF method.

$$SOC = \frac{Q_0}{3600\ X\ C_0} \qquad (3)$$

Where Q_0 is fraction of charge in the battery in terms of coulomb (C) and C_0 is actual battery capacity in terms of Ah. Though, this method has an advantage of simplicity and accurately tracking of battery's dynamic behavior, it takes several hours for Li-ion batteries to estimate SOC value[10].

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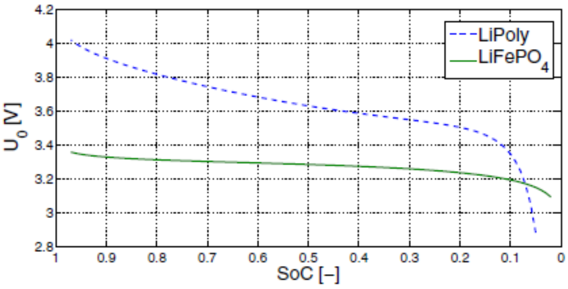

Fig. 6 EMF voltage U_0 as function of SoC

d. Electrochemical Impedance Spectroscopy (EIS)

An EIS method battery impedance is measured by applying small amplitude AC signals at different excitation frequencies with different charge and discharge conditions. The battery impedance can be defined as eq. (4).

$$R_{EIS}(\omega) = \frac{U_{AC}}{I_{AC}} e^{j\varphi} \qquad (4)$$

where U_{AC} is the measured peak amplitude voltage, I_{AC} is the measured peak amplitude current,$\varphi$is phase shift between V and I.Magnitude of R_{EIS} is indicated by Nyquist diagram and Bode plot [13] as shown in Figure-7. By measuring present impedance and comparing with known impedance value at different SOC levels, present value of battery SOC can be calculated [14]. The main advantage is method is accurate SOC estimate as it depicts dynamic behavior of battery's electrochemical process and its unique impedance value for different battery chemistries. Since SOC accuracy depends on accurate impedance measurement, this consume more time and very hard to adaptfor SOC measurementsin real-time. In addition, accuracy of SOC is influenced by temperature variation and battery aging [15].

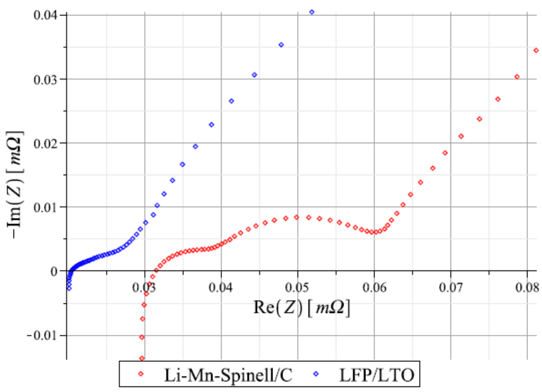

Fig.7 Nyquist plot of LFP/LTO & Li-Mn-Spinell/C cell

B. Book-Keeping Method:

Book-keeping method uses battery's current discharge rate and accumulate over a time to predict SOC value. This method considers various characteristics of battery including battery temperature, battery charge/discharge efficiency, self-discharge, capacity loss etc., [14].Figure-8 shows the practical set-up of a Book-Keeping method [8].

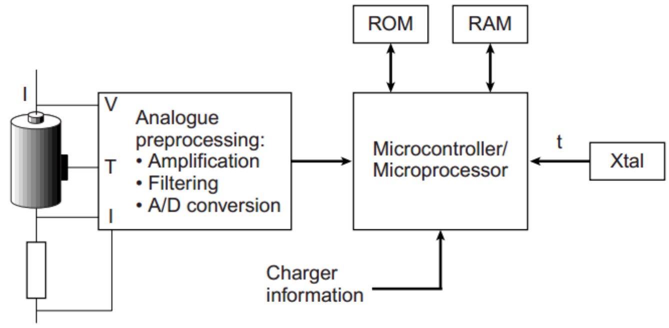

Fig.8 Practical set-up of a book-keeping system

a. Coulomb Counting (CC) method:

