Comparative Study on SOC Estimation Techniques for Optimal Battery Sizing for Hybrid Vehicles

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Abstract**—**Automotive Industry is growing at a very fast rate. Hence problems pertaining to the increasing CO2 levels in the atmosphere and the ever increasing fuel rates also increase. Electric and Hybrid electric technology has become the latest milestone for the automotive industry. In Hybrid Electric Vehicles (HEV), the reliable range of operation is characterized by batteries and battery state of charge (SOC), that describes its remaining capacity, is an important factor for providing the control strategy for the battery management system (BMS) in plug-in hybrid electric vehicles (PHEV) and electric vehicles (EV). Accuracy in estimation of the SOC is necessary not only to protect the battery, prevent it's over discharge, and improve the battery life but also to allow the application to make rational control strategies to save energy. However, the chemical energy of a battery which is a chemical energy storage source cannot be directly accessed and this issue makes the estimation of the SOC of a battery difficult. Hence, estimation of the SOC accurately becomes very complex and is difficult to implement, as there are parametric uncertainties and the battery models are limited. In fact, in practice several examples of models of the estimation of the SOC are found which have poor accuracy and reliability. Hence a comparative study done in this paper on the various methods will help choose the right method based on the requirements and the application. This paper also reviews a case study on modeling and simulation of one of the methods of SOC estimation and efforts have been put in obtaining the performance of Li-ion batteries by calculating the SOC using Coulomb counting method in MATLAB Simulink.

Keywords*-State of Charge (SOC); Battery capacity; lithium-ion battery; state of charge; state of health; SOC dependence on battery parameters.*

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I. INTRODUCTION

For determination of an electrical system capacity and selection of optimum component, the approach of modeling and simulation is beneficial. In the simulation of an electrical system, the battery sub-model is very crucial, and the fidelity of the battery model needs to be high in order to obtain meaningful simulation results. Some important papers were surveyed to study the modeling and simulation of Lithium-ion Battery for Optimal Battery Sizing for Hybrid Vehicles.

Over the next decade, due to the increasing concern over global warming and fossil fuel depletion [1], the electric and hybrid electric technology powered by lithium batteries is expected to become more common. However, some challenges still remain unresolved, the state of charge estimation being the most notable one, which provides information about the vehicle's range capability to the driver.

In battery technology, State-of-charge (SOC) determination is an increasingly important issue. In addition to the immediate display of the remaining battery capacity to the user, precise knowledge of SOC exerts additional control over the charging/discharging process, which can be employed to increase battery life [3]. Some studies have presented a state of charge (SOC) and a state of health (SOH) estimation method for batteries [2] by explaining the measurements of battery's terminal voltage, current and temperature that are used in the process of SOC calculation.

The Vehicles on today's battlefield need batteries for more than just starting, lighting and ignition (SLI) loads [6]. Power requirements and the need to provide this power during silent watch scenarios have been steadily increasing as modern vehicles use increasingly more sophisticated communications and other electronics systems.

Along with this need for more power is a need to communicate to the war fighter the state of their vehicle batteries. Battery management that provides the war fighter with accurate information about the current state of charge and health of their vehicle batteries will allow them to use the energy in their batteries without fear of not being able to start their vehicle after a silent watch. Lithium Ion batteries, particularly Nano phosphate, show great potential for providing long life, high capacity, light weight, safe solutions to these issues, enhancing the war fighter's capabilities in the field.

Battery state of charge (SOC) is a critical parameter for the control of propulsion systems in plug-in hybrid electric vehicles (PHEV) and electric vehicles (EV) [5]. It has been explained that the parameter estimation algorithm can be used, that estimates six electrical parameters for Li-ion batteries and provides a reliable SOC based on one of the estimated battery parameters, i.e. open circuit voltage (OCV). Simulation and based on the study made in the papers, vehicle validation results show good robustness and adaptation of the algorithm with high computational efficiency and low implementation complexity.

II. STATE OF CHARGE (SOC) OF A BATTERY

In determining the battery output, the most important parameter is the battery capacity. Battery capacity is a measure of battery's capability for sustained discharge of the current over certain period of time [1]. SOC is an alternative representation of the battery capacity. SOC also helps obtain the state of health (SOH) of the battery.

