State of Charge Estimation Techniques

Kshitija A. Gaikwad
Instrumentation & Control dept., VIT
Pune, India

Prof. Vijaykumar Bhanuse
Instrumentation & Control dept., VIT
Pune, India

Abstract— **In recent years, there has been a tremendous advancement in battery technology due to the development of EVs and HEVs. But still, the State of Charge (SOC) estimation remains a challenge in battery engineering. SOC is defined as the ratio of remaining charge to the maximum capacity of the battery. SOC estimation is of prime importance with regard to battery safety and maintenance. This paper reviews different SOC estimation techniques along with their advantages and disadvantages.**

Keywords—BMS; SOC; SOH; EVs; HEVs.

I. INTRODUCTION

Due to growing environmental concerns and depletion of conventional fuels, automobile industry in currently focusing on development of Electric (EVs) and Hybrid Electric Vehicle (HEVs). A rechargeable high voltage battery is the driving force for EVs/HEVs. A Battery Management System (BMS) is necessary to ensure the safe operation of the battery. BMS consists of sensors, electronic units housed on or away from the battery and a display unit.

- Functions of BMS:

1) Monitoring of battery current, voltage (individual cell voltages as well as pack voltage)
2) Temperature monitoring (pack temp)
3) State Of Charge(SOC) and Sate Of Health(SOH estimation)
4) Balancing of cells
5) Generating Safety Critical alarm and derating the output if required.
6) Emergency Shutdown in Critical state.

In this paper, we are going to explore various SOC estimation techniques. Before, proceeding further, let us understand what do you mean by SOC? SOC of a cell or a battery at a given instant is the ratio of the charge available at that point to the charge available when it is full charged. It is expressed in percent, from 100% when full to 0% when empty. Analogous to how much fuel is available in car's tank.

- Importance of SOC

1) SOC indicates whether available charge is sufficient enough to carry out a particular function or not.
2) Knowledge of SOC helps in operating the battery in the limits of charge and discharge.
3) Very high or low SOC tends to permanently damage to battery.

SOC estimation is difficult as it represents internal state of the battery. There is no sensor /instrument to measure SOC directly. It needs to be inferred from battery voltage or battery current. Hence, the word SOC Estimation and not SOC measurement.

II. SOC ESTIMATION TECHNIQUES

A. OCV Method

OCV refers to Open Circuit Voltage of the battery (battery no load condition). It is the simplest method for SOC estimation. With some battery chemistries, OCV voltage is linear function of SOC. Thus, measuring the OCV we can predict the SOC of the battery easily. While with other Li-ion chemistries, OCV vs SOC is a flat curve [18]. In such condition, usage of this method is limited. Other limitations using this method. It is an offline method. Battery should not be connected to any load for at least 2 hours to accurately measure the OCV. Also, OCV not only varies with SOC, but with a cell's internal resistance.

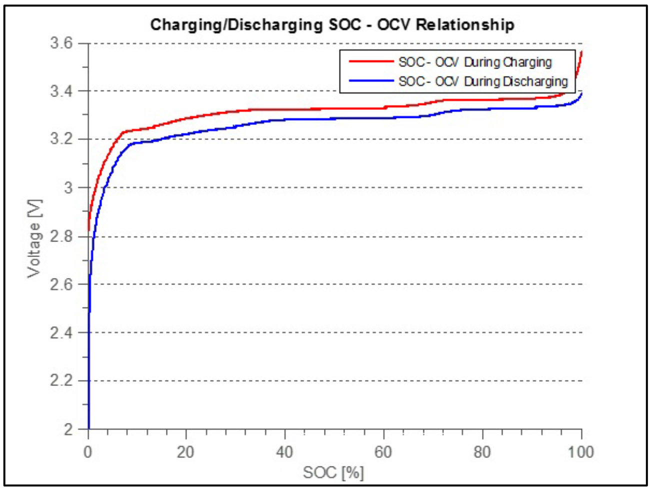

Figure 1: SOC Vs OCV Curve

As you can observe in the figure above, SOC range 20 - 80% OCV does not vary considerably. This makes SOC Estimation difficult in this region. Thus, to conclude it is a laboratory method and can be only used at extreme ends (When battery is nearly full or empty). Also, a good method for initial SOC Estimation.

