CHALMERS

A Method for Evaluating Battery State of Charge Estimation Accuracy

Master's Thesis in the Master Degree Programme, Systems, Control and Mechatronics

FREDDY TRINH

Department of Signals and Systems
Division of Automatic Control
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2012

Master's Thesis EX080/2012

MASTER'S THESIS EX080/2012

A method for evaluating battery State of Charge Estimation accuracy

FREDDY TRINH

Department of Signals and Systems
Division of Automatic Control
CHALMERS UNIVERSITY OF TECHNOLOGY
Gothenburg, Sweden 2012

A method for evaluating battery State of Charge estimation accuracy

Freddy Trinh

© FREDDY TRINH, 2012

Master's Thesis EX080/2012
Department of Signals and Systems
Division of Automatic Control
CHALMERS UNIVERSITY OF TECHNOLOGY
SE-412 96 Gothenburg
Sweden
Telephone +46(0)31-772 1000

Chalmers Reproservice
Gothenburg, Sweden 2012

A method for evaluating battery State of Charge estimation accuracy

FREDDY TRINH

Chalmers University of Technology
Department of Signals and Systems
Division of Automatic Control

ABSTRACT

Battery State of Charge estimation is one of the key procedures in battery management systems. An accurate State of Charge estimation can enhance the performance of the battery and increase the security of the electric vehicle. The goal of this thesis was to propose a method to evaluate the State of Charge estimation accuracy of an estimator developed by Volvo Group Trucks Technology. The method is designed in such a way that it can be adapted to any battery system. This thesis also describes the various measurement errors and their effects on the proposed method and the overall State of Charge estimation accuracy. Various tests and simulations in virtual test bench are examined. In conclusion the proposed method works satisfactorily.

Keywords: battery, State of Charge, SoC, Open Circuit Voltage, OCV, estimator, evaluation method, Kalman filter, electric vehicle

TABLE OF CONTENTS

1. Introduction ... 1
  1.1. Background ... 1
  1.2. Goal ... 1
  1.3. Limitations ... 2
  1.4. Thesis Outline ... 2
2. Basic Theory ... 3
  2.1. Energy Storage Systems ... 3
  2.2. Battery System ... 4
  2.3. State of Charge ... 5
  2.4. Equivalent Circuit Model ... 6
3. Literature Survey ... 7
4. Load Cycles ... 9
  4.1. Types of Load Profile ... 9
  4.2. Hybrid Electric Vehicle ... 10
  4.3. Plug-In Hybrid Electric Vehicle ... 11
5. Measure For Determining The SoC Estimation Accuracy ... 13
6. Virtual Test Bench ... 15
  6.1. Battery Model ... 15
  6.2. SoC Estimation Model ... 15
  6.3. Sensor Model ... 16
  6.4. Virtual Test Rig ... 17
  6.5. Evaluation of SoC Estimates in A Test Rig ... 18
7. The Proposed Method to Determine $SoCref$ in A Battery system ... 19
  7.1. Finding an Accurate $SoCref$ ... 19
    7.1.1. Error due to the voltage sensor ... 21
    7.1.2. Error due to the temperature sensor ... 23
    7.1.3. Integration error due to the current sensor ... 24
8. Test Result in Virtual Test Bench ... 27
  8.1. Evaluation of The Proposed $SoCref$ Method ... 27
  8.2. Evaluation of The SoC Estimator in A Virtual Test Rig ... 30
9. Discussion and Conclusion ... 33
10. Bibliography ... 35

Appendix 37
A. Battery model specification 37
B. K-curve 38

1. INTRODUCTION

This Master's thesis has been proposed and carried out at Volvo Group Trucks Technology (Volvo GTT) in Gothenburg, Sweden. This chapter gives the background to why Volvo GTT decided to initiate this thesis work.

1.1. BACKGROUND

Batteries have benefited greatly from the technological advancement, enabling sufficient power density for use in electric drive vehicles such as Hybrid Electric vehicles and Plug-In electric vehicles. When compared to other battery technologies, lithium-ion (Li-Ion) batteries has several advantages in various aspects, such as higher energy densities and longer lifetimes. One of the key parameter that represents the available capacity in a battery is the battery State-of-Charge (SoC). There are basically two main methods used in SoC determination, i.e. measuring the battery open circuit voltage (OCV) and integrating the current flow into and out of the battery pack (known as Coulumb Counting (CC)). However, due to the driving conditions in electric drive vehicles SoC is relatively difficult to determine accurately with the conventional methods mentioned above. In recent years, many researchers and companies have therefore been working to improve the accuracy of SoC estimates.

For this purpose Volvo GTT has developed a prototype battery system (BS). The system consists of a battery management unit (BMU) and a number of Li-Ion batteries. The main task of the BMU is to estimate and control the battery SoC using Extended Kalman Filters (EKF). As the cell technology is very sensitive to overcharging, an incorrect estimation could in the worst case lead to cell damage or even a fire. On the other hand, an accurate estimation will provide advantages such as prolonged battery life and enhanced performance, as well as increased vehicle efficiency.

Despite an extensive research on SoC estimation, there is little work reported on methods to evaluate the SoC estimation accuracy for a real battery system. Most of the SoC estimation accuracy evaluation methods found in the reports and technical releases are more suited for a virtual test bench than for a real system.

1.2. GOAL

The goal of this thesis project was to develop a general method for evaluating the SoC estimation accuracy of an estimator developed by Volvo GTT.

1.3. LIMITATIONS

This thesis project will not consider the development of the software and algorithms, i.e. the SoC estimator and the cell balancing algorithm, nor the selection and construction of the BS. Additional factors during the evaluation such as ageing of the cells, ambient temperature, BS-fatigue etc. are also excluded.

The thesis project considers only electrochemical energy storage technologies, as lithium ion batteries, that are compatible with the BS.

1.4. THESIS OUTLINE

In Chapter 2 the basic theory for the components in a battery system are presented. This chapter provides the background material required for the readers to understand the work carried out in this thesis

Chapter 3 presents three papers relevant for this thesis. The purpose is to compile the different ideas behind the measures/methods that have been used to evaluate SoC estimators. A brief summary of the discussed ideas in terms of the pros and cons are also listed in the form of a table in Chapter 5.

Chapter 4 presents three different load cycles that are used to evaluate the developed SoC estimator.

The proposed evaluation method is presented in Chapter 7 and the test simulations are presented in Chapter 8.

Finally the conclusions are presented in Chapter 9.

2. BASIC THEORY

This section presents the basic theory of the contents of a BS. The first subsection presents an overview of the different energy storage technologies for PHEVs and HEVs. The second subsection gives an overview of a battery system while the final two subsections present briefly the theory of battery state of charge (known as SoC) and the equivalent circuit battery model

2.1. ENERGY STORAGE SYSTEMS

An overview of different energy storage devices for HEV applications has been presented by Conte, F. (2006). The studied devices consist of lead acid batteries, nickel metal hybrid batteries (NiMH), lithium based batteries, and electric double layer capacitors. Figure 2.1 shows a plot of the above mentioned devices. It gives the specific energy and the specific power relationship, and helps to identify the optimal operative range for each technology (Gelso, 2012).

Commonly used battery technologies, such as lead acid batteries, suffer of problems of low energy density. The adoption of such batteries for alternative vehicles like HEV is therefore limited. As a result of this, Li-Ion batteries with higher energy density and specific energy are more suitable (Conte, 2006).