CC method estimate SOC value by performing integration on amount of current flowing in and out of battery over a time period when battery is in charging or discharging state. This is represented mathematically aseq. (5).

$$SOC(t) = SOC(t_0) + \frac{1}{C_n}\int_{t_0}^{t_0+t} I\,(d\tau)\,.100\% \qquad (5)$$

where $C_n$specify nominal capacity,$SOC(t_0)$ indicate initial condition of SOC, $I(d\tau)$ is the rate of change in charging/discharging current. Figure-9 shows basic principle of Coulomb Counting (CC) method to estimate SOC [8]. This method is easy to implement and need less computation power. But significant amount of inaccuracies occurs due to uncertainty of battery variables such as temperature, noise and current etc., Another drawback is, even small error on initial SOC value accumulated into larger amount due to integration operation. In addition to this, estimation accuracy is affected by several other factors which includes current sensor precision, discharge rate and battery ageing [5].

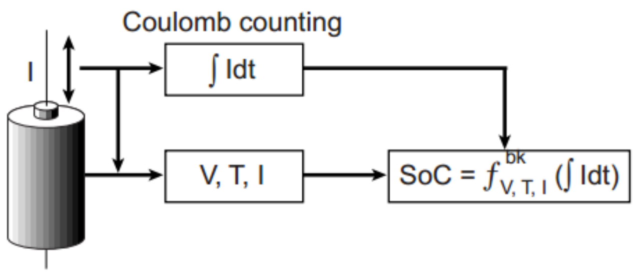

Fig.9 – SOC Estimation by Coulomb-Counting Method

b. Modified Coulomb Counting method

In modified CC method SOC estimation accuracy is increased by corrected current as an input [14]. Corrected current is a function of discharge current, which can be expressed as following quadratic eq. (6).

$$I_c(t) = k_2 I(t)^2 + k_1 I(t) + k_0 \qquad (6)$$

Where k_0, k_1 and k_2 are values attained by experiment. Battery SOC can be estimated by eq. (7).

$$SOC(t) = SOC(t_0) + \frac{1}{C_n}\int_{t_0}^{t_0+t} I_C\,(d\tau)\,.100\% \qquad (7)$$

Experimental result specify that modified CC method improvise the SOC accuracy compared with conventional CC method. However, this method has same drawbacks of conventional CC method.

C. Model based methods:

OCV methods are not suitable while EVs are in operational condition, since it requires appropriate amount of rest time to estimate SOC. To achieve online SOC estimation, model of Li-ion batteries must be developed. The dynamic behavior of Lithium batteryis modelled by two methods, Equivalent Circuit Model(ECM) & Electrochemical Model(EChM). Whereas, EChM represents battery's electro any chemical dynamics along with its internal materials.

a. Equivalent Circuit Model(ECM)

This is one of the broadly adapted model by many researchers to estimate battery SOC for EV applications. Most of the ECM models uses Resistor(R), capacitor(C) and DC voltage source to simulate the electrical characteristics of Li-ion batteries [16]. The schematic diagram of commonly used is improved Thevenin model structure [17] as shown in Figure-10.

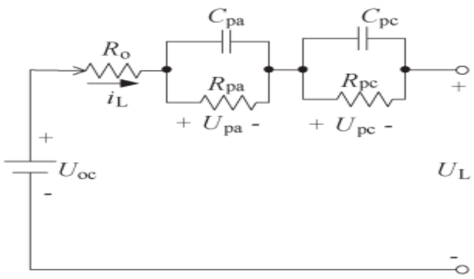

Fig.10 Schematic of the improved Thevenin model

where Uoc denotes battery OCV value which varies in nonlinear manner with respect to SOC, R_0 ohmic resistance of the battery, i_L indicates load current which can be measured from current sensor, R_{pa} and C_{pa} denotes polarization resistance and capacitance, concentration polarization resistance R_{pc},C_{pc}concentration polarization capacitance. U_{pa}, U_{pc} are voltage on C_{pa}, C_{pc} respectively which can be directly measured from voltage sensor. Behavior of the circuit is describedin eq. (8).