The common expression is:

$$SOC(t+\delta t) = 1 - \frac{USEDCAP(t+\delta t)}{CAP(t+\delta t)}$$

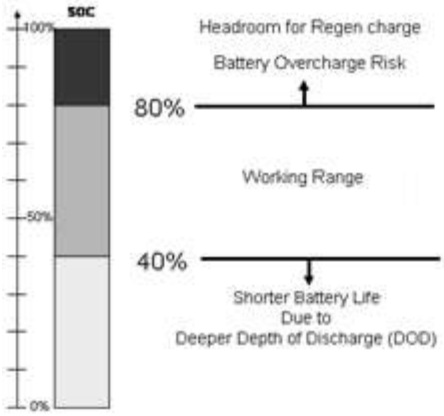

Figure 1. HEV Battery Operating Range

III. Comparative Study on Various SOC Estimation Techniques

There are various methods or approaches by which the State of Charge of a Battery can be estimated:

A. *Voltage based SOC correction*

Relationship between the battery open-circuit voltage and SOC is used by the Open-circuit-voltage method to estimate SOC by measuring the battery open-circuit voltage. Open-circuit voltage method being a high precision and simple method also has a higher demand of rest time. In order to obtain the stable value of open-circuit voltage, the battery should be stalling for long time. It is only applicable to the electric car in the stop state, not for the dynamic battery SOC estimate. However, in a hybrid power system, the start, charge and discharge are frequent and the working conditions are complex and changing with time. Due to the volatile working current, it is difficult for open-circuit voltage to achieve stability in a short time. And many factors such as the stop state of SOC, discharge current, change frequency influence the needed time for stability hence making its determination difficult.

The advantage is that, in general, after the battery rests for a long time (typically several hours) an equilibrium voltage is measured, and is considered as the OCV. Then, with the help of lookup table, the OCV is used to find the correct SOC. But the disadvantage is that, however, such a several-hour rest is very rare in the PHEV and EV applications. Recently, new methods estimating OCV online and inferring SOC from the estimated OCV have been developed. Also, these methods are more suitable in small-power electronic application, where the required power is usually near to be constant and small. It also has limitations with respect to measurement of OCV in cold temperature environment.

B. *Mass recuperation model*

In the JPL/Purdue model [4], recovery of the battery capacity from intermittent discharges is considered in the SOC determination by a “mass recuperation” concept.

“Mass recuperation” reflects the fact that the capacity changes due to intermittent discharges and varies with the discharge rate. It assumes that there is an optimal capacity and that some of this capacity is recuperated during periods of little or no activity.

But the disadvantage is that, this model accounts for capacity changes during intermittent discharging, but self-discharge is neglected.

C. *Fractional utilization model*

The fractional utilization model assumes that during each time increment of a driving schedule, a portion of the battery mass is depleted and a fraction of mass is regained during regenerative braking and regeneration. This mass concept is an equivalent representation of the SOC. It employs mass recuperation concept.

The disadvantage of this representation is that the mass recuperation concept is not an exact representation of the electrochemical and physical-chemical process in battery. The active mass is difficult to determine for the specific battery. The properties of the cell electrodes are affected not only by the composition of the active mass but also by factors such as heating, discharging pattern, aging, and temperature. Besides, the total mass in the fractional utilization model, and the optimal capacity in the Purdue model, assumed to be a constant can hardly give a credible and close account on the capacity losses.

Some facts pertaining to this method are that,

- Fractional utilization model applies to constant power discharge only, which is not the case in most HEV driving condition.
- The mass transfer time constant in Purdue model for determining the mass recuperation is assumed to be known. This makes the model difficult to apply in applications where this information is not available or measurable.

D. *ADVISOR model*

ADVISOR implements its battery model by using Peukert capacity as the total capacity and the Ah capacity for the used capacity in SOC definition. It is based on the known parameters of V_{oc} and R under each SOC.

E. *Neural Networks and Fuzzy Logic*

Artificial neural network is one of the oldest techniques and has a history of half a century. Currently it has got a wide range of applications and as far as the nonlinear dynamic system modeling is considered, it is the main research method used. The battery is a highly nonlinear system which is hard to establish the accurate mathematical model of charging and discharging process. A nonlinear basic characteristic with parallel structure exists in neural network along with the learning ability. Thus, corresponding output can be given to external incentives and complex nonlinear system in any precision can be approached. With the use of neural network technique, high prediction accuracy and efficiency can be obtained. So it can be an effective approach to simulate the dynamic characteristics of the battery and have accurate SOC estimation.