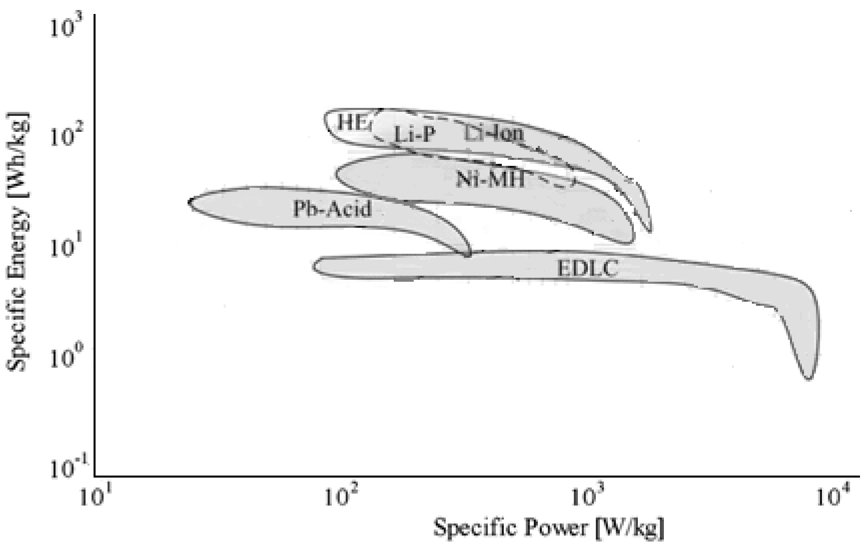


FIGURE 2.1 DIFFERENT ENERGY STORAGE TECHNOLOGIES IN TERMS OF SPECIFIC ENERGY AND POWER.

2.2. BATTERY SYSTEM

A Battery system, as shown in Figure 2.2, monitors the battery pack operations and performs the safety steps in case of a hazardous event. First, the system measures the voltage, current and temperature, and in some cases other quantities such as the pressure. These parameters are processed and used as input parameters to the BMU, which relies on mathematical models based on differential/difference equations and lookup tables. These models are developed to estimate the state of battery in terms of the State of Charge, State of Health, the State of Function etc. (Conte, 2006). A BMU also communicates with the vehicle systems to control the charging/discharging, cell balancing, battery temperature, etc.

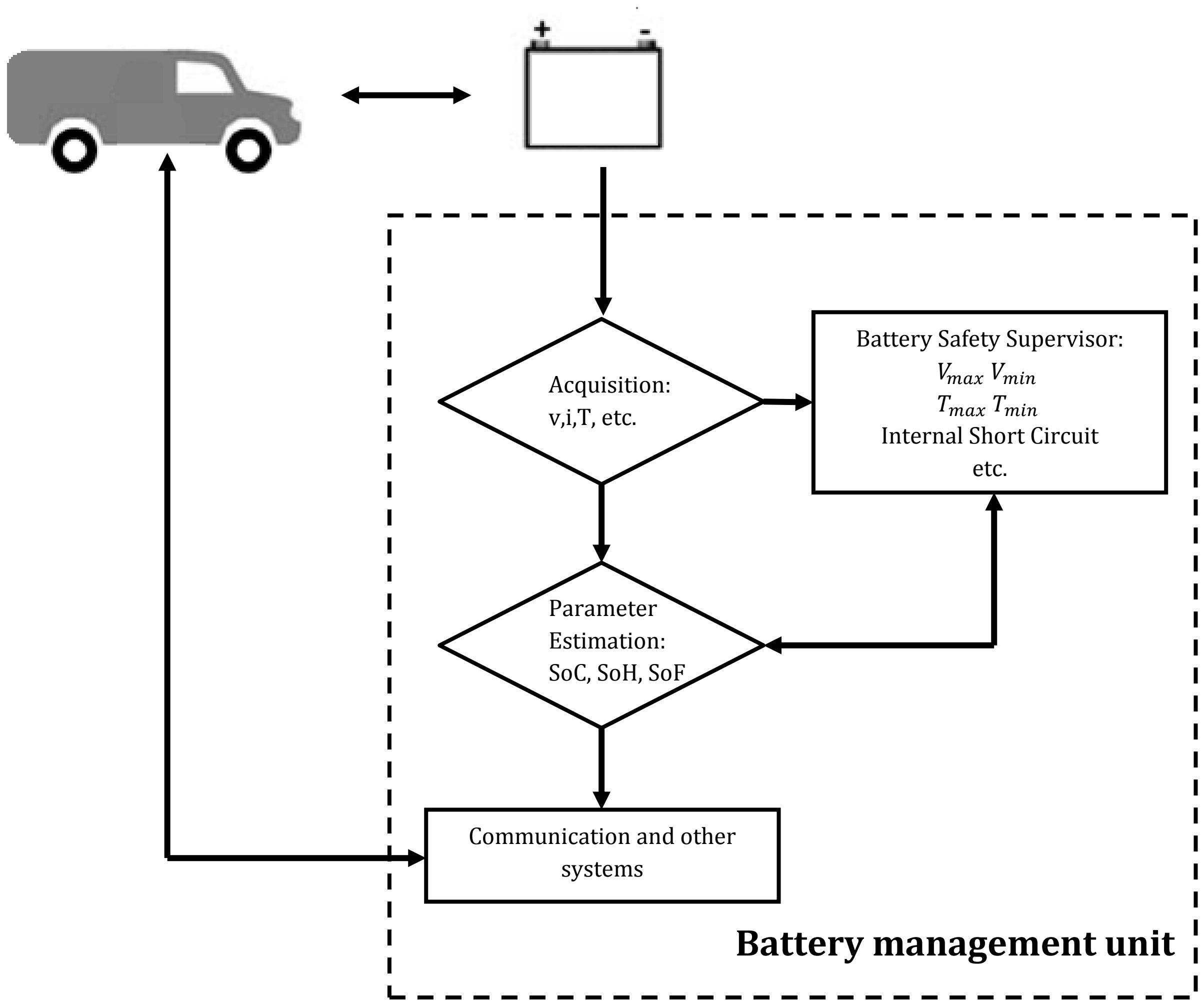


FIGURE 2.2 A BLOCK DIAGRAM OF A BATTERY SYSTEM.

2.3. State of Charge

Battery State-of-charge (SoC) is defined as the percentage of the present capacity of maximum battery capacity (MIT, 2008). The SoC has been introduced for the purpose of human-machine interaction and internal vehicle system control (Pop, et al., 2005). The units of SoC are percentage points (100% or 1.0 = fully charged and 0% or 0.0 = empty).

The SoC of a battery pack can be determined by measuring the difference in electric potential between two terminals, known as the Open Circuit Voltage (OCV), or by integrating the current flow in and out of the battery pack over time (known as Coulomb Counting (CC)). These methods are however not capable of determining the SoC accurately for HEV and PHEV applications. A small OCV measurement error in the flat region of the OCV curve, i.e. region B in Figure 2.3, gives a large SoC error. In addition, the CC can introduce an integration error if the cell current is integrated over a longer period of time.

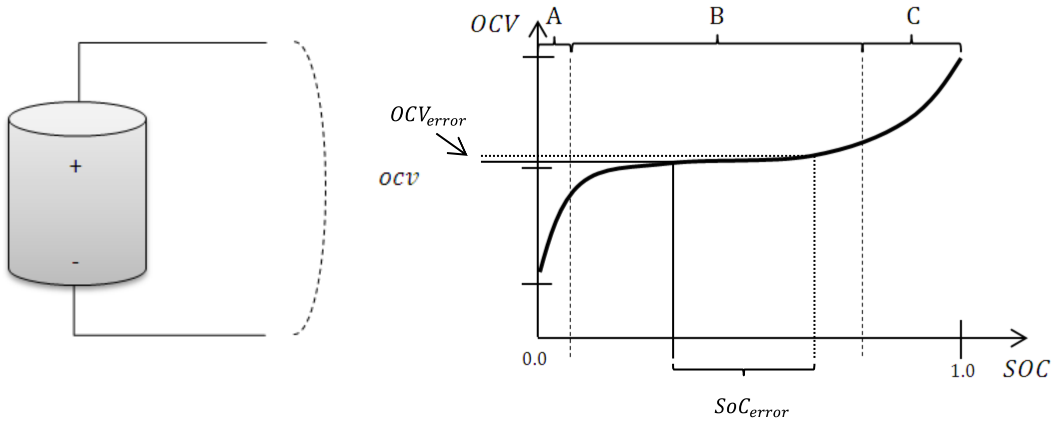


FIGURE 2.3 A GENERAL LAYOUT OF AN OCV-CURVE. IN REGION A AND C, A LARGE OCV MEASUREMENT ERROR WILL GIVE A SMALL SOC ERROR. ON THE OTHER HAND IN REGION B, A SMALL OCV MEASUREMENT ERROR WILL GIVE A LARGE SOC ERROR.