$$\begin{cases} \dot{U}_{pa} = -\dfrac{U_{pa}}{(R_{pa}C_{pa})} + \dfrac{i_L}{C_{pa}} \\ \dot{U}_{pc} = -\dfrac{U_{pc}}{(R_{pc}C_{pc})} + \dfrac{i_L}{C_{pc}} \\ U_L = U_{OC} - U_{pa} - U_{pc} - i_L R_0 \end{cases} \quad (8)$$

Main benefits of ECM methods are, implementation easiness and less computation time. But ECM methods can estimate SOC accurately only for new batteries and this model can't simulate all electrochemical processes of the battery which impact inaccuracy in final SOC value. Nevertheless, ECM methods are widely used along withExtended Kalman-Filter (EKF) for accurate SOC measurements.

b. Electrochemical Model (EChM)

The EChM model can be represented with Partial Differential Equation(PDE) which is based on battery chemical dynamics, mass transfer and thermodynamics [6]. The vital task of EchM based SOC estimation is to measure Li concentration on positive/negative electrodes[18]. Further SOC of the battery will be calculated by defining Li-concentration present at electrodes from EChM model [19]. This method is unable to estimate online SOC due to the complexity involved in solving PDE equation and also thisleads to over fitting condition. To solve this issue,reduced-order EChM approach is followed in [20].

D. Adaptive Filter Approach

All SOC estimation methods discussed so far has limitation in practical implementation as they require to bring the battery into stable state to generate a valid reading. One solution to overcome this problem is to used high precision sensors and transducers to increase SOC accuracy. An alternative solution to this problem is, to use adaptive filter based methods. This method combines direct/book-keeping methods with model based method to automatically update its output for the changes in the input. Though, Adaptive filter method demonstrate fast convergence and time efficiency it suffers to solve complex mathematical equation [15].

a. Kalman Filter(KF) method

The KF method is most powerful approach to predict the SOC value by modelling battery including unknown parameters. By using set of mathematical equations, KF system continuously predict and correct as the system functions [10]. In KF algorithm, recursive result is achieved by using optimal linear filtering [15]. The advantage of KF method is, it automatically updates output value for the change in input value. Figure-11 describes Kalman Filter iteration algorithm for SOC estimation. This feature extends the use of KF method in real-time dynamic behavior applications such as EVs batteries. Main benefits of KF method is high accuracy and reliable SOC estimation method under the external disturbance conditions. Some of the factors affect accuracy of KF methods are temperature and improper battery model. This method is not suitable for non-linear system SOC estimation. Improvised version of KF method required to estimate SOC for a non-linear system such as UKF, AKF, PKF etc., [15].

b. Recursive Least Square(RLS) Method

RLS method is an another adaptive filter technique used to estimate SOC efficiently by calculating parameters which minimize the effect of least square error between correct output signal and estimated output signal [5].Figure-12 explains RLS parameter estimation algorithm with a single forgetting factor [21]. This model diminishes SOC error and noise present in the obtained Voltage value. This method has high accuracy with less error rate (1.032%) compared to all other SOC estimation techniques. Weakness of RLS method is, it suffers from unstable operation, high complexity and high computational time[10].

c. H-infinity based method (H ∞)

H infinity algorithm simply represented as time-varying battery parameters with high robustness under specific condition. Figure-13 represents general procedure followed for H infinity based SOC measurement [6]. In [22], H infinity based SOC estimation was implemented using second order RC circuit by considering time depended parameters such as current, temperature etc.[23], then test is

