

Implementing Fuzzy Logic to Improve the Accuracy of SoC Estimation for Li-ion Battery

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Abstract:- Over the decade, Electric Vehicles have revolutionized the automobile market. It is currently the vehicle of choice. For any electric vehicle, the battery plays a crucial role in comprehending the working of it. With the advent of the Battery Management System (BMS), it is easy to manage the power delivery to a battery load and also to understand the State of Charge (SoC) of a battery. Precision in SoC estimation of batteries is an essential task of the BMS. A blend of the existing methods for SoC estimation is used to get accurate results. In this paper, we have used one direct method and one indirect method namely coulomb counting and fuzzy logic respectively to demonstrate the improvement in the accuracy of SoC estimation. This paper also reviews on estimating SoC using various methods, its subsequent shortcomings and the future scope.

Keywords – State of Charge (SoC), Battery Management System(BMS), Fuzzy Logic, Coulomb Counting, Electric Vehicle (EV), Extended Kalman Filter(EKF), Artificial Neural Network(ANN)

I. INTRODUCTION.

Electric vehicles are vehicles that run either partially or fully on electricity. Depending on the part that drives the power, EVs are classified into- HEV (Hybrid Electric Vehicle) and BEV (Battery Electric vehicle). Unlike mainstream vehicles that use only gasoline or diesel-powered engine, EVs use an electric motor energised by electricity from batteries. These battery powers all or some parts of the vehicle.

Although EVs are highly sophisticated when compared to an IC engine, they have their glitches. Some such challenges with an EV include electric or electronic architecture, cooling aspects, Material technology, battery swapping, power switching, V to G communication etc. Accurate estimation of SoC being one such onerous challenge.

The state of charge (SoC) of a cell depicts the capacity that is currently available as a function of the rated capacity. The units of SoC are percentage points ranging from 0% to 100%. If the

SoC is 100%, then the cell is said to be fully charged, whereas a SoC of 0% indicates that the cell is completely discharged. An EV is charged based on the SoC reading. In practical applications, the SoC is not allowed to go beyond 50%. Similarly, as a cell starts aging, it loses the capacity that it is capable of holding. This means that for an aged cell, 100% SoC would be equivalent to a 75%-80% SoC of

a new cell. The inverse of SoC is referred to as Depth of Discharge (DoD) . This is an alternative form of the same measure.

Accurate estimation of SoC plays a pre-eminent role because a battery has to be maintained in a safe operating range for longer life span. Aging of the battery, battery temperature and C-rate are some of the factors that affect the SoC of a battery. Accurate SoC estimation is a predominant field of research.

II. DIFFERENT SoC ESTIMATION TECHNIQUES

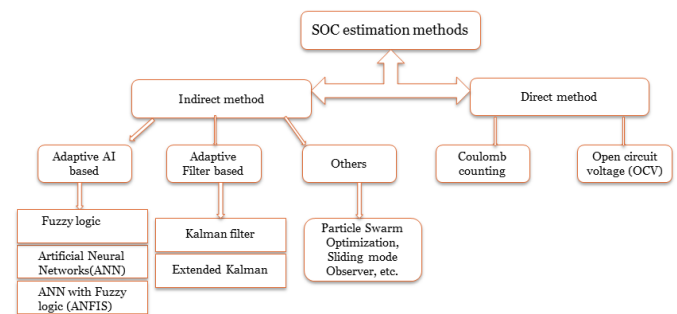


Figure 1.0 Classification of different types of SoC estimation methods.

Various SoC estimation methods are as follows-

- Extended Kalman Filter - There are several works in literature attempting to estimate SoC using Kalman Filter; majority of them being based on electrochemical models or ad hoc models. It works as a prediction-correction model that is independent of battery model precision. This type of estimation has high complex matrix operations that could lead to numerical instability. Some of the factors that affect the accuracy of Kalman Filter methods are temperature and improper battery model.
- Artificial Neural Network (ANN) - It is inspired by biological neurons and requires intense computing for estimation. Such an estimation requires training for a new battery. ANN depends on the hardware (a requirement for processors with parallel processing power). ANN with a back-propagation method is sensitive to noisy data.
- Fuzzy Logic - It offers a modern approach to solve SoC related queries that may contain ambiguous,

vague and imprecise input information/data. Fuzzy Logic is relatively less complicated when compared to ANN and this intelligent technique allows the translation of logic statements into non-linear mapping. Such a method can work with no or minimal data making the necessity for prerequisites ruled out. The modelling is not so cumbersome and makes it a flexible, user-friendly approach.

