Modeling and State Of Charge Estimation of a Electric Vehicle Battery

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Abstract: This paper describes about the performance analysis of a EV battery by implementing a mathematical battery model and comparing the battery parameters (SOC, battery voltage, battery current) with a MATLAB/SIMULINK battery model. To analyze the performance of the battery, a Simulink battery model of nominal voltage of 12V and rated capacity of 2.7Ah is taken to observe the complete discharging and charging of the battery based on the running time of the model. A mathematical model of nominal voltage(24V) and rated capacity(30Ah) is taken to compare the parameters with the Simulink battery model. This paper aims to compare the parameters of the battery for model validation through percentage error calculation.

KEYWORDS: EV, SOC, MATLAB/SIMULINK, model validation

DOI of the Article: https://doi.org/10.46501/IJMTST0706026

Available online at: http://www.ijmtst.com/vol7issue06.html

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To Cite this Article: Juhi Jasiha E and Dr. Rajeswari R. Modeling and State of Charge Estimation of a Electric Vehicle Battery. *International Journal for Modern Trends in Sceicen and Technology* 2021, *7*, 0706125, pp. 147-153. https://doi.org/10.46501/IJMTST0706026

Article Info. Received: 16 May 2021; Accepted: 6 June 2021; Published: 13 June 2021

INTRODUCTION

Petroleum resources throughout the world is decreasing at a high rate due to the large dependency of the transportation sector on petroleum as the primary fuel. Due to this there is a vast greenhouse gas emission that is degrading the quality of air and causing harm to life and environment. Therefore an alternate propulsion technologies have been increasingly pursued by the automobile industries and this led to the increased development rate of the Hybrid Electric Vehicles (HEV) or Battery Fed Electric Vehicle technology (BFEV) for the past two decades.

STRUCTURE OF PAPER

The paper is organized as follows: In Section 1, the introduction of the paper is provided along with the structure, important terms, objectives and overall description. In Section 2 we discuss related work. In Section 3 we discuss about the charging and discharging test to be done for the SOC estimation of the battery and also the modeling equations taken for model validation. Section 4 discuss about the Simulink model to observe the complete discharging and charging og the battery and also discuss the developed mathematical battery model. Section 5 discuss about the results obtained from the Simulink and mathematical model for model validation through percentage error calculation. Section 6 tells us about the future scope and concludes the paper with references.

OBJECTIVES

This project aims to analyze the performance of the battery by observing complete discharging and charging of the Simulink battery model. This project also aims to implement a mathematical battery model and to compare the parameters of the battery with a Matlab/Simulink model for model validation through percentage error calculation.

RELATED WORK

Zhimin Xi, Member, IEEE, Modjtaba Dahmardeh, Bing Xia, Yuhong Fu, Chris Mi, Fellow,IEEE[1] proposed about State of charge (SOC) estimation of lithium- ion batteries has been extensively studied and the estimation accuracy was mainly investigated through the development of various battery models and dynamic estimation algorithms. All battery models, however, contain inherent model bias due to the simplifications and assumptions, which cannot be effectively addressed through the development of various algorithms such as Kalman filtering (KF) or particle filtering (PF). Consequently, as observed in some study, battery SOC estimation using a typical extended KF in fact is not very accurate where the error could range from 5% to 10% or even more depending on the battery characteristics. This paper proposes bias characterization of the battery model so that accuracy of the baseline model could be significantly improved and eventually SOC estimation could be much more accurate than the one only using the baseline model. This paper reports great potential for improving battery SOC estimation with the bias characterization and proposes two methods for actual bias modeling. In particular, the polynomial regression model and the Gaussian process (GP) regression model are proposed to examine the effects of the two methods on bias modeling and SOC estimation using a typical battery circuit model.

Mark Sitterly, Student Member, IEEE, Le Yi Wang, Senior Member, IEEE, G. George Yin, Fellow, IEEE, and Caisheng Wang, Senior Member, IEEE[2] Renewable energy generation, vehicle electrification, and smart grids rely critically on energy storage devices for en- hancement of operations, reliability, and efficiency. Battery sys- tems consist of many battery cells, which have different character- istics even when they are new, and change with time and operating conditions due to a variety of factors such as aging, operational conditions, and chemical property variations. Their effective man- agement requires high fidelity models. This paper aims to develop identification algorithms that capture individualized characteris- tics of each battery cell and produce updated models in real time. It is shown that typical battery models may not be identifiable, unique battery model features require modified input/output expressions, and standard least-squares methods will encounter identification bias. This paper devises modified model structures and identifica- tion algorithms to resolve these issues. System identifiability, algo- rithm convergence, identification bias, and bias correction mecha- nisms are rigorously established. A typical battery model structure is used to illustrate utilities of the methods.