2.4. Equivalent Circuit Model

An equivalent electrical circuit can be used to describe and model a battery using basic elements, such as resistors and capacitors. Typically, the inner resistance is modeled with an ohmic resistor. Transient effects are then captured by connecting an RC-network in series. The elements of this kind of models are time-varying and change depending on the condition and state of the battery.

The Thevenin model is widely used to model Li-ion batteries. It consists of a voltage source (OCV) in series with a resistor and a capacitor and resistor in parallel as seen in Figure 2.4, (Lee, et al., 2008).

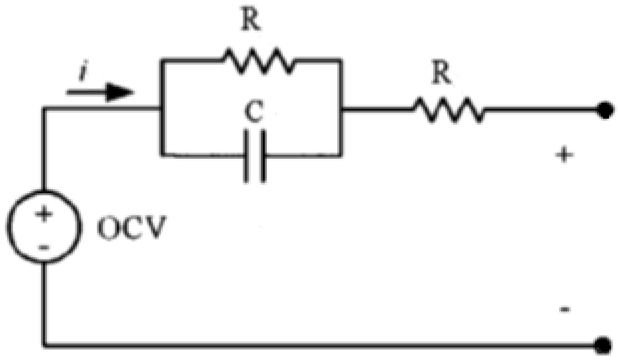


FIGURE 2.4. THE THEVENIN MODEL.

3. Literature Survey

This section presents three different references surveyed. The literature survey was done to compile different ideas behind the methods that have been used to evaluate the SoC estimator.

– Lithium-Ion Battery Parameter Estimation for State-of-Charge

The objective of this paper (Mao, et al., 2011) is to develop and evaluate an onboard adaptive observer that estimates battery parameters such as State-of-Charge. The paper presents also an evaluation procedure which is carried out by simulating the estimator in parallel with a battery model as reference. The results of the simulation are shown in the presented paper. They are found to be satisfactory despite the presence of noise. It can also be seen in the figures that the comparison of the SoCs is carried out after a rest period at the end of each run. The purpose of the rest period is to acquire a more accurate reference value, since it allows the OCV to converge to a steady state level.

– The Comparative Study of State-of-Charge Estimation on Extended Kalman filter and Adaptive Neuro-Fuzzy Algorithms

Another method to analyze the accuracy of an estimator is discussed by Wang Z. et al. (2011). Two developed SoC estimators, the Extended Kalman Filter (EKF) and the Adaptive Neuro-Fuzzy Inference System (ANFIS)[1], are validated and run in parallel with a generic battery model, which is used as a reference. The cell current test profile was designed by the U.S. Department of Energy National Laboratory (Howell, 2010) , and is called the Hybrid Pulse Power Characterization Test[2].

However, Wang Z. et al. (2011) presented a method to measure the SoC estimation error of the estimator. The measure is known as the average SoC estimation error and is defined by,

EQUATION 3.1

$$SoC_{error} = \frac{\sum_{t_{start}}^{t_{end}} |SoC_{ref}(t) - SoC_{est}(t)|}{\sum_{t_{start}}^{t_{end}} t}$$

[1] ANFIS is a combination of the Takagi_Sugeno fuzzy inference system and neural networks.
[2] The purpose of Hybrid Pulse Power Characterization Test profile is to evaluate the total dynamic power and the energy capability over a device, e.g. PHEV or HEV.

– Evaluation and Test of A BMU for Hybrid Electric Vehicles

In a thesis by Nejedly (2012) various test procedures to evaluate the SoC estimator are discussed. One of the test procedures that is presented in the thesis is so called *State-of-Charge Accuracy*. The procedure developed is used to determine the error of the estimated SoC of an estimator at the end of a test drive without using the battery model as a reference.

As shown in Figure 3.1, the procedure starts with a fully charged cell which is then cycled using a given cell current profile as depicted in the figure. After a predefined time, t_A, the cell discharges with a constant current until the estimated SoC merges with the assumed "true" SoC. The current is integrated in parallel. The merging occurs when the battery SoC is closed to the end-point of the OCV curve, region A in Figure 2.3. In this region the estimator can simply estimate SoC accurately by measuring the OCV. The difference between the estimated SoC and the true SoC can accurately be calculated,

EQUATION 3.2
$$SoC_{error}(t_A) = |SoC_{real}(t_A) - SoC_{est}(t_A)| = |\Delta SoC_{est} - \Delta SoC_{real}|$$
$$\approx \left|\left(SoC_{est}(t_A) - SoC_{est}(t_B)\right) - \int_{t_A}^{t_B} \frac{i}{C}\,dt\right|$$

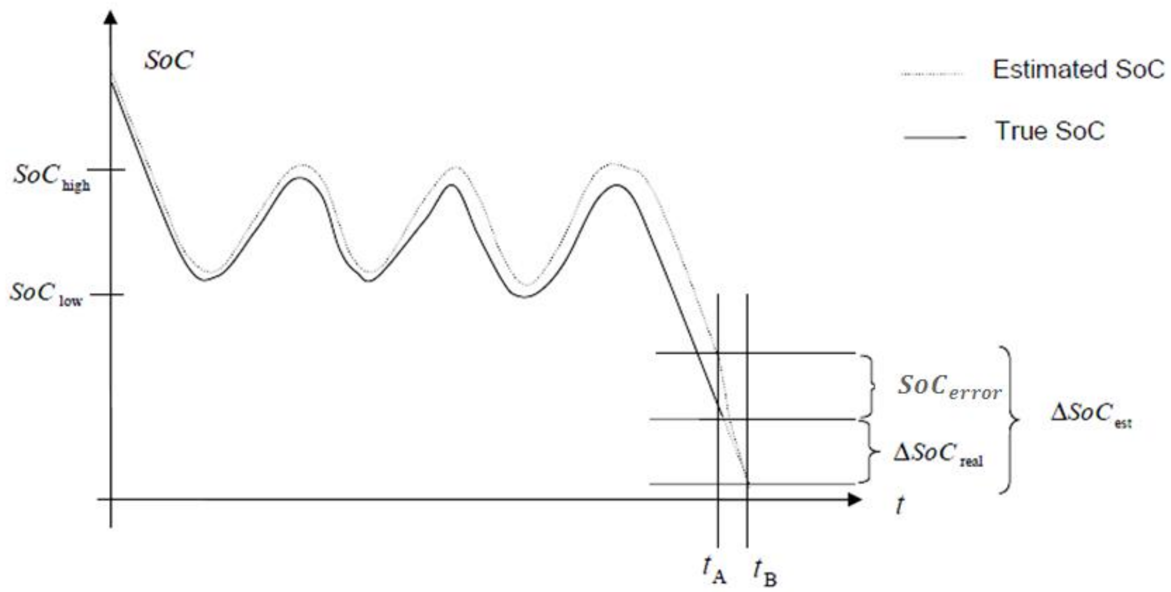


FIGURE 3.1 EVALUATION PROCEDURE DEPICTED IN (NEJEDLY, 2011), WHERE t_A IS THE TIME THE CONSTANT DISCHARGE PROCEDURE STARTS AND t_B IS THE TIME THE ESTIMATED SOC INTERSECTS THE TRUE SOC.