- Artificial neural network fuzzy inference system - In this method merged fuzzy neural networks (Fuzzy logic + artificial neural networks) are combined with reduced form genetic algorithms or any algorithm to obtain accurate results. It achieves a faster learning rate and lower estimation error. ANFIS includes the benefits of both ANN and the fuzzy logic systems.

- Open Circuit Voltage - This method requires longer resting time of the battery, thus referred to as offline prediction. OCV is the voltage difference of electric potential between two terminals of a battery when disconnected from load. It is an open-loop estimation [1].

It is observed that just one method cannot give accurate results. Hence, it is usually preferred to use a combination of more than one method to obtain error-free results. In this paper, we use coulomb counting along with fuzzy logic to obtain precise results.

III. FUZZY LOGIC.

Fuzzy logic is an approach to computing based on “degrees of truth” rather than the usual “true or false” (1 or 0) Boolean logic on which the modern computer is based. It consists mainly of four things.

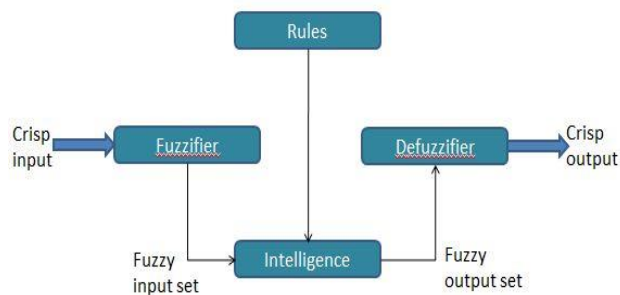


Figure 2.0 Fuzzy logic system.

1. Fuzzification: It is the process that allows the continuous valued variables to be transformed into linguistic variables. In other words it is the process of converting crisp input set into fuzzy input set. Degree of truth which is an extension of evaluation in fuzzy logic is known as membership function. There are various membership functions:

- Triangular
- Trapezoidal
- Gaussian
- Piecewise linear
- Singleton

The used membership function in the proposed model is trapezoidal membership function and parameters specified are the vectors $[a \ b \ c \ d]$.

- The membership function shape depends on the values of b and c :
- The resulting membership function when b is lesser than c is trapezoidal.
- The resulting membership function is equivalent to a triangular membership function when b is equal to c .
- When c is lesser than b , the resulting membership function is triangular with a maximum value less than unity.

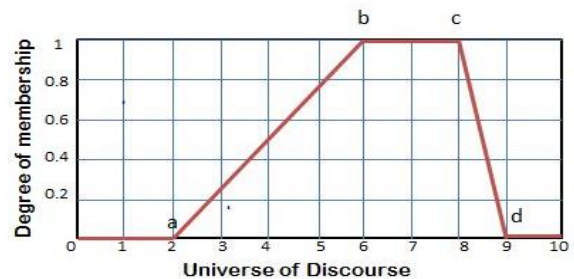


Figure 2.1 Trapezoidal Membership function of Fuzzy logic system.

2. Fuzzy rule set: These rules are set by intuitions and trials. These rules contain fuzzy if then rules which tells the input output relationship and also gives parameters for the fuzzy inference engine [2].

3. Fuzzy inference engine: It is the process of using fuzzy logic to formulate the mapping from a given input to an output. The mapping further provides a basis from which decisions can be made. The types of Fuzzy inference systems that can be implemented are Mamdani type and Sugeno type.

In a Mamdani system, the output of each rule is a fuzzy set. Since Mamdani systems have more intuitive and easier to understand rule bases, they are well-suited to expert system applications where the rules are created from human expert knowledge hence the inference system used in the proposed model is the Mamdani system.

Defuzzification: It is the final step in a fuzzy inference mechanism. It is the process of converting fuzzy output set which is obtained after applying fuzzy rules, into crisp values (numerical values).