Ryan Ahmed and Mohamed El Sayed[3] represents a paradigm shift from conventional, fossil-fuel-based vehicles into the second-generation electric and hybrid vehicles. Electric vehicles (EVs) provide numerous advantages compared with conventional vehicles because they are more efficient, sustainable, greener, and cleaner. The commercial market penetration and success of EVs depend on the efficiency, safety, cost, and lifetime of the traction battery pack. One of the current key electrification challenges is to accurately estimate the battery pack state of charge (SOC) and state of health (SOH), and there- fore provide an estimate of the remaining driving range at various battery states of life. To estimate the battery SOC, a high-fidelity battery model along with a robust, accurate estimation strategy is necessary. This paper provides three main contributions: 1) introducing a new SOC parameterization strategy and employ- ing it in setting up optimizer constraints to estimate battery parameters; 2) identification of the full-set of the reduced-order electrochemical battery model parameters by using noninvasive genetic algorithm optimization on a fresh battery; and 3) model validation by using real-world driving cycles. Extensive tests have been conducted on lithium iron phosphate-based cells widely used in high-power automotive applications. Models can be effectively used onboard of battery management system.

Kaveh Sarrafan, Kashem M. Muttaqi, and Danny Sutanto [4] A precise estimation of the state of charge (SoC) of the lithium-ion battery is crucial for reducing range-anxiety and improving the performance of the electric vehicle (EV) battery management system. An accurate estimation of the SoC, however, has remained elusive due to the complex and nonlinear behavior of the battery. In this paper, a new mixed estimation model (MEM) for the battery parameters and the SoC estimation is proposed, where the route is specified before the travel. The new MEM uses a combination of a battery power- based method (BPBM), a combined model, and a partial adaptive forgetting factor recursive least-square (PAFF-RLS) SoC calibration algorithm to make use of the best characteristics of each model to determine a better and more accurate SoC estimation. The partial adaptive forgetting factors solves the issue of the different rate changes in the battery parameters and reduces the complexity of the algorithm compared to the fully adaptive recursive models. The BPBM allows various travelling factors to be included in the model, such as the environmental conditions, the effect of auxiliary loads, and the traffic congestion. To verify the validity of the PAFF-RLS algorithm, two laboratory tests using real-time driving cycles have been conducted on a 2012 Nissan Leaf 31.1 Ah Manganese-oxide Li- ion battery cell. The effectiveness of the MEM model has been demonstrated by driving the Nissan Leaf along two selected routes in Australia. The results demonstrate the great accuracy of the proposed method for the SoC estimation, when compared with those from the previous models.

SOC ESTIMATION OF A EV BATTERY

The state of charge (SOC) of a battery represents the capacity of the battery available based on the rated capacity of the battery. The SOC of a battery usually varies between 0% and 100%. If the SOC is 100%, then the EV battery is said to be fully charged, when the SOC is 0% , then the battery is said to be completely discharged. Generally, the SOC is not allowed to go beyond 50%and therefore the cell is recharged when the SOC reaches 50%. Similarly, when a cell starts aging, the maximum SOC starts decreasing. So thereby for an aged cell, a 100% SOC would be equivalent to a 75%–80% SOC of a new cell.

Charging And Discharging Tests

Charging and discharging test for a MATLAB/Simulink battery is done in this paper to analyse the performance of a battery. A nominal voltage of 12V and rated capacity of 2.7Ah is taken to observe complete discharging and charging based on the running time of the Simulink model and also depends on the battery response time.

Battery Modeling

Formathematical modeling of a battery, the following are the equations required to determine SOC, voltage and current in the battery

Battery voltage:

$$V_{bat} = E_0 + V_{pol} - R_i - R_{pol}(i) + V_{exp}$$

where,

E_0 = battery constant voltage given

V_{pol} = polarization voltage

[polarization refers to the effect of reducing the performance of the battery]

R_i = voltage drop across the battery

R_{pol} = polarization resistance [resistance between the electrode and electrolyte of battery]

V_{exp} = exponential voltage [voltage of the battery decreases exponentially during discharging]

$$V_{pol} = K * \frac{Q}{Q - it}$$

$$R_{pol} = \mathrm{K} * \frac{\mathrm{Q}}{\mathrm{Q - it}} \quad \text{for i} > 0\ (discharging)$$

$$R_{pol} = K * \frac{Q}{it - 0.1Q} \quad for\ i < 0\ (charging)$$

$V_{exp} = A_{exp}$ (- B*it)

where, K = polarization voltage constant (0.006)

A = exponential zone amplitude (2.01)

E_0 = battery constant voltage (24)

B = exponential zone time constant inverse (2.03)

Q = rated capacity of the battery (30)

R = internal resistance (0.008)

<u>SOC of the battery:</u>

$$Soc = Soc_0 - \frac{it}{Q}$$

where

Soc_0 is the initial state of charge given to the battery

<u>Battery current:</u>

$$it = \frac{1}{C_n} \int idt$$

where, C_n is the integration constant

SIMULATION RESULTS AND DISCUSSION

Simulink model to observe complete discharging:

The Simulink model to observe complete discharging of battery is given below in figure 1.