B. Coulomb Counting

Coulomb Counting is the most readily used algorithm for SOC estimation. It is based on the fundamental relation between charge and current. Integrating the current in and out of the battery to give relative value of charge.

$$Q_{tn} = Q_{t0} - \int_0^{tn} I(t)\, dt$$

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 07, July-2019

Where, Q_{tn} = Residual Capacity at nth time
Q_{t0} = Initial battery capacity
I (t) = Battery current.

To start with initial SOC of the battery should be known from then onwards CC algorithm is implemented. Limitations of this algorithm are cell leakage current is not considered. Current sensor offset, can result in drift in SOC estimation. As Li-ion cells have low self- discharge, there leakage current is not a problem here but offset in current sensor drifts the SOC graph [18].

C. Electro-Chemical Spectroscopy

EIS is an AC technique where a small magnitude AC signal typically mV is injected into battery terminals and resultant voltage response is measured. The measured DC Battery impedance is dependent on magnitude of applied signal, magnitude of response signal and its phase shift.

$$Z(f) \quad = \frac{Vmax}{Imax} e^{j\theta}$$

Where, V_{max} is AC voltage response, I_{max} magnitude of lagging current response and θ is the phase angle between them. EIS is carried out over a wide range of frequencies to model battery's behavior. Load current causes impedance to vary nonlinearly with SOC [1]. Different C rates yields different values of impedance at same SOC. Also, the change in impedance is barely negligible in the region of partial to full SOC [4]. Therefore, using EIS alone for estimating battery SOC will not yield accurate results.

- EIS can be used in two different ways to predict SOC:

1) To parameterize ECM and then use ECM to predict SOC
2) To infer SOC directly from EIS impedance measurements.

In [3] EIS along with OCV method and Current measurement is used. As impedance merely changes in high SOC region of discharge curve, SOC is predicted by combination of OCV and CC method. In low SOC region impedance changes drastically and therefore EIS measurements are considered. For both the regions curve fitting technique is implied. In [4] implements EIS in a hardware where a DC/DC converter is used to inject Ac ripple voltage. Digital signal Processing tools are used to measure the impedance. This test is performed over the entire SOC range. The Measured impedance along with instantaneous values of input voltage and phase shift between voltage and current is fed to an ANN. A database model is thus created to estimate SOC.

Due to charge and discharge cycles, battery impedance increases as battery capacity fades. If EIS measurements are carried out in real time battery ageing effects can be incorporated in SOC prediction [5].In [5], online estimation using EIS as current battery model decades with time. The excitation frequency of the Ac input is varied and impedance for a wide frequency is observed. This is plotted in Nyquist plot. This is used to parameterize the ECM and further used for estimating SOC.

D. Kalman Filter

A Kalman Filter is a state estimation Algorithm. It is used where a system state cannot be measured directly. In context to Battery SOC, KF is used to find the best estimate of internal state SOC from an indirect measurement of voltage and battery current. KF is known to eliminate noises from different sensors as well as to reduce the effect of process noise. KF is based on state space representation. It works on assumption that both process and sensor noise are gaussian in nature.

$$x_k = Ax_{k-1} + Bu_k$$
$$y_k = Cx_k + Du_k$$

Building a mathematical model of the real system. When a known input is applied to this model. An estimated output is obtained. But, since mathematical model is only an approximation of your real system, actual output and estimated output do not match. The goal of KF is to minimize this difference. It controls the error difference. Batteries are modelled using ECM. KF is generally used in combination with ECM. KF is a recursive two-step process [15].