Different Defuzzification Methods:

- Centre of Sums Method (COS):
- Centre of gravity (COG) / Centroid of Area (COA) Method:
- Centre of Area / Bisector of Area Method (BOA):
- Weighted Average Method:
- Maxima Methods:
 - First of Maxima Method (FOM)
 - Last of Maxima Method (LOM)
 - Mean of Maxima Method (MOM)

The defuzzification method widely used is the centroid method. In this method the total area is divided into a number of sub-areas. The area and the centre of gravity or centroid of each sub-area is calculated.

For discrete membership function, the defuzzified value denoted as x^* using COG is defined as the ratio of summation product of sample element x_i and membership function $\mu(x_i)$ to that of the summation of membership function.

For continuous membership function, x^* is defined as the ratio of integral product of sample element and membership function to that of integral of membership function.

IV. PROPOSED PROTOTYPE.

A Li-ion battery is a portable battery that is commonly utilized in electronic applications. It is widely used due to its high power-to-weight ratio, high energy efficiency and good high-temperature performance. Initial SoC can be obtained by operating the battery in different modes that are charging, discharging and open circuit mode. In this paper, we propose to use a Li-ion battery with an initial state of charge fixed to 100%. The battery is discharged thereafter. A coulomb counter cannot identify the initial charge of a battery. The initial SoC has to be known for CC estimation. In a coulomb counter, small errors accumulate over time due to the integral term [3]. This is overcome by feeding the error from the coulomb counter to a fuzzy logic controller.

The model is operated with an ideal Li-ion battery with 3.6V nominal voltage, 10 ohm resistance and 2.6Ah rated capacity. The discharge time depends on the load considered. Here, the complete discharge takes place before 6.6 hours. The source of the fuzzy logic controller is the output from the coulomb counter [4].

$$SOC(t) = SOC(t-1) + \int_0^t \frac{I}{C_{bat}} dt$$

Where:

SOC (t) – Battery SoC at time t (%)

SOC (t-1) – Battery initial SoC (%)

I – Charge/ Discharge Current [A]

t – time (h)

The proposed battery model is as follows –

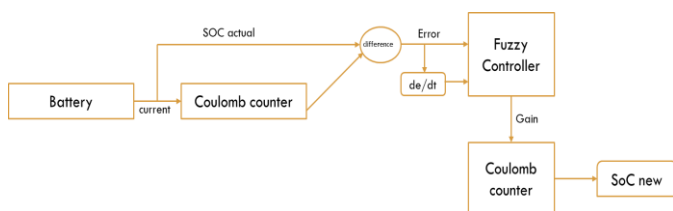


Figure 3.0 Block diagram of proposed model.

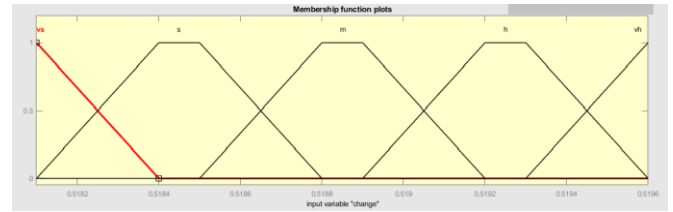


Figure 3.1 Membership function of error.

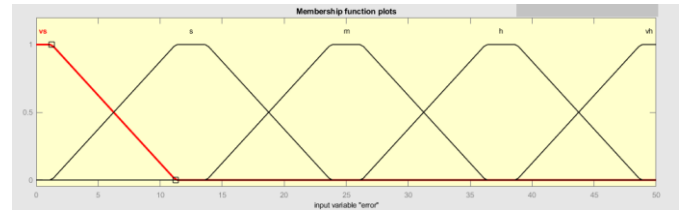


Figure 3.2 Membership function of change in error.

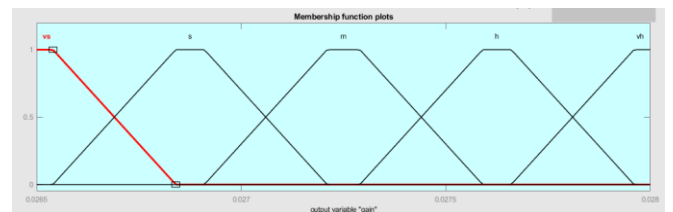


Figure 3.3 Membership function fuzzy output gain.