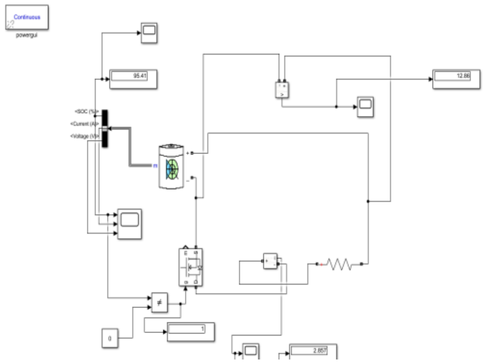

Figure 1 Simulink model for battery discharging

For battery discharging, a battery pack of nominal voltage of 12V and rated capacity of 30Ah is taken. The initial SOC of the battery is maintained as 96. Voltage measurement reads the voltage across the battery and current measurement with the resistive load reads the current in the battery. MOSFET is used as a switch and relational helps to turn ON and turn OFF the MOSFET, The SOC, battery voltage and current discharges according to the running time of the model and response time of the battery which is given below in figure 2. The battery parameters completely becomes zero when it discharges completely as shown in figure 3.

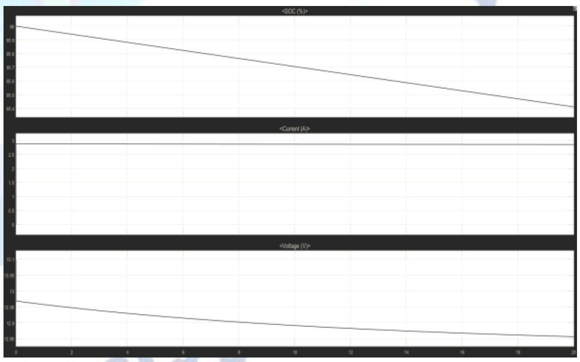

Figure 2 battery discharging during initial stage

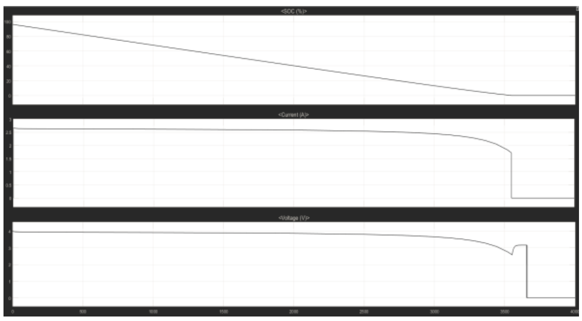

Figure 3 complete discharging of battery

Simulink model to observe charging of battery:

The Simulink model to observe charging of a battery is given below in figure 4.

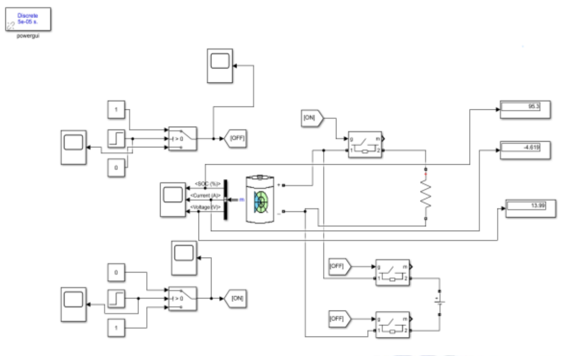

Figure 4 Simulink model for battery charging

For battery charging, the same battery pack of nominal voltage of 12V and rated capacity of 2.7Ah is taken for simulation. The initial SOC of the battery is maintained as 95. A unit step input is given to the two switches where anyone of the switches should be turned ON at the same time where the other switch will be remained OFF. When the switch is turned ON, the battery discharges through the resistive load connected across the battery. When the switch is off, the battery charges through the DC load connected to the battery with ideal switches. The waveform of the parameters observed during battery charging is given in figure 5.