For SOC estimation, the method utilizes three layers of typical neural network rate: input layer, output layer and the middle layer. Based on the actual need the number of neurons of input layer and output layer is determined. Generally it is a linear function. The complexity of the problem and analysis

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precision defines the number of neurons in the middle layer. For SOC estimation, the input variables are voltage, current, power, temperature, accumulated released power, resistance, environmental temperature, etc. Based on how appropriate the choice of neural network input variables is, there will be a direct influence on the accuracy of the models and calculation. Generally, to all the types of batteries, the method of neural networks can be applied. The issue faced in using this technique is that a large number of reference data is need for the training and there is a heavy influenced of the trained data and training methods on the estimation error.

The advantage is that, it is usually possible to have a good SOC estimation with the method of neural networks. But the disadvantage is that, the computational power needed is high, which is not usually available in an embedded system.

F. Coulomb Counting Method

Coulomb counting method or Ah counting method uses the integral of load current to estimate SOC. This method is a simple and stable method if the current is measured accurately and there is enough data for the start of state estimation and can be used for all electric car batteries. Firstly, there is a requirement of fixed start state of SOC for estimation for the Ah counting method. In fact, the start work or end work may happen at any time in the hybrid power system. Therefore, SOC measurement errors appear larger in the initial stage. Secondly, only for stable load occasions, the Ah counting method is suitable. But since each work device for homework need different power, the working condition is complex when hybrid power system works. Due to higher change frequency, the battery often tends to be working in severe electrochemical reaction process. Thus the accumulative measurement error of SOC becomes larger.

More details are provided in section IV of this paper.

G. Model-Based method

The Model-Based method is an indirect method because it uses the relationship between the battery voltage, usually the Open-Circuit-Voltage (OCV), and the battery State-of-Charge to provide the estimation. A battery model is used to compute the OCV by the Model-based method. The model proposed in [7] has been used.

According to that model, the OCV can be computed as:

$$V_{OCV}(SoC) = V_m(t) - G(s)I_m(t)$$

where

$$G(s) = \left(R_0 + \frac{R_1}{1 + sR_1C_1} + \frac{R_2}{1 + sR_2C_2}\right)$$

and $I_m(t)$ and $V_m(t)$ are the measured current and voltage of the battery. Based on the Open-Circuit-Voltage, the SoC value is then estimated using the relationship between OCV and SOC. The Model-based method uses a battery model to compute the OCV.

As compared to the Coulomb-Counting method, the Model-Based algorithm is more complex because an interpolation is performed in the latter. However advantage is that, since uses more information, it can theoretically provide a more accurate estimation. [2].

Even though it still has some disadvantages of this method:

- It needs an accurate battery model to estimate the Open- Circuit-Voltage.
- It uses the relationship between the Open-Circuit-Voltage and SOC, which usually in lithium-ion batteries is highly constant over the most part of their SOC range (which amplifies the impact of the noise on the estimated SOC).

For these reasons, even if we assume to have a highly accurate model, the estimated SOC will be affected by the measurements noise. Even if the estimated SOC is close to the real one, it is highly noisy, even if it is filtered. This characteristic affects the algorithm capability to copy the real SOC behavior during short periods of time.

H. Mix estimation algorithm

A combination of two simple approaches-the Coulomb-Counting and the Model-Based can be used for SOC estimation and an algorithm based on this mixing scheme is called the mix estimation algorithm.

The capability of the mix algorithm to deal with measurement errors can be analyzed by comparing it with respect to the Coulomb-Counting and the Model-Based approaches.

The characteristics of the mix estimation algorithm are as follows:

- Since it has current (I_m) and voltage (V_m) as the inputs of the model and estimated SoC $\left(\widehat{SOC}\right)$ as the output of the system, it is a MISO system.
- Since the battery model is non-linear and the relationship defined by $V_{OCV}\left(\widehat{SOC}\right)$ is non-linear, it is a non-linear algorithm.

Firstly, linearization has been done in order to study the stability and analyze the error sensitivity for the algorithm; specifically $V_{OCV}\left(\widehat{SOC}\right)$ [10].