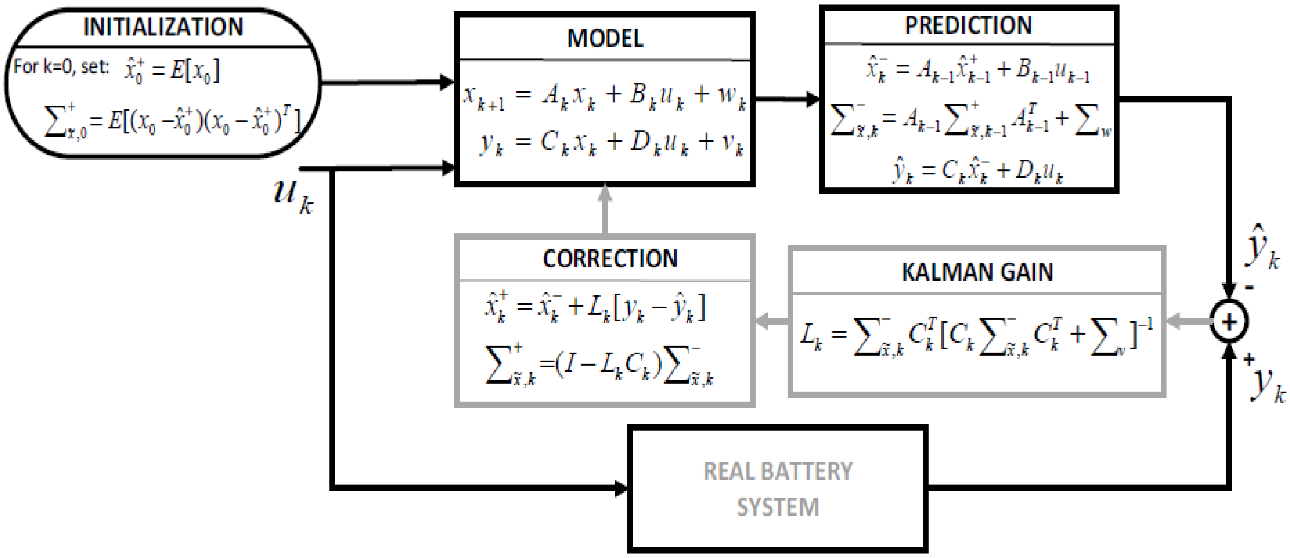

Fig.11 Kalman Filter iteration algorithm for SOC estimation

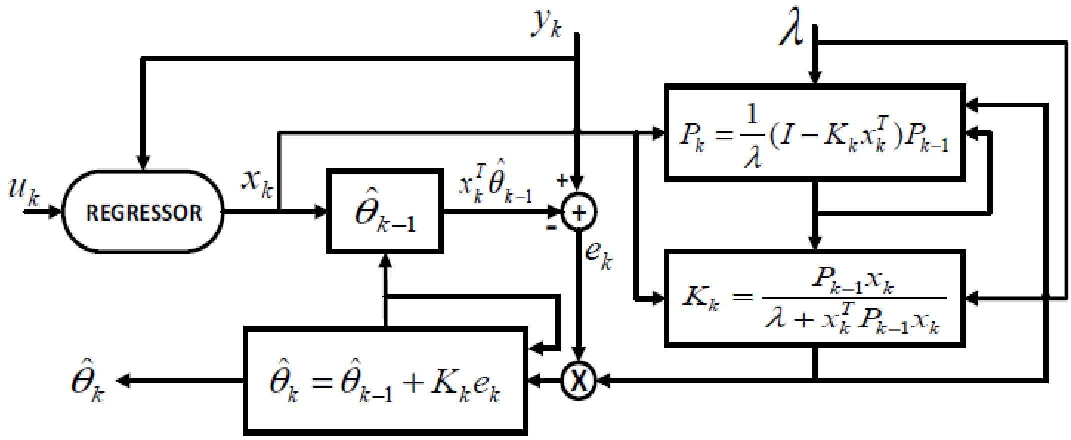

Fig. 12 Recursive Least Square(RLS) algorithm for SOC estimation

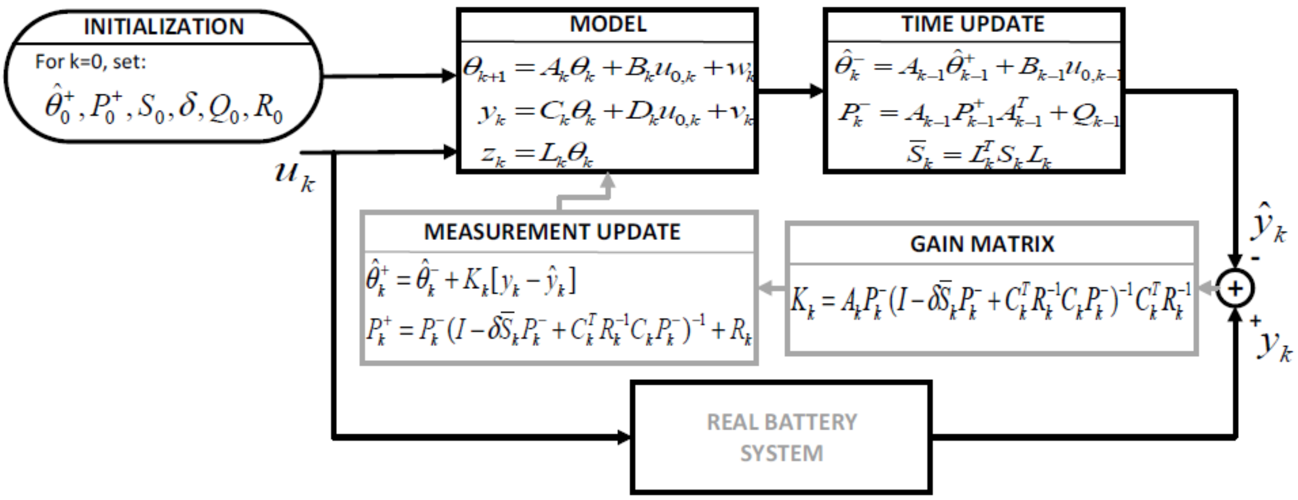

Fig. 13 H∞ filter algorithm for SOC estimation

performed to extract model parameters such as voltage, resistance. This suggested model undergone six UDDC for validation, the test result indicates battery accuracy with manageable SOC error of 2.49%. Furthermore, accuracy of SOC estimation improved by improvising H infinity algorithm such method includes Adaptive H infinity (AHI), Dual H-infinity Filter(DHI). Main disadvantages of H infinity methods are high computational cost and final SOC value depends on the voltage measured from voltage sensor so precision voltage sensor is very essential [24].

d. Particle Filter (PF) method

PF method estimate SOC by approximating the non-linear system Probability Density Function(PDF) by performing the Monte-Carlo simulation technique with random particles [15]. The benefit of Monte-Carlo simulation technique is, accurate estimation of SOC by neglecting hysteresis effect. Two PF model approaches are proposed by [25], to estimate SOC and the measured parameters from model exactly indicates terminal voltage variation with respect to the variation of temperature, current and SOC. Also it demonstrates PF method is six times faster than EKF method in terms of computational speed. Improved PF method called Unscented Particle Filter (UPF) method has more advantagethan UKF and EKF algorithm by reducing Root Mean Square Error value [26].