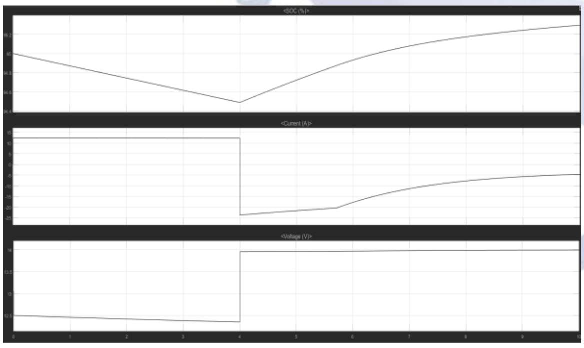

Figure 5 waveform of charging of battery

Battery modeling for model validation:

The Simulink mathematical model of a battery for model validation through percentage error calculation is given in figure 6. The mathematical equations used in this model are mentioned inside the subsystem block in figure 7.

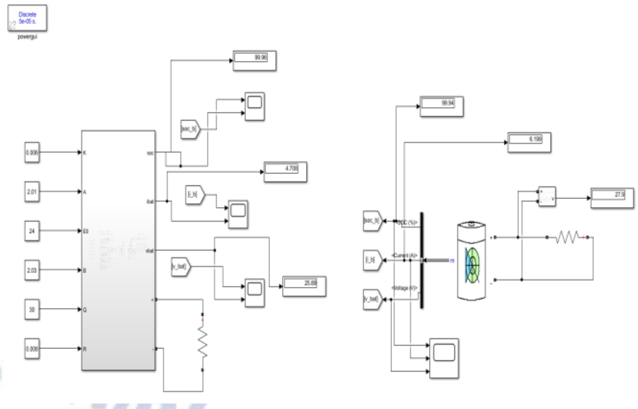

Figure 6 Mathematical battery model

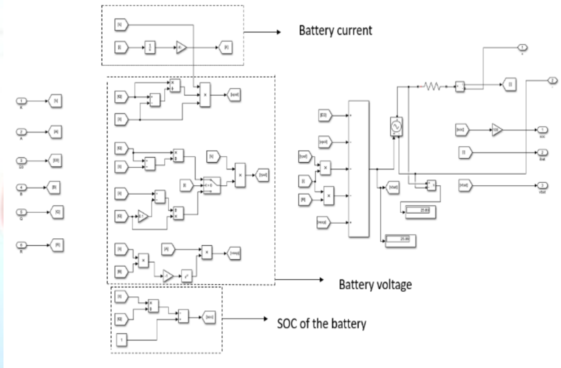

Figure 7 Subsystem Block of battery model

The compared waveforms of the mathematical model with the MATLAB/SIMULINK model are given in figure 8, figure 9 and figure 10.

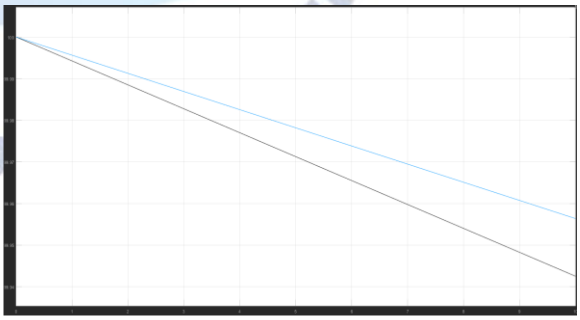

Figure 8 SOC of the battery

Figure 9 Battery voltage

Figure 10 Battery current

MODEL VALIDATION FOR PEREENTAGE ERROR CALCULATION

PARAMTERS OF BATTERY	MATHEMATICAL BATTERY MODEL	MATLAB/ SIMULINK BATTERY
Stateof Charge	99.96	99.94
Battery voltage	25.89	27.9
Battery current	4.708	6.199

Table 1 comparative results obtained from modelling

Percentage Error Calculation

Percentage error is generally calculated in a system or a electrical model to analyze the percentage variations between the measured values of the compared model or a system. Here the results of the parameters from the mathematical model and Simulink model are taken to calculate percentage error.

Percentage error:

$$\%error = \frac{measured\ \ value - theoretical\ \ value}{theoretical\ \ value} * 100$$

Percentage error calculation for EV battery: $\%error = \frac{measured\ \ value\left(mat\,hematical\ \ model\right) - measured\ \ value\left(simulink\ \ model\right)}{initial\ \ value\ \ assigned}$ *100

% error for SOC:

%error =((99.96-99.94)/100)*100

= 0.02%

where initial SOC for both the models are assigned to be 100.

% error for current:

%error = ((4.708-6.199)/16)*100

= 9.31%

where the current for both the models are assigned to be 16A.

% error for voltage:

%error = ((25.89-27.9)/24)*100

= 8.375%

where the nominal voltage for both the models are assigned to be 24V.

CONCLUSION AND FUTURE SCOPE

Model validation through percentage error calculation for a battery model of nominal voltage (24V) and rated capacity of (30Ah) have been done. A good battery model can maintain a percentage error upto 10% - 15%. Here our model has maintained the percentage error below 10%. For further reduction of percentage errors in a battery model filter algorithms can be used for battery management systems.

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