The linearization is performed as:

$$\begin{aligned} V_{OCV}\left(\widehat{SOC}\right) &= V_{OCV_{DC}}\left(\widehat{SOC}\right) \\ &= V_{OCV_{DC}}(\overline{SOC} + \delta SOC) \\ &\approx \frac{\delta V_{OCV\_DC}}{\delta SOC}(\overline{SOC})\delta SOC \\ &= K_{SOC}\delta SOC \end{aligned}$$

where $\delta SOC = \widehat{SOC} - \overline{SOC}$

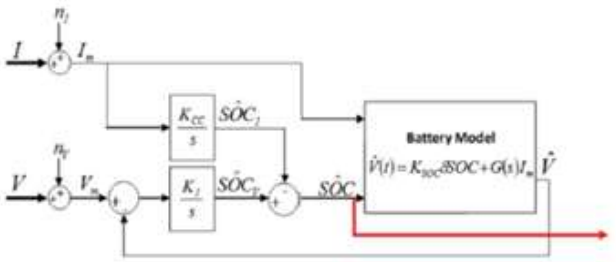

Figure 2. Mix algorithm schematic: linearized detailed scheme.

Selection of the working point $(\overline{SOC})$ has an impact on the value of K_{SOC} and the algorithm behavior. The results imply that that the relationship between SOC and the Open-Circuit-Voltage is monotonically increasing. Thus $K_{SOC} > 0$.

The advantage is that, the mix algorithm that has low computation complexity provides a robust SOC estimation with respect to noisy measures, wrong initializations and modeling errors. The Coulomb counting and a Model-based method is combined in a closed-loop configuration.

I. *Estimation for State of Charge using OCV by RLS estimation technique*

By this method, the internal parameters of a second-order Li-ion battery model can be extracted adaptively. One of the extracted parameters is the battery OCV and it is used further battery SOC estimation.

The approach applies a well-known recursive least square (RLS) estimation technique to the battery parameter estimation problem. The purposes of using this RLS method are as follows [8].

- The first purpose is with less predetermined look-up tables, adaptive estimation of one or more battery parameters in real time for SOC estimation and other potential applications. Such a solution offers better adaptation to the environment and driving conditions. Meanwhile as an onboard application, the algorithm has to be designed for high computational efficiency as well as low implementation cost.
- The second purpose is to achieve high accuracy and robustness in battery parameter estimation, especially for the OCV. This is a necessary condition of providing an accurate and reliable SOC for battery control and electrical power management.

The overall estimation error is within 3% in this case as per the work in reference papers. The advantage is that, the results show effectiveness in SOC estimation and it is robust to initial conditions, battery variations, and operation environment.

The constraint here is that the battery should rest for hours in order to measure OCV.

J. *Kalman filtering techniques*

The research about Kalman filtering method for the estimation of battery SOC has begun in the recent years. As compared to the other methods this method is applicable to all kinds of battery, especially for the SOC estimate of hybrid car batteries whose current wave is very severe.

The basic idea of Kalman filter theory is making the minimum variance in terms of the optimal estimation of the power system state [12]. The battery is regarded as a power system and SOC as an internal state of the system for the application of SOC estimation. In general, the mathematical form of battery model state equation can be represented as:

$$x_{k+1} = A_k x_k + B_k u_k + w_k$$

$$= f(x_k, u_k) + w_k$$

Observed equation:

$$y_k = C_k x_k + v_k$$

$$= g(x_k, u_k) + v_k$$

where, the variables such as battery electric current, temperature, surplus capacity, resistance, etc are usually contained in the system input vector u_k. The output of the system y_k is usually the working voltage of the battery; the state variable x_k contains the battery SOC and $f(x_k, u_k)$ and $g(x_k, u_k)$ are nonlinear equation determined by the battery model which should be linearized in the calculation process. Here, the algorithm of SOC estimation is a set of recursive formulas which includes the number of SOC estimate and reflects on the estimation error by using the covariance matrix to give the estimate error range. The equation is the basis which described SOC as the state vector in the battery model state equations:

$$SOC_{k+1} = SOC_k - \frac{\eta(i_k) i_k \Delta t}{C}$$

The advantage of this method is that, it not only gives the estimate of SOC but also gives the SOC estimate error.