Initialization:

$$x_0{}^{\wedge+} = E[x_0]$$
$$P_0{}^{\wedge+} = E[(x - x_0)(x - x_0)^T]$$

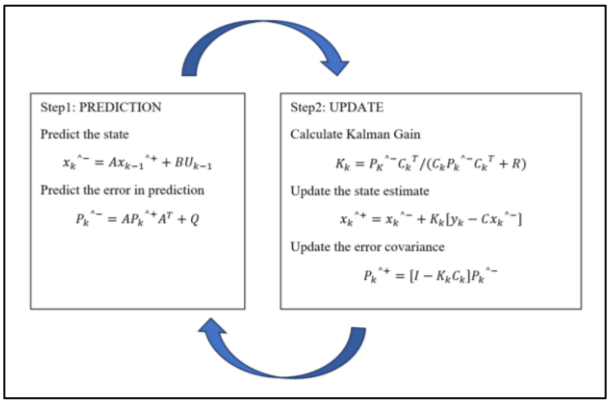

Figure 2: Kalman Filter Algorithm

Prediction:

Here the system model is used to calculate a priori state estimate $x_0{}^{\wedge+}$ and error covariance matrix $P_0{}^{\wedge+}$

Update:

Uses the priori estimate and priori error covariance along with current measurement to obtain the Posterior estimate. KG is calculated such that it minimizes the error covariance.

Where, $x_0{}^{\wedge+}$ =initial state of the system
$P_0{}^{\wedge+}$ = Initial error covariance
$x_k{}^{\wedge-}$ = Priori state estimate
$P_k{}^{\wedge-}$ = priori error covariance
A= state matrix
B= input matrix
C= observation matrix
Q= process error covariance
$x_k{}^{\wedge+}$ = Posterior state estimate
K_k = Kalman Gain

International Journal of Engineering Research & Technology (IJERT)
ISSN: 2278-0181
Vol. 8 Issue 07, July-2019

$P_k^{\wedge +}$= posterior error covariance
R= measurement error covariance
y_k= measurement at k

KG is the measure of how heavily the posterior estimate depends on measurement or on the model prediction.

E. Extended Kalman Filter

In real, no system is completely linear and KF is defined for linear systems only. In such a system, the state function or the observation function or both may be nonlinear [16]. Nonlinear state space system is as follows

$$x_k = f(x_{k-1}, u_k) + w_k$$
$$y_k = g(x_k, u_k) + v_k$$

$$w_k \sim N(0, Q) \text{ and } v_k \sim N(0, R)$$

$$A = \frac{\partial f(x_{k-1}, u_k)}{\partial x_{k-1}}$$

$$B = \frac{\partial f(x_{k-1}, u_k)}{\partial u_k}$$

$$C = \frac{\partial g(x_k, u_k)}{\partial x_k}$$

$$D = \frac{\partial g(x_k, u_k)}{\partial u_k}$$

Nonlinear functions f and g are linearized locally at each time step using Taylor series expansion and considering only first order terms known as Jacobians. A & B are first partial derivatives of function f w.r.t x_{k-1} and u_k.Matrices C and D are first partial derivatives of function g w.r.t x_{k-1} and u_k[17]. The Algorithm for Extended Kalman filter remains the same as that of Kalman filter. The Only difference lies with calculation of matrices.

F. Artificial Neural Networks

An Artificial Neural Network is an information processing algorithm that works similarly to the biological neurons in human brain. Neural Networks are characterized by their ability to model non-linear systems and their self-learning capability. A typical ANN consists of an input layer, one more hidden layer and an output layer. Each neuron in every layer is connected to each other neuron in succeeding layer. Depending, on the complexity and precision required, number of hidden layers vary. At input layer, battery parameters – terminal voltage, battery current both in past and present are used as input variables. Output is SOC [6]. In order to train the network, data sets are fed to the network.

In [6] NN was implemented using the software MathWorks MATLAB®. In addition to present values of terminal voltage and battery current, their past values are also used as input variables. As previous time inputs are considered, a better understanding is provided to the Neural Network. SOC is dependent on its previous value as well as external inputs.