E. Data-Driven Approach:

Modelling a battery with their complex electrochemical process and unknown operating condition is a very challenging task in model-based SOC estimation. In contrast to other approaches, data driven method simply use the relationship between input and output data to construct the SOC estimation algorithm[27]. Accurate battery model, assumption and estimations considered in representing battery models are neglected [4]. Some of the advantages of these method includes universal mathematical model, easy to model most complicated control system. These method requires high volume of training data and high computation cost to estimate SOC. Some of the popular data-driven method followed to estimate SOC are discussed under this section.

a. Fuzzy Logic(FL) based estimation

Fuzzy Logic is another effective method to represent the battery's non-linear behavior by using appropriate dataset. Four stages of implementing FL based SOC estimation involves (i). Fuzzification: converting obtained system parameters into fuzzy sets (ii). Fuzzy Rule-Base: designed based on system operating method and experiences (iii). De-fuzzification: transform fuzzy rules into output values. SOC prediction using FL is proposed in [28] using data collected from EIS/CC method for Li-ion batteries. This method estimates battery SOC with 5% as error rate. Although FL is a very effective method for SOC estimation, it requires high speed processing unit and larger memory block to perform complex computations. Also, this method can be combined with other SOC techniquesto improve SOC accuracy [5].

b. Fuzzy based Neural Network(FNN)