The disadvantage of this method is the high requirements. Open-circuit voltage method and discharge test method are used mainly in the laboratory. For approximate estimation of SOC before the test, open circuit voltage method is used. Discharge test method is used for the precise measurement of the remaining power after the battery was used.

The Ah counting method combined with open-circuit voltage method considering the different charge and discharge rate and self discharge has been utilized here. The Kalman filtering method is an area that is still in research. Even when the initial SOC value is incorrect, this method can provides the estimated SOC value converging to the actual SOC value. Hence the problems of battery self-discharge can be solved here.

Using state-space battery models is favoured because it is closed loop (self-corrected), online, and offers a dynamic SOC estimation error range. This category is most suitable for real-time battery management and electrical system control [6]. As the KF cannot be used directly for state prediction of a nonlinear system the EKF and UKF-based methods are the most widely used.

K. *Extended Kalman Filter (EKF)*

Kalman filtering method cannot be put into use directly when the system's state equation is nonlinear as system equation discretization is required. This kind of discretization of nonlinear equation for the Kalman filtering method is called extended Kalman filtering method (EKF) [4].

The disadvantage of EKF is that, for optimal estimation, an accurate model and the knowledge on the statistic properties of noises is required for EKF.

Actually, the above mentioned two conditions cannot be easily achieved in the real time environment when the vehicle is running because it is difficult to determine the battery model by a set of fixed parameters due to the strong time-variant property of battery and vehicle driving conditions affect the characteristics of measurement noises and this dependency is hard to obtain in advance for the estimation.

Also, if the assumptions of local linearity are violated, linearization will lead to highly unstable filters.

Another constraint is that the EKF must compute the Jacobian matrix and this makes it unsuitable for highly nonlinear systems with non-Gaussian noise.

L. *Unscented Kalman Filter (UKF)*

The UKF is another extension of the KF and is also a recursive minimum mean square error (MMSE) estimator [2].

The advantage is that, it is computationally efficient, making it suitable for embedded system implementation.

The UKF has been demonstrated to outperform the KF and EKF in terms of accuracy and robustness for nonlinear estimation. The UKF does not need to calculate the Jacobian matrix and does not require noise to be Gaussian, which makes it more appealing for SOC estimation because battery systems are highly nonlinear and the noise properties are typically not known.

M. Equivalent Coulombic efficiency (ECE)

The ratio of the discharged capacity to the capacity needed to be charged to the initial state before discharge defines the coulombic efficiency of battery packs and it can be calculated as [1]:

$$\eta = \int_0^{t_d} I_d \, dt \Big/ \int_0^{t_c} I_c dt$$

where I_d is the discharging current; t_d is the discharging time; I_c is the charging current; and tc is the charging time.

In simple terms, the coulombic efficiency shown in above equation is the ratio of the discharging capacity to the charging capacity.

It varies according to current rate, and hence accurate calculation of both charge and discharge coulombic efficiency is needed for an accurate SOC estimation.

N. Modified ECE Method

In Modified Equivalent Coulombic Efficieny method both charging coulombic efficiency and the discharging coulombic efficiency are considered to calculate the equivalent charging and discharging capacity of the battery separately. Hence this improves the accuracy of the SOC estimation as it provides a relation how the practically consumed capacity can be calculated using the charging and discharge capacity.

The charging and discharging processes for different current rates can be converted into a single process for constant current. Let Q_0 be the initial capacity. Q_{CN} is the charging capacity at current I_{CN}; where $Q_{CN} = I_{CN}t_{CN}$; and t_{CN} is the charging time; Q_{DN} is the discharging capacity at current I_{DN}; where $Q_{DN} = I_{DN}t_{DN}$; and t_{DN} is the discharging time. The equivalent charging capacity Q_c and its discharging capacity Q_D are calculated by equations below

$$Q_c = \frac{Q_{CN}}{\eta_{c/3}}\eta_c = \frac{I_{CN}t_{CN}}{\eta_{c/3}}\eta_c$$

$$Q_D = \frac{Q_{DN}}{\eta_D}\eta_{c/3} = \frac{I_{DN}t_{DN}}{\eta_D}\eta_{c/3}$$