4. LOAD CYCLES

This chapter presents the load cycles used to evaluate the estimator in a virtual test bench. The cycles have been selected with respect to the intended application of the system. The cycles are shown later in this section. Note that load cycles differ between countries, operators, vehicle configurations, etc. and there is no standard load cycle defined (Hellgren, 2012).

4.1. TYPES OF LOAD PROFILE

In Table 4.1, the advantages and disadvantages of using Current, Voltage, State-of-Charge, and vehicle speed as load profile are summarized. The proposed profile is the cell current load, since no additional effort is required to remodel the provided battery model and the developed observer.

TABLE 4.1 PRESENTS DIFFERENT TYPES OF LOAD PROFILE IN TERMS OF PROS AND CONS. THE PROPOSED TYPE OF LOAD PROFILE IS THE CELL CURRENT

#	Input signal:	Comment	Pros	Cons
1	i	Cell current as load cycle	+Can be used directly as input without any conversion	-Can be difficult to visualize the behavior of the vehicle -Difficult to get the desired SoC profile
2	u	Cell voltage as load cycle		-u_{output} needs to feed back to the Input I_{input} -A conversion is needed
3	SoC	SoC as load cycle	+Easy to model the desired SoC profile	-SoC_{output} needs to feed back to the Input I_{input} -A conversion is needed
4	v	Velocity as load cycle	+The profile can directly be recorded from the vehicle +Easy to visualize the behavior of the vehicle	-Requires conversion to current

4.2. HYBRID ELECTRIC VEHICLE

Figure 4.1 shows a drive cycle from a HEV city-bus route in Gothenburg, Sweden. The approximate SoC-range of the cycles is 0.38 to 0.60 and the ambient temperature is kept constant at 23°C. The first plot in Figure 4.1 shows a simulated 20 minute cell current profile and the second plot shows the SoC profile of the HEV load cycle.

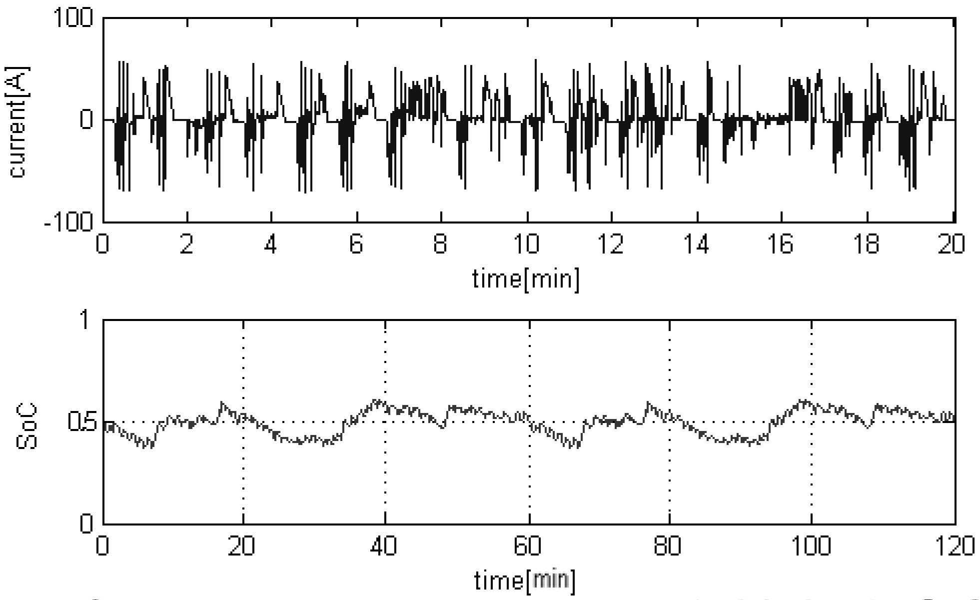


FIGURE 4.1 A HYBRID ELECTRIC VEHICLE LOAD CYCLE. NOTE THAT THE TIME SCALE IS NOT THE SAME FOR THE TWO PLOTS.

4.3. Plug-In Hybrid Electric Vehicle

The first plot in Figure 4.2 shows a simulated 20 minute cell current profile and the second plot shows the SoC profile of a Plug-in hybrid electric vehicle load cycle. The approximate SoC-range of the cycles is around 0.10 to 0.90 and the ambient temperature is constant at 23°C. The cycle has been extracted from a vehicle simulation model of a medium-sized-city bus and run in a charge depleting mode. The model switches to charge-sustaining mode when the battery pack has reached its minimum capacity state. Note that the battery pack in PHEVs are cycled in a different manner than in HEVs. For PHEVs the battery pack is recharging either when the vehicles are standing still at a charging station or at braking/idling instances. Compared to HEVs the batteries are charging at braking/idling instances.

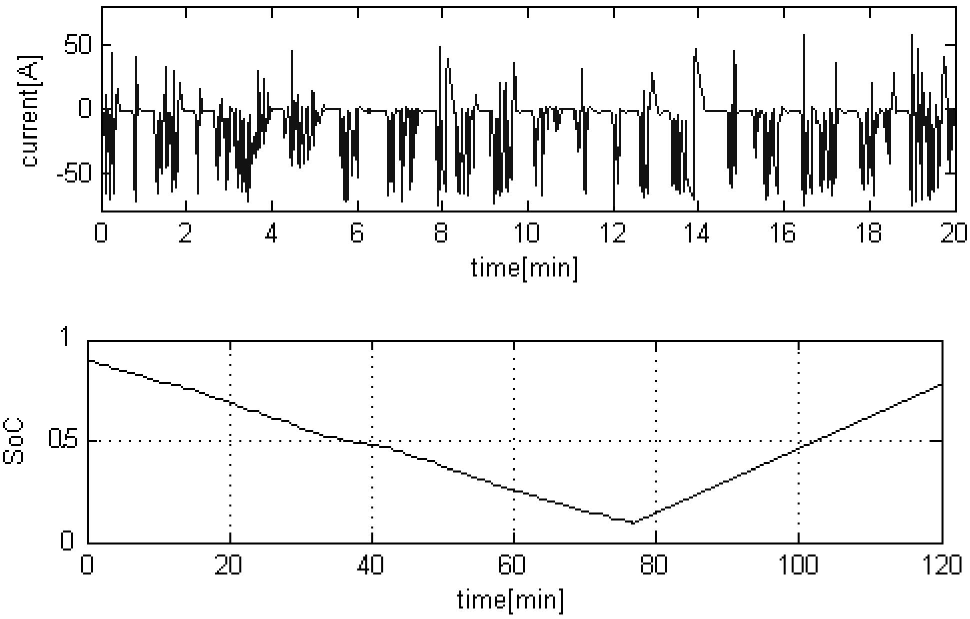


FIGURE 4.2 A PLUG-IN ELECTRIC VEHICLE LOAD CYCLE. NOTE THAT THE TIME SCALE IS NOT THE SAME FOR THE TWO PLOTS.

5. Measure For Determining The SoC Estimation Accuracy

Table 5.1 presents four different SoC estimation error measures, denoted as SoC_{error}. SoC_{error} is measured either as the mean with standard deviation, max error, final error or root mean square error, and is carried out after each test run.

Note from the table that only the final error measure (the third measure) that does not require a battery model to be applied. This measure makes use of the measured battery OCV to determine the reference SoC at the end of a test run, see Figure 2.3.

The other three SoC_{error} measures presented in the table, require a good battery model as reference. If not, the result can be unreliable.

TABLE 5.1 METHODS TO MEASURE THE SoC_{error}.