In order to reduce SOC estimations error rate in conventional FL based methods, a FNN based method is proposed. In FNN algorithm, SOC estimation is carried out by using Reduced-form Genetic Algorithm(RGA). The non-linear dynamic of battery is represented by using 12 inputs and 1 output for SOC estimation [29]. An advanced Fuzzy based neural network algorithm named ANFIS is highly effective in SOC estimations. ANFIS method proposed in [30] uses battery temperature and capacity distribution as inputs and produces output as a state of available capacity. This method is verified using battery discharge process and results in accurate SOC with error rate lesser than 1%. Limitation of ANFIS is, performance of the SOC estimation is affected for large number of inputs.

c.Artificial Neural network(ANN)

As ANN can effectively simulate any non-linear behavior of the system, this method is most suitable choice for battery SOC estimation [31]. Neural Network are constructed by 3 layers input, output and hidden layers as shown in Figure-14 [32]. The mathematical relationship between input, output layer is governed by hidden layer. Without knowing details battery internal structure and initial SOC, the ANN estimate the SOC using trained data. Commonly used ANN architectures are Feed Forward Neural Network(FFNN) and Back Propagation Neural Network(BPNN) [5]. In FFNN no feedback is involved, input signals forward through network from input to output neurons. Whereas, BPNN has a feedback and learning take place during the propagation of input signal from input layer into output layer. The obtained outputs are related with expected output and error rate is calculated. Then weights are modified to reduce the SOC error rate. The main drawback of ANN method, it requires large number of neurons to increase the accuracy which affect real-life implementation in EVs. Also, for training larger datasets more iterations are required.

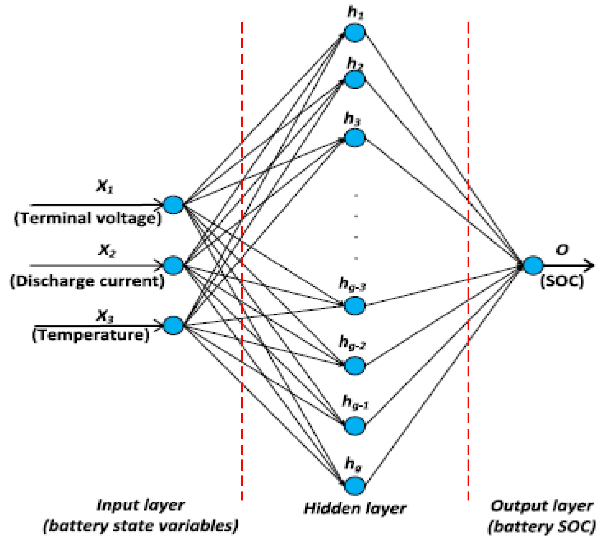

Fig. 14 Structure of ANN for SOC estimation

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d. Genetic Algorithm(GA)

GA is an optimization tool, in which parameters related to the system are optimized and described in the form called Chromosomes. For SOC assessment, chromosome is represented as vector and it has the elements which is a battery parameter and SOC is considered as element of this vector. This algorithm begins with random set of chromosome vector and further undergo iterative selection process, crossover & mutation to compute effective result as shown in Figure-15[5]. In [33], Li-ion battery SOC estimation is carried out by combining CC method and model- based method. GA is used to optimize the battery parameters and verified by various drive cycles. The results show that better accuracy achieved for SOC estimation with the error rate of less than 1%.

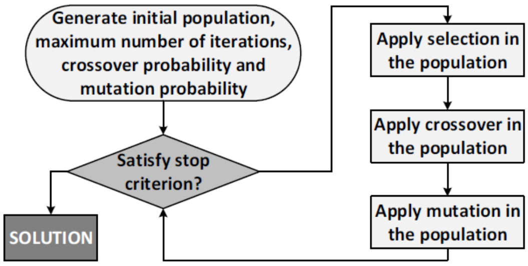

Fig. 15 Genetic Algorithm

e.Support Vector Machine (SVM)

SVM converts lower dimension non-linear model into higher dimension linear model by using regression algorithm [34]. The derived version of SVM is called Support Vector Regression(SVR) is majorly used for battery SOC estimation. In [35] basic idea of SVM and SVR is discussed in detail. SVR algorithm simulate the battery model parameters by using independent variable such as Voltage, Current and Temperature under battery charging/discharging condition. The final result shows are verified and it conclude that accurate SOC estimation is achieved with error rate of 0.97%.