The practical consumed capacity Q_T at room temperature under the actual discharge/charge rate for the entire operating process of the battery packs, is calculated by Equation below. The baselines of each term in Equation above (are all with C/3 rate): $Q_T = Q_0 + \sum Q_C\eta_{C/3} - \sum Q_D$

$$Q_T = Q_0 + \sum I_{CN}t_{CN}\eta_C - \sum \frac{I_{DN}t_{DN}}{\eta_D}\eta_{C/3}$$

Thus, the modified SOC considering the actually practically consumed battery capacity from the charging and discharge capacity is defined as:

$$SOC(t) = \frac{Q_T}{C}$$

O. Modified-ECE + EKF

A modified ECE method that considers self-discharge and the influence of temperature and SOC on the coulombic efficiency with an EKF - based method that makes the approximate initial SOC value converge to its real value [1] are combined and the resultant method is called the Modified-ECE +EKF method.

This method that gives SOC estimation within 1% of its real value is considered to have better accuracy than just the ECE + EKF and ECE + UKF methods.

P. Machine learning strategies

These are Black-box battery models. In order to establish black-boxes so that mapping of the measurable data to SoC can be done, the machine learning strategies were introduced. The strategies here include the Neural Network (NN), fuzzy NN and evolutionary NN and support vector machine (SVM).Basically these are based on principles like ANN, fuzzy logic optimization and SVM. Generally, these models are implemented by computational intelligence-based approaches.

The advantage is that, they can provide good SOC estimation through their abilities to approximate nonlinear function surfaces when an appropriate training data set is provided as input to the model.

But the disadvantage is that, these data-oriented methods cannot avoid their intrinsic problems such as large number of training data covering the whole possible range of operation, the selection of model structure and the balance between under-fitting and over-fitting. Meanwhile, when suffered from kinds of noises, the estimation result becomes theoretically unpredictable. Most SOC estimation models of this type are used offline because the learning process imposes a heavy computational load. Also, only if sufficient and reliable training data are available, good performance of the estimator is achievable. Hence under certain battery operating conditions these problems can lead to poor robustness of the estimation technique.

IV. MODELING: A CASE ANALYSIS ON COULOMB COUNTING METHOD

Based on the comparative study presented in section 3, it is observed that the most common method is based on Coulomb counting due to its simplicity for implementation. Coulomb counting (usually denoted as Ah method) is one of the most applicable SOC indicators, which simply accumulates the charges transferred in or out of the battery. Coulomb counting family is a kind of open-loop estimators which require accurate measurement of battery current.

The advantage is that

- The implementation of Non-model-based coulomb counting method is inexpensive and also reliable.
- On an embedded system, it is easily implementable.
- Only with fewer amounts of data, the calculation of SOC is done by this method based on the following formulas

$$SOC(t) = SOC(0) - \frac{1}{Ah_{nom}}\int_0^t I_m(t)\, dt$$

$$SOC(t) = \frac{Ah_{nom} - \int_0^t I(t)dt}{Ah_{nom}}$$

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$$SOC(t) = SOC(t_0) - \int_0^t \frac{\eta I(t)}{C} dt$$

where,
$I_m(t)$ is the current extracted from the battery (which is assumed positive while discharging the battery),
Ah_{nom} is the nominal battery capacity,
$\eta = 1$ for discharge and $\eta < 1$ for charge under standard conditions with a constant C/3 rate.

A. Simulation and Results

The State of charge (SOC) of the battery is estimated using the coulomb counting method and the modeling is done using MATLAB Simulink. The results obtained are verified by comparing the results with the SOC behavior obtained from the battery model created using GT-Suite (Ideal condition considered by GT battery model).