Back- propagation is used to train the network. To perform under dynamic conditions, a varying battery current data set is considered. In [7], EKF in combination with NN is used and concluded that EKF-NN provides better results than EKF or NN alone. A battery with hysteresis is modeled and SOC estimated from EKF is fed to NN as input. In [9], a simple NN having 2 inputs, 1 hidden layer and 1 output layer is used. Back propagation algorithm is used. Voltage and current are inputs while SOC is output.

G. Fuzzy Logic

Fuzzy Logic describes fuzziness of the system. It is a multi-valued logic that allows intermediate values to be defined. Fuzzy logic is an extension of Boolean logic where there is no absolute truth but uncertainty. It is widely used to model nonlinear systems with high accuracy.

- FL uses the following 4 steps:

1) Fuzzification: It is the process of making a Boolean quantity into a fuzzy value and this is achieved by different membership functions. These functions define the degree of fuzziness.
2) Fuzzy Rule base: Fuzzy rules (If-then rules) are built according to system knowledge.
3) Interference: All the fuzzy rules are converted into fuzzy output variables.
4) De-fuzzification: It is the process of converting fuzzy back to a scalar value.

FL can be used where battery SOC in terms of high or low is enough rather than the precise SOC. In [10] two RC circuit model is used. All the model parameters are extracted experimentally. SOC and temperature are input variables for a FL controller and output is battery voltage. FL is used to build a battery model and this model is used in other SOC estimation techniques [11]. Cheng et al. in [12] is used to adjust the error covariance matrix in KF algorithm. In [13] FL is not directly used to estimate SOC but used to calculate polarization resistance. Where as in [14] SOC is directly estimated from FL controller.

III. CONCLUSION

SOC estimation is a complex task involving various factors such as battery modelling, temperature, effects, capacity fade due to cycling, sensor and measurement noise. Among all the SOC estimation methods discussed above, one or more methods can be combined according to user specific requirements to attain desired accuracy in SOC estimation.

All the methods are summarized in the below table 1.

Table 1: Summary of SOC Estimation Techniques

Method	Advantages	Disadvantages
OCV	• Easy method • Useful to determine SOC at extreme ends.	• Long rest time required • Offline method • Not applicable to all battery types
Coulomb Counting	• Relatively easy computation • Online	• Accuracy affected due to drift • Sensor error cannot be rectified.
ANN	• Applicable to all battery types • Online • No battery mathematical model required	• Data driven model required • Huge data set for training the network
EIS	• Can be online • SOH information also available	• External instrumentation required
KF /EKF	• Online	• Large computational capacity required. • Battery model is required. • Works on assumptions
Fuzzy logic	• Online • Applicable to all battery chemistries.	• High computational cost.

ACKNOWLEDGMENT

I, sincerely thank Mr. M.R. Saraf (H.O.D- SDL, AML and TG, ARAI) and Mrs. Ujjwala Karle (GM, Technology Group, ARAI) for giving me the opportunity to work as an intern at Technology Group Dept. I thank my guide Mr. Ravindra. G. Shah for his constant guidance. My mentor Mr. M. Siva for his insights and all the members of Technology Group for their valuable contribution.

ABBREVIATIONS

ANN- Artificial Neural Network

BMS- Battery Management System

CC- Coulomb Counting

EIS- Electro-chemical Impedance Spectroscopy

EKF- Extended Kalman filter

EVs- Electric Vehicles

FL- Fuzzy Logic

HEVs- Hybrid Electric Vehicles.

KF- Kalman Filter

OCV- Open Circuit Voltage.

SOC- State of Charge

SOH- State of Health

REFERENCES

[1] F. Huet, R. P. Nogueira, P. Lailler, and L. Torcheux, “Investigation of the high-frequency resistance of a lead-acid battery,” J. Power Sources, vol. 158, no. 2, pp. 1012–1018, Aug. 2006.

[2] E. Karden and R. W. De Doncker, “The non-linear low-frequency impedance of lead/acid batteries during discharge, charge and float operation,” in Proc. Intelec, Oct. 14–18, 2001, pp. 65–72.