III. RESULT & DISCUSSIONS

This main objective of this paper is to illustrates detailed analysis of various SOC estimation approaches used for Lithium-ion batteries in EVs. Table-2 summariesvarious kinds of SOC estimation techniques along with their advantages, limitations and average error rate in percentage comparison. Each SOC estimation method has its own pros and cons. Though there are many SOC estimation algorithms are available only few of them were used in practical EVs application. CC method is one among the other SOC estimation method adapted in real cars. Also combination of CC method and OCV method increase the SOC accuracy by eliminating accumulated error. During the estimation of SOC various factors influencing battery capacity such as voltage, temperature, current, self-discharge, operating conditions and battery ageing must be taken into account. For model based SOC estimation approaches it is most recommended to consider all kinds of battery characteristics including electrochemical, electro thermal process and all battery dynamics. Data-driven based SOC estimation is considered as more accurately estimating SOC, but complex computation makes bottleneck to real-world applications. This can be overcome by simplifying the complexity according to the capability of the computation unit without compromising accuracy.

Table- 2 Comparison of various SOC estimation methods

SOC Approach	Strength	Weakness	Avg. Error %	Ref.
OCV	Easy to implement, Accurate	Offline method, Time intensive, High energy loss	5 %	[36]
IR	Simple and Easy, online method,	Less accurate, difficult to observe SOC	≤ ±2%	[37]
EMF	Simple and low cost	Computation time	-	[12]
EIS	Accurate and low cost	Impact of ageing and temperature	-	[38]
CC	Easy and low computational power	Difficult to find initial SOC value, inaccurate result under disturbance condition	≤ ±4%	[39]
ECM	Online, high accuracy	Accuracy depends on model accuracy, electrochemical behavior not considered	≤ ±5%	[9]
EChM	Online, high accuracy	Accuracy depends on model accuracy, complex processing	≤ ±5%	[19]
H ∞	Accurate, computational cost, time efficiency	Accuracy affected by temperature effect, ageing and hysteresis	≤ ± 2.49%	[40]
RLS	High accuracy	High computation time	≤ ± 1.03%	[41]
PF	High accuracy, less computational time	Require complex math tool	-	[25]
KF	Online, dynamic, Accurate if not affected by noise	Can't be used directly, require high complex math equation	≤ ± 1.76%	[42]
GA	High accuracy and neglect most of the noise in signal	Complex computation and tuning of model parameter is essential	≤ ±2%	[43]
ANN	Ability to work under non-linear environment	High memory requirement	≤ ± 4.6%	[44]
FL	Accurate	Complex computation and costly processor	≤ ±5%	[28]
SVM	Quick and accurate	Complex computation and time consuming	≤ ±6%	[45]

This paperalso suggests few recommendations [9][12] [19] [25] [28] [36-45] for the research on future advancements of

SOC estimation methods.

(i). For developing an intelligent BMS, choose high precision sensor, actuators and controllers

(ii). Future research must consider various external disturbances and uncertainties encountered by battery while estimating SOC value.

(iii) Toincrease the performance of SOC estimation under non-linear system condition a suitable controller is required

(iv) Further importance must be delivered to develop improved training algorithm for artificial intelligence method and optimal parameter selection of battery model.

IV. CONCLUSION

Estimation of Li-ion battery SOC is vital role of BMS in EVs. To identify the best SOC estimation approach, an extensive investigation carried out on existing SOC estimation algorithm by concentrating on their benefits and limitations. Five most dominant SOC approaches taken into account and detail analysis with systematic evaluation was carried out. In spite of large number of SoC prediction algorithm suggested by researchers many of which has to make a trade-off between computational complexity and implementation cost. Still a cost effective estimation of battery SOC remains open contest for researchers. In future, more attention must be given to develop a non-complex SOC estimation algorithm which is feasible to implement on BMS of the EVs.

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