The highlighted parts of fig 3.1, fig 3.2 and fig 3.3 illustrates that when the error and change in error is very small, the gain is also very small by fig 3.4. Numerically, when the error is 1.25 and change in error is 0.5181, the gain obtained is 0.02654.

dE	vs	s	M	H	VH
vs	vs	S	M	H	VH
S	S	S	M	H	VH
M	M	M	M	H	VH
H	H	H	H	H	VH
VH	VH	VH	VH	VH	VH

Figure 3.4 Fuzzy rule table.

V. SIMULATED MODEL AND RESULTS.

The diagram below depicts the model employed. It includes a resistive load along with measurements for ambient temperature. The current drawn from the battery is given to a coulomb counter and the SoC error obtained as the output along with its derivative is inputted to a FLC whose output is fed to another coulomb counter, which is a replica of the first.

A Mamdani approach based fuzzy controller is incorporated. The fuzzy inference system was built for a 5x5 table to get accurate results. From various trials, it can be observed that the simulation results change for different battery types, applied load, fuzzy logic approach and the battery parameters that are taken into account.

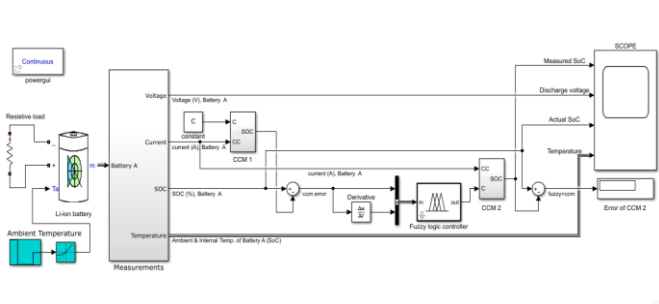


Figure 4.0 Simulated model for SoC estimation.

Various graphs are obtained taking SoC error vs time and voltage vs SoC.

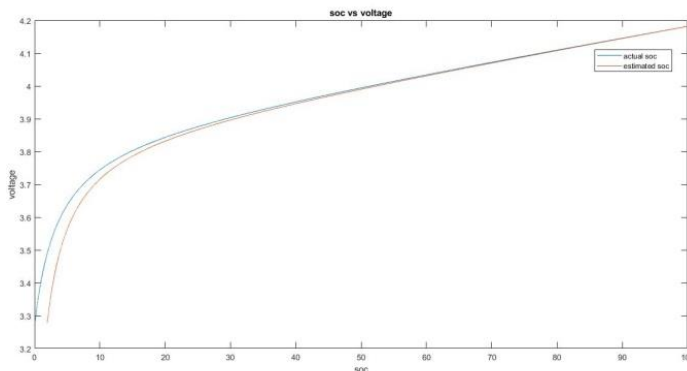


Figure 4.1 soc vs voltage graph.

The graph in fig 4.1 depicts the SoC vs voltage curve for the simulated model. When the battery is fully discharged, it is observed that the SoC gradually decreases with decrease in voltage. Initially when the SoC was 100%, the voltage is 4.184 volts and when the SoC is 0, the voltage discharges to 3.269 volts.

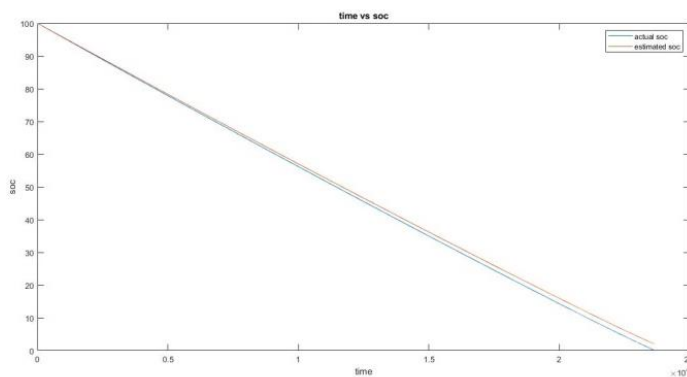


Figure 4.2 time vs soc.

The graph in fig 4.2 demonstrates that SoC gradually decreases with time whose decay rate depends on the load provided to the battery. This is the time vs SoC characteristic behaviour of the model when its fully discharged from an initial SoC of 100% to a final SoC of 0% ; the estimated error being 1.9% .