#	Measure	Comment	Pros	Cons
1	$SoC_{error} = \frac{\sum_{t=0}^{T} \lvert SoC_{ref}(t) - SoC_{est}(t) \rvert}{T} \pm \sigma$	Average $\pm$ standard deviation (Sun, et al., 2011)	+Good to remove the outliers. + Gives the accuracy and precision of the estimator	-Only possible in a virtual environment, where the reference SoC is available at every time step -Requires many data points and the reference
2	$SoC_{error} = \max\lvert SoC_{ref} - SoC_{est} \rvert$	Maximum error	+Good to find the worst SoC estimate of a test run.	-The max error can be an outlier. -The reference SoC needs to be known at every time step - Is only efficient in virtual test bench
3	$SoC_{error} = \lvert SoC_{ref}(t_{end}) - SoC_{est}(t_{end}) \rvert$	Presented in (Mao, et al., 2011) The reference SoC (SoC_{ref}) is determined by measuring the OCV of the battery after the rest time, see Section 3.	+Good when there is a bias in the estimate (the error either increases or decreases monotonically) +Need only the reference at the end of the test run.	-Can give an inaccurate SoC_{ref} measurement in the linear part of the OCV
4	$SoC_{error} = \sqrt{\frac{1}{n}\left(\left(SoC_{ref}(0) - SoC_{est}(0)\right)^2 + \cdots + \left(SoC_{ref}(T) - SoC_{est}(T)\right)^2\right)}$	RMSE, is a frequently used measure of the differences between an estimator and the actually observed value.	+Good when the variates are positive and negative	-Only possible for virtual environment, where the reference SoC is available at every time step -Requires many data points

The measured errors SoC_{error} (which are determined after a number of tests) can then be weighted as the presented SoC estimation accuracy measures in Table 5.2. The SoC estimation accuracy is denoted as $SoC_{accuracy}$ and is

$$SoC_{accuracy} = 1.0 - SoC_{final\ error}$$

TABLE 5.2 THE SOC ESTIMATION ACCURACY MEASURES.

#	Measure	Comment	Pros	Cons
1	$SoC_{final\ error} = \sum_{m=0}^{M} \frac{SoC_{error,m}}{M} \pm \sigma$	Calculates the mean and the associated confidence interval, <u>where the standard deviation σ is calculate using SoC_{error}s</u>	+Good when the standard deviation/accuracy of $SoC_{error}s$ are the same or unknown	-Does not indicate the max error -Does not consider the standard deviation of the calculated $SoC_{error}s$.
2	$SoC_{final\ error} = \frac{\sum_{m=0}^{M} \frac{SoC_{error,m}}{\sigma_m^2}}{\sum_{m=0}^{M} \frac{1}{\sigma_m^2}} \pm \sqrt{\frac{1}{\sum_{m=0}^{M} \frac{1}{\sigma_m^2}}}$	Calculates the weighted mean and the weighted standard deviation using the individual standard deviation Each SoC_{error} has difference standard deviation σ_m	+This measure consider also the standard deviaton/accuracy of the SoC_{error}, +Good when the standard deviation/accuracy of each SoC error is <u>not</u> the same	-Does not indicate the max error
3	$SoC_{final\ error} = \max(SoC_{error,m})$	Largest error	+Indicates the worst SoC_{error}	-The value can be a outlier

6. VIRTUAL TEST BENCH

Sections 6.1-6.3 present the battery and sensor models. These models are used in the thesis to evaluate the SoC estimator, which is presented in section 6.2. The last section discusses a procedure to evaluate the SoC estimation accuracy in different test rigs.

6.1. BATTERY MODEL

A Li-Ion battery model, developed by Volvo GTT, is extensively used to elaborate the method for evaluating the SoC estimation accuracy. The model is developed to predict the response of the cell voltage to the cell current in the battery pack. It is designed to work for both NiMH and Li-Ion batteries and the parameters are determined from a set of well-defined measurements taken in-house at Volvo GTT (Groot & Lunden, 2006). The specifications of the battery model are provided in Appendix A.

However, after several tests it is found that there is an error in the OCV curve (somewhere at 0.75 SoC) of the battery model and can bias the evaluation.

6.2. SOC ESTIMATION MODEL

A SoC estimator based on Extended Kalman Filters (EKF) is used to estimate the true SoC in a battery cell. The EKF uses cell current, cell voltage and the cell temperature as input variables (Gelso, 2012).

A Kalman Filter is a well-known method to estimate the state variables of dynamic systems by means of a set of recursive equations, and it is optimal if the system is linear and the noise is white and Gaussian. There are two main steps, first "Time Update", and then "Measurement Update". In the time update, the states at the current time step are estimated based on the states and their covariances from the previous time step. In the measurement update, the measurement information at the current time step is considered to refine the estimated states (Plett, 2004). The procedure is illustrated in Figure 6.1.

Due to the nonlinearities in the battery models, a nonlinear version of the Kalman Filter, the so called Extended Kalman Filter, is used. The EKF linearizes the system at every time step to approximate the nonlinear system (Plett, 2004).

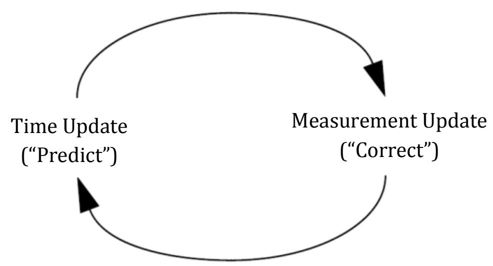


FIGURE 6.1 THE ONGOING DISCRETE KALMAN FILTER CYCLE.

6.3. SENSOR MODEL

The uncertainties of the sensors that are utilized in the BS are indicated in Table 6.1. This data is procured from the specifications provided by the manufactures (LEM, 2007; Avago-Technologies, 2011). Since there is no specification data available for the temperature sensor at the moment, the uncertainty is assumed to be ± 2°C. The value has been discussed and procured from an engineer at Volvo GTT.

TABLE 6.1 SENSOR SPECIFICATION (LEM, 2007) (AVAGO-TECHNOLOGIES, 2011)

Sensor	Property	Value	@ Temperature
Voltage	Gain tolerance	$\pm$ 0.5%	$25^{o}C$
Current	Offset current	$\pm 0.5A$	$25^{o}C$
Temperature	Gain tolerance	$\pm 2^{o}C$	

The uncertainties are considered as additive and the primary causes are the input parameters: cell current i, cell voltage u, and cell temperature T_{cell}. The sensors are modeled as depicted in Figure 6.2, where the sensor uncertainties are denoted by Δ.

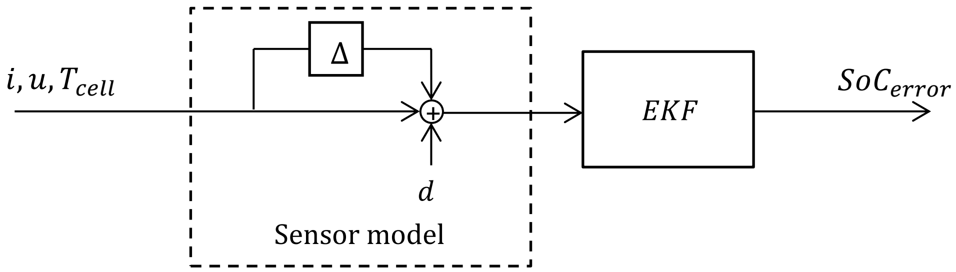


FIGURE 6.2 THE SENSOR MODEL. THE INPUT UNCERTAINTIES ARE DENOTED Δ AND THE MEASUREMENT NOISES ARE DENOTED d. THE MAGNITUDES OF THE UNCERTAINTIES ARE SPECIFIED IN TABLE 6.1.

Figure 6.3 presents the simulated result of the OCV measurement error at different SoC due to the voltage sensor. From the figure, the OCV measurement error can be assumed to be constant at a value of $c = 0.0163V$. In fact, the difference between the minimum and maximum error is very small, and thus the average is used.