[3] Martin Coleman, Chi Kwan Lee, Chunbo Zhu, and William Gerard 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, OCTOBER 2007

[4] Alex Densmore, Moin Hanif “Determining Battery SoC Using Electrochemical Impedance Spectroscopy and the Extreme Learning Machine”

[5] Andreas Christensen, Adetunji Adebusuyi “ Using on-board Electrochemical Impedance Spectroscopy in Battery Management Systems”, World Electric Vehicle Journal Vol. 6 - ISSN 2032-6653 - © 2013

[6] Ismail, M.; Dlyma, R.; Elrakaybi, A.; Ahmed, R.; Habibi, S. Battery state of charge estimation using an artificial neural network. In Proceedings of the 2017 IEEE Transportation Electrification Conference and Expo (ITEC), Chicago, IL, USA, 22–24 June 2017; pp. 342–349.

[7] Zhihang Chen, Shiqi Qiu, M.Abul Masrur, Yi Lu Murphey “Battery State of Charge Estimation Based on a Combined Model of Extended Kalman Filter and Neural Networks.”

[8] Shahriari, M.; Farrokhi, M. “Online state-of-health estimation of vrla batteries using state of charge.” IEEE Trans.Ind. Electron. 2013, 60, 191–202.

[9] Yan, Q.; Wang, Y.”Predicting for power battery soc based on neural network.” In Proceedings of the 2017 36th Chinese Control Conference (CCC), Dalian, China, 26–28 July 2017; pp. 4140–4143.

[10] Du Jiani, Liu Zhita, Wang Youyi and Wen Changyun.” A Fuzzy Logic-based Model for Li-ion Battery with SOC and Temperature Effect.” 2014 11th IEEE International Conference on Control & Automation (ICCA) June 18-20, 2014. Taichung, Taiwan.

[11] Ma, L.” Lithium-ion battery life evaluation method based on fuzzy nonlinear accelerated degradation process. “In Proceedings of the 2016 10th International Conference on Software, Knowledge, Information Management & Applications (SKIMA), Chengdu, China, 15–17 December 2016; pp. 309–313.

[12] Cheng, P.; Zhou, Y.; Song, Z.; Ou, Y. “Modeling and soc estimation of lifepo4 battery. “In Proceedings of the 2016 IEEE International Conference on Robotics and Biomimetics (ROBIO), Qingdao, China, 3–7 December 2016; pp. 2140–2144.

[13] Burgos-Mellado, C.; Orchard, M.E.; Kazerani, M.; Cárdenas, R.; Sáez, D. Particle-filtering-based estimation of maximum available power state in lithium-ion batteries. Appl. Energy 2016, 161, 349–363.

[14] Zheng, Y.; Ouyang, M.; Lu, L.; Li, J.; Han, X.; Xu, L. On-line equalization for lithium-ion battery packs based on charging cell voltages: Part 2. Fuzzy logic equalization. J. Power Sources 2014, 247, 460–466.

[15] Florin CIORTEA, Marian NEMES, Sorin HINTEA.” Graphical Interpretation of the Extended Kalman Filter: Estimating the State-of-Charge of a Lithium Iron Phosphate Cell” Advances in Electrical and Computer Engineering Volume 18, Number 3, 2018

[16] Zhihao Yu 1, Ruituo Huai 2 and Linjing Xiao 1,”State-of-Charge Estimation for Lithium-Ion Batteries Using a Kalman Filter Based on Local Linearization” Energies 2015, 8, 7854-7873; doi:10.3390/en8087854

[17] Tarun Huria, Massimo Ceraolo, Javier Gazzarri, Robyn Jackey.” High Fidelity Electrical Model with Thermal Dependence for Characterization and Simulation of High Power Lithium Battery Cells.”

[18] Davide Andrea, “Battery Management Systems for Large Lithium-Ion Battery Packs”, 1st Edition, Artech House.