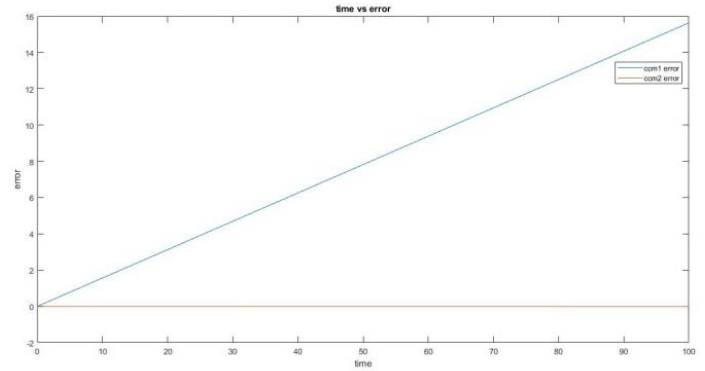


Figure 4.3 time vs error.

The time vs error behaviour of the model when its discharged for 100 sec is as shown in fig 4.3. The graph contains the error obtained while estimating the SoC from CCM 1 and CCM

2. Initial SoC is 100%. When the model was simulated for 100 seconds, the actual SoC is 99.5% and the SoC obtained in CCM 1 is 83.92% with the error of 15.64 whereas the SoC obtained in CCM 2 is 99.56% with the error of -0.01. It can be observed that the error obtained by using fuzzy logic is minute compared to coulomb counting.

From the simulated graphs, it is evident that coulomb counting has significant errors because of which this method becomes inefficient. The small errors accumulate over time in the coulomb counter due to the integral term in the formula. To overcome the loophole with a coulomb counter, the output of the counter is given to a fuzzy inference system, which when fed back to another coulomb counter exhibits a remarkable improvement. The error so obtained is negligible.

The initial SoC was set to 100%. On simulating the model for 100 seconds, the results obtained were as follows-

- Actual SoC dropped to 98.52%
- The output of Coulomb counter 1 dipped to 46.66%
- The outcome of fuzzy logic and coulomb counter 2 was 98.51; which is very close to the actual SoC.

VI. MERITS AND DEMERITS OF THE PROPOSED MODEL.

The proposed model shows that one method from the direct and indirect method each could reduce the estimation error to a large extent as both the models are coalesce.

A Fuzzy Logic System is flexible and allows modification in the rules. Even imprecise, distorted and error input information is also accepted by the system. The output of a FLS completely depends on the rules generated making it system independent.

Coulomb counting is a simple solution towards accurate SoC estimation. The losses obtained in the estimation reduce the total energy delivered, and what is available at the tail-end is always less than what had been put in. Despite this, coulomb counting works well, especially with Li-ion that offers low self-discharge and high coulombic efficiency.

Coulomb counting, also referred to as Ah method has a drawback that the initial SoC of the battery has to be known. This is not always possible. This method uses the current drawn from the battery to determine its SoC. However, the accumulated error in current measurement may cause inaccurate estimation as the accuracy also depends on sensor measurement.

Wang et al. [6] proposed a new SOC estimation method, denoted as “KalmanAh method”. This paper states that the estimation error using coulomb counting is as large as 11.4 % whereas our proposed prototype provides errors of less than 2%.

VII. FUTURE SCOPE.

The model is proposed for a single battery. Practically, EVs use enormous battery packs with a necessity of equalization of each of them. A battery model would hence make it easier to work on sizable battery packs. Higher-order battery models with combinations of R and C will give accurate results by minimizing the error. By considering battery aging, temperature, discharging cycles and total cycle life of the battery the error can be minimized to a larger extent and thus get the desired output.

Furthermore, modern methods like Extended Kalman Filter [7], [8] or Artificial Neural Networks along with Fuzzy Logic would fairly provide notable results.

VIII. CONCLUSION.

The state of charge provides users with information on how long a battery can perform before it has to be charged or replaced. It is of foremost importance to track the SoC, especially in EVs. An innovative estimation method that integrates coulomb counting and fuzzy logic system has been proposed to combine the quality features available in them. This MATLAB simulation model boosted the accuracy of SoC estimation.

IX. ACKNOWLEDGEMENT.

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