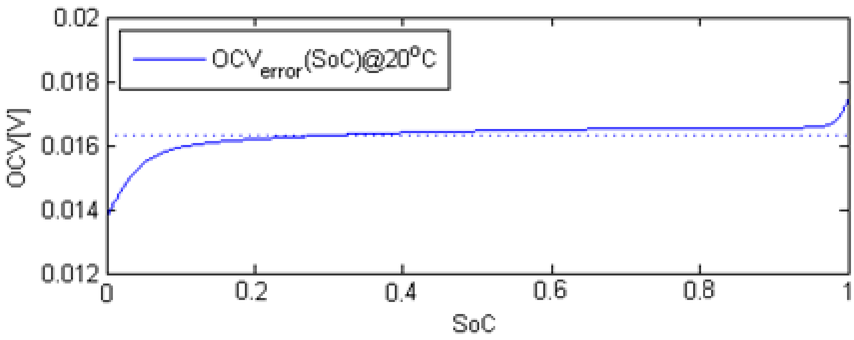


FIGURE 6.3 THE VOLTAGE ERROR DUE TO THE FAULT TOLERANCE. THE SOLID BLUE LINE IS THE ORIGINAL OCV_{error}. THE DOTTED BLUE LINE REPRESENTS IS THE AVERAGED ERROR c.

6.4. VIRTUAL TEST RIG

The virtual test rig/virtual battery system is set up as depicted in Figure 6.4. Where $\bar{y}(t)$ is a set of output variables from the battery model, for instance the cell temperature, cell voltage and the battery states. $\hat{y}(t)$ is the estimate of $\bar{y}(t)$based on the input $y_n(t)$.

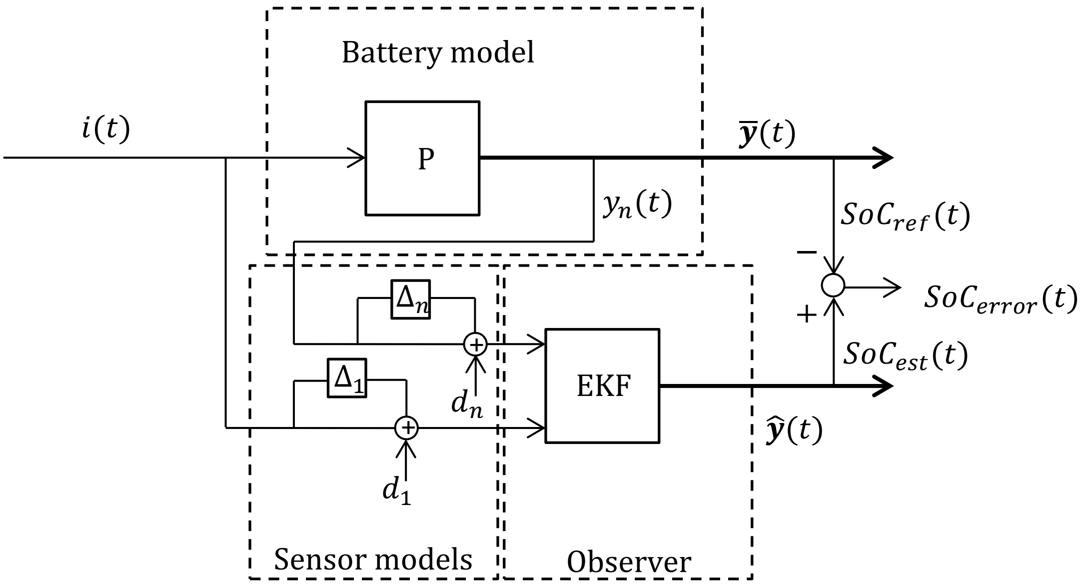


FIGURE 6.4 A BLOCK DIAGRAM OF THE VIRTUAL TEST BENCH.

6.5. Evaluation of SoC Estimates in A Test Rig

This section presents three different test rigs that can be used to evaluate the SoC estimation accuracy. The setup of the test rig is depicted in Figure 6.5.

The top part of the figure depicts a real battery test rig where the estimator and battery model is implemented in the system and run in parallel. The middle part of the figure depicts a virtual test rig where a virtual battery system is used. To utilize this virtual test rig a good battery model is required. This means that the battery model has a good mimic of a real battery pack and provides reliable SoC reference.

Due to some problems in the provided battery model ,as discussed in section 6.1 and 7.1, a second virtual test rig is presented and is used in the simulation tests in section 8. This test rig is depicted in the bottom part of the figure and is similar to the above mentioned test rig. The main difference is that the SoC simulated by the battery model is considered unknown/unreliable and the evaluation is only carried out at the end of the test run. Disturbances ($d_1, d_{2,\dots}$) in the form of measurement noise and sensor uncertainties ($\Delta_1, \Delta_2, \dots$) are then introduced to the test rig by utilizing the additional sensor models to mimic the real battery system. The measurement noise is assumed to be white Gaussian noise.

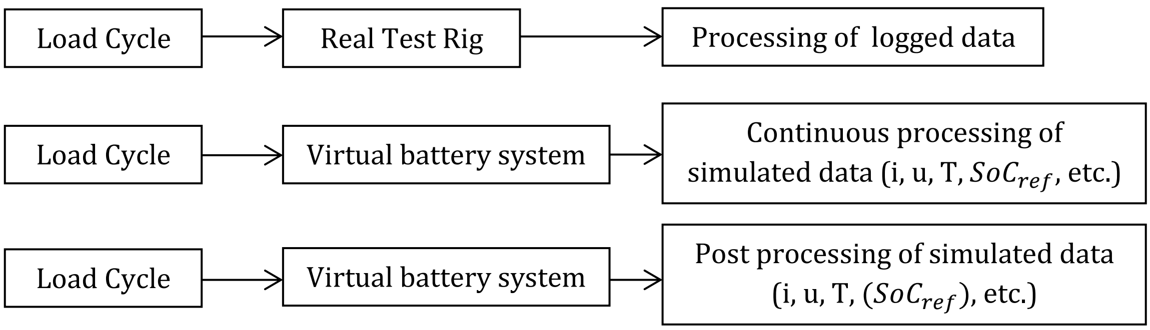


FIGURE 6.5 TOP: REAL TEST RIG, MIDDLE: VIRTUAL TEST RIG (SoC_{ref} KNOWN), AND BOTTOM: VIRTUAL TEST RIG (SoC_{ref} IS UNKNOWN)

7. THE PROPOSED METHOD TO DETERMINE SoC_{ref} IN A BATTERY SYSTEM

This section proposes a method to determine an accurate reference SoC, denoted as SoC_{ref}, based on the discussions in Section 2-6. The main idea of this method is to make use of the end regions of the OCV curve and CC. The procedure is described in Table 7.1 and Figure 7.1 on page 20. The purpose of this method is to acquire a more accurate SoC_{ref} than directly measure the OCV.

The evaluation tests of this proposed method are presented in Section 8. It is found that the proposed method works satisfactorily.

The following subsection discusses different error scenarios that can occur due to the measurement errors.

7.1. FINDING AN ACCURATE SoC_{ref}

This subsection presents different error scenarios that can occur when the presented method is used in a real battery system. The battery voltage, temperature, and discharge current are considered. As seen later from these subsections, the main error source appears to be the voltage measurement.

First, the error from each sensor is identified and discussed. Next, discussion follows regarding a procedure to set the parameters ($SoC_{est}(t_B)$, discharge current and cell temperature) such that an accurate $SoC_{ref}(t_A)$ can be found.

TABLE 7.1 THE PROPOSED METHOD TO DETERMINE THE REFERENCE SOC. SEE ALSO FIGURE 7.1.

Step:	Comment
1	Start with a fully charged battery.
2	Discharge the battery until the cycling region is reached, then cycle it for a given application profile.
3	After a predefined time[1] t_A, as shown in Figure 7.1, start the discharge-sustaining mode and Coulomb Counting (CC) in parallel. Discharge the battery until $SoC_{est}(t_B)$ is reached[2] (how to determine $SoC_{est}(t_B)$ is discussed in the text). The purpose of discharging the battery is to acquire a more accurate SoC measurement from the OCV curve.
4	At $SoC_{est}(t_B)$, stop the discharge-sustaining mode and CC. Keep the battery in steady state mode (no current enters and leaves the battery). The purpose of keeping the battery in this mode is to allow the OCV to reach the true OCV, which is a transition that can take hours (Nejedly, 2011). This causes the estimated SoC to converge to a constant value, as denoted $SoC_{est}(t_C)$ in Figure 7.1.
5	$SoC_{ref}(t_A)$ can be determined by first drawing a horizontal line at $SoC_{est}(t_C)$ and backtracking it to the stopping instance t_B. From t_B, a linear line (blue solid line in the figure) between t_A and t_B can be drawn, as shown in the figure. The slope of the line is calculated by using the integrated current procured in step 3 as, $$slope = -\frac{\left(\int_{t_A}^{t_B} \frac{i}{C} dt\right)}{t_B - t_A}$$ Thus, $SoC_{ref}(t_A)$ is now found and SoC_{error} at t_A can be calculated as, $$SoC_{error}(t_A) = \left|SoC_{ref}(t_A) - SoC_{est}(t_A)\right| = \left|SoC_{est}(t_A) - SoC_{est}(t_B) - \int_{t_A}^{t_B} \frac{i}{C} dt + SoC_{error}(t_B)\right|$$

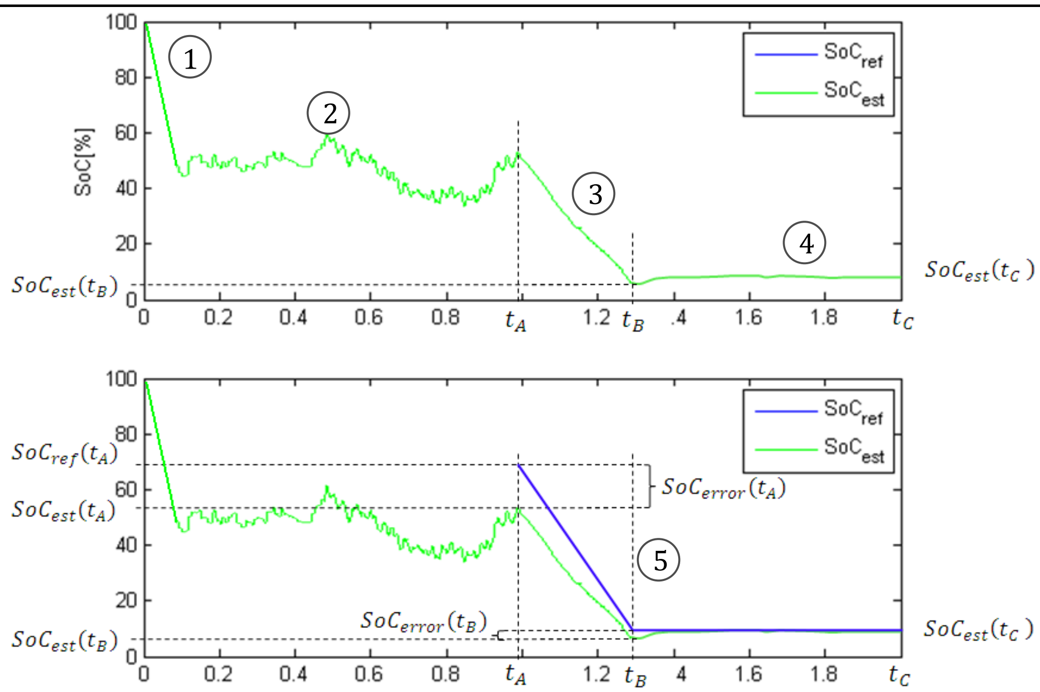


FIGURE 7.1 COMPLEMENTED WITH TABLE 7.1,

---

[1] The cycling time t_A is predefined by the tester and can be of any value.

[2] The estimate $SoC_{est}(t_B)$ depends mainly on the required tolerance/accuracy of $SoC_{ref}(t_A)$. If it is required an accuracy of 0.01 (1%), then the battery has to discharge until $SoC_{est}(t_B) \leq 0.08$ (8%), see Section 7.1 for explanation.

7.1.1. *ERROR DUE TO THE VOLTAGE SENSOR*

Figure 7.2 shows the lower part of the OCV curve of the battery cell and the errors due to the OCV measurement error. Normally this curve is used to read the SoC from a measured OCV of the battery. The SoC is then used as a reference to validate the estimator(which is the third SoC_{error} measure in Table 5.1). However, an OCV measurement error can give a very inaccurate SoC_{ref}, especially when the battery SoC is somewhere in the middle region of the OCV curve, see Figure 2.3. For instance, if the measured OCV is $3.3V \pm 0.0163\ V$, then the corresponding SoC is 0.50 ± 0.16 .

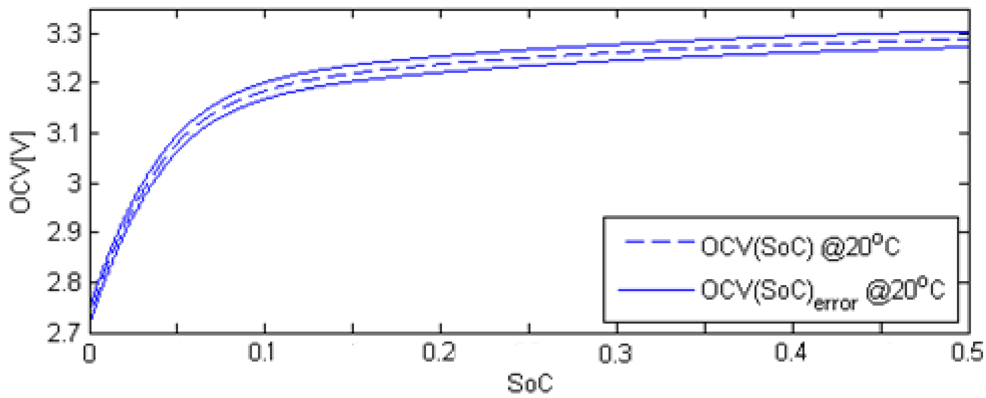


FIGURE 7.2 THE OCV CURVE AND THE OCV MEASUREMENT ERROR. THE PLOT SHOWS ONLY THE LOWER REGION OF THE OCV CURVE.

Due to this accuracy problem a method is proposed in Table 7.1. As described in the table, first the battery is cycled for a predefined time and stopped, for instance at 3.3V (SoC ≈0.50). The battery is then discharged until the OCV reaches the endpoint. The purpose of discharging the battery is to acquire a more accurate reference SoC measurement than that what is available in the middle region of the OCV curve.

The amount by which the battery has to be discharged in step 3 and 4 in Table 7.1 (the value of $SoC_{est}(t_B)$) is determined from

EQUATION 7.1
$$k = \frac{c}{SoC_{ref\ error}}$$

and the k-curve[1] shown in Figure 7.3. For example, to find $\mathrm{SoC_{est}(t_B)}$ that gives a $SoC_{ref}(\mathrm{t_A})$ with maximum absolute error $SoC_{ref\ error} = 0.01$, a k-value has to be determined first

$$k = \frac{c}{SoC_{ref\ error}} = \frac{0.0163}{0.01} = \frac{0.0163}{1\%} = 0.0163$$

where c is the averaged OCV_{error} (see Section 6.3). Using the calculated k, $\mathrm{SoC_{est}(t_B)}$ can be read from the plot in Figure 7.3,

[1] The k-curve is used to determine the $SoC_{est}(t_B)$. The deduction of the curve is presented in Appendix B.

$$\mathrm{SoC_{est}}(\mathrm{t_B}) = 8\% = 0.08$$

This means that the battery has to be discharged until $\mathrm{SoC_{est}}(t_B) \leq 0.08$. Note that the temperature and current sensor error are not considered.

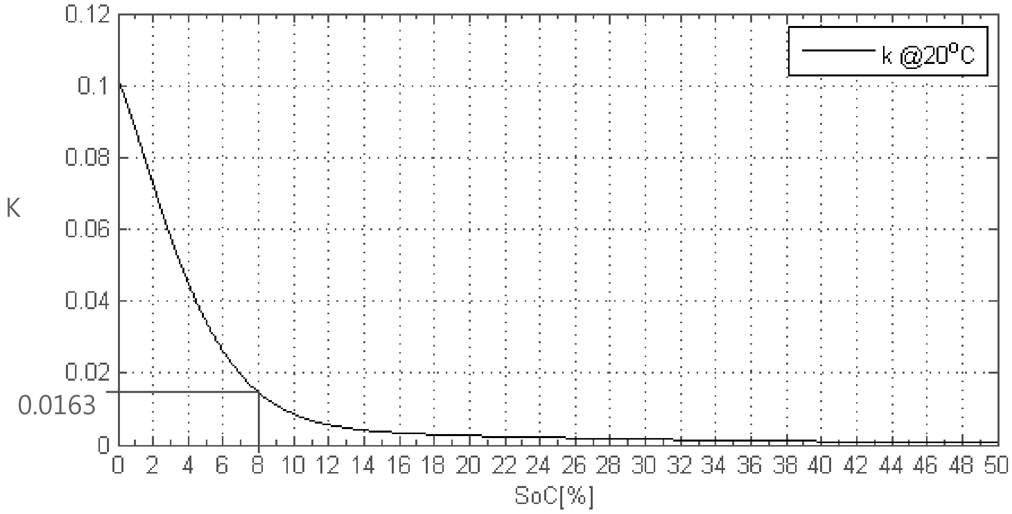


FIGURE 7.3 k-CURVE.

7.1.2. ERROR DUE TO THE TEMPERATURE SENSOR

Figure 7.4 shows the k-curve and the corresponding simulated error due to the temperature sensor uncertainty at 20°C. Since there is no specification for the sensor the uncertainty is assumed to be ± 2°C. The value has been discussed and procured from Andersson (2012) at Volvo GTT. The figure illustrates that the temperature measurement error has no significant effect on the curve and can therefore be ignored.

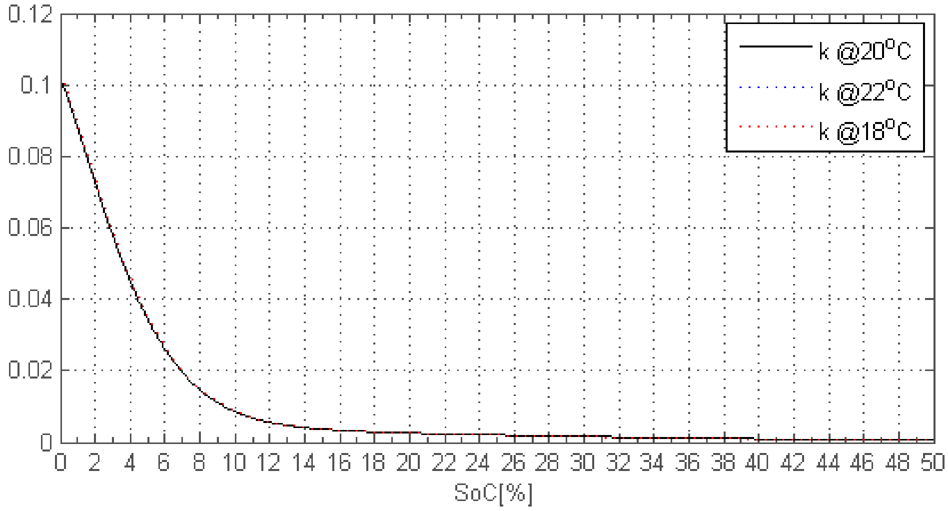


FIGURE 7.4 K-CURVE WITH ERROR. THE SOLID LINE IS THE K-CURVE AND THE DOTTED RED AND BLUE LINES ARE THE UNCERTAINTY OF K-CURVES DUE TO THE TEMPERATURE SENSOR. IT IS SHOWN HERE THAT THE ERROR IS VERY SMALL AND CAN BE IGNORED.

7.1.3. *INTEGRATION ERROR DUE TO THE CURRENT SENSOR*

One problem with the proposed method is the usage of the integral of the cell current flow between t_A and t_B. The current integration is subject to several causes of errors that accumulate over time. Because of the errors the selection of discharge current is considered as an optimization problem. The model is stated in Table 7.3. The purpose of the optimization is to find the optimal discharge current that maximizes the accuracy of the reference SoC at time t_A (known as $SoC_{ref}(t_A)$).

The local optimum of the problem is shown in Table 7.2 and the corresponding discharge cell current is found be 3C-rate[1] ($= i_{max}$). Furthermore, it can be seen in the table that the cell temperature during the discharge instance is within the allowed range. Note that the cell temperature model has a validity of ± 3°C in the optimized region and ± 6°C in the extended region, see Appendix A. In the worst case scenario the true temperature can vary between 29-45°C.

However, after extensive tests it was found that the provided cell temperature model is not reliable, since the cell temperature never exceeds 40°C regardless the cell current. Hence, the presented optimization model and acquired discharged current are not considered as final due to the invalid cell temperature model.

As seen from the results in Table 7.2, the accuracy of SoC_{ref} is primarily due to the voltage sensor error, hence also the current integration can be ignored

TABLE 7.2 RESULTS OF THE OPTIMIZATION PROBLEM.

Local optimum $SoC_{current\ integration\ error}$	$SoC_{est}(t_A)$	Max cell temp. [°C]	Comment
0.0012	0.80	38.7	The ambient temperature and the initial cell temperature are set to 23°C. The $SoC_{ref}(t_B)$ is set to 0.02.
0.0011	0.70	38.3	
0.0009	0.60	37.7	
0.0007	0.50	37	
0.0006	0.40	36.3	
0.0004	0.30	35.5	

[1] Nominal current = 1 C- rate (complete discharge in 1 hour)

Variables

i	*Discharge current*
T	*Cell temperature*
t_A	*The time when discharge instance starts*
t_B	*The time when* SoC_{ref} *intersects* $SoC_{est}(t_B)$*, see Figure 7.5*
t_C	*The time* $\lvert SoC_{est} - SoC_{ref} \rvert < 0.0015$*, see Figure 7.1*

TABLE 7.3 OPTIMIZATION MODEL

Optimization model	Comment
$\min \lvert \boldsymbol{SoC_{current\ integration\ error}} \rvert$	Objective function. $\lvert SoC_{current\ integration\ error} \rvert = \lvert SoC_{ref}(t_A) - SoC_{ref,current\ integration\ error} \rvert$
$\boldsymbol{i < i_{max}}$	Cell current constraint
$\boldsymbol{T < T_{max}}$	Cell temperature constraint
$\lvert \boldsymbol{t_B - t_C} \rvert < \boldsymbol{t_{max}}$	The steady state time should be less then t_{max}, see Figure 7.1
$\boldsymbol{t_B, t_C, T = simulink(i)}$	The parameter t_B, t_C and T is calculated using the provided battery model in Simulink
$\boldsymbol{t_B, t_c < t_{max}}$	Time constraints
$\boldsymbol{i, T, t_A, \ldots > 0\ and\ \mathbb{N}}$	$\mathbb{N}$ is natural numbers