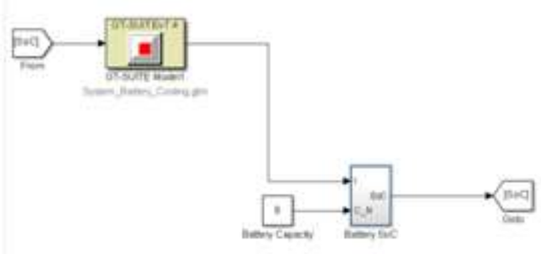

Figure 3. Implementation in Matlab Simulink

Figure 4. GT Suite Battery Model

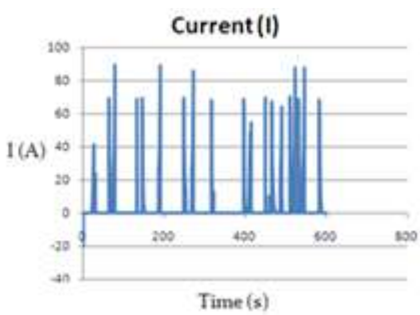

Figure 5. Input Current profile

B. Snap shots of the Simulation of the SIMULINK Model interfaced with the GT Model

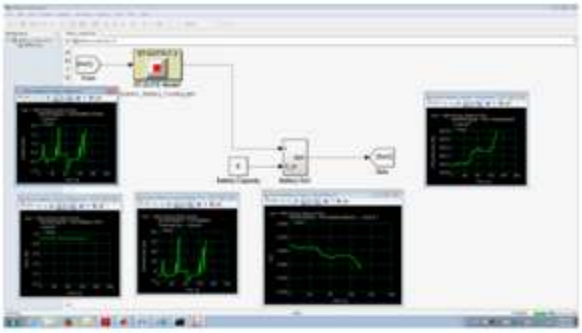

Figure 6. At the beginning of core simulation

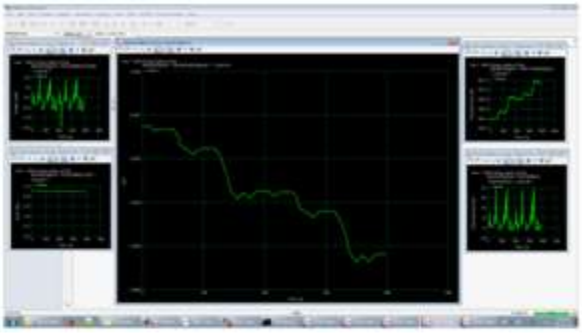

Figure 7. At the end of core simulation

C. Comparison of obtained and ideal behavior

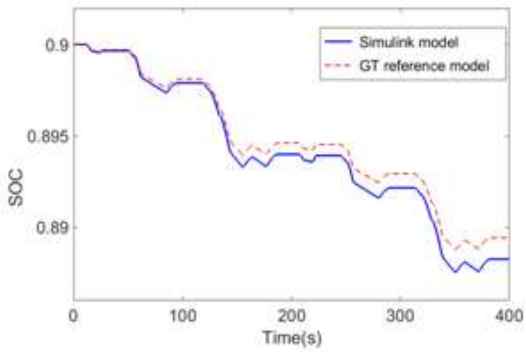

Figure 8. SOC v/s time graph from the SIMULINK Mode

RMSE of SOC = 0.00070064

D. Analysis of the Modeling technique

However both, the behavior obtained from the coulomb counting method and the one provided by the GT battery m0del are closely matching, it has to be noted that both of these are considering ideal conditions for the operation of the battery and the dynamic behavior of the battery is not considered.

Hence, this method has some issues that largely limit its application to PHEV/EV.

- There is a requirement of the initial SOC value, which is often unavailable.
- The ability to recover from a wrong SOC value is not achieved by this method.

- Due to the presence of sensing errors the error will accumulate over the period of time. The sensor accuracy, current magnitude, and trip length are the factors affecting the magnitude of error.
- Measurement of columbic efficiency accurately is difficult.
- If fed with a constant input, its output diverges with a ramp trend as it is based on a simple integrator, which is an unstable system.
- When the battery works at low or high temperatures the error is larger.
- Due to uncertain disturbances, practically the open-loop algorithm often results in the accumulation of measurement errors.

Accumulation of current noise is possible and the ability of self-correction is not present in the technique. The estimation result can diverge in the presence of zero-drift, i.e., if the mean of noise is nonzero.

However an initial SOC estimate cannot be possibly obtained with this method and any error on the current measure, most of all offset errors, can highly affect the estimation accuracy.

Hence advanced estimation techniques have to be used in order to capture the dynamic behavior of the battery.

V. Conclusion

In this paper, various methods of State of Charge (SOC) estimation have been briefed and for all these methods, a comparative study is presented consisting of the advantages and disadvantages of each of the methods in relevance to a hybrid vehicle battery system. As an example for the modeling of a SOC estimation technique for a battery, the coulomb counting method is implemented. A case analysis is done on the coulomb counting method providing the simulation and results. Also, a detailed analysis is done on the results obtained in relevance to the suitability of the approach for the hybrid electric vehicle battery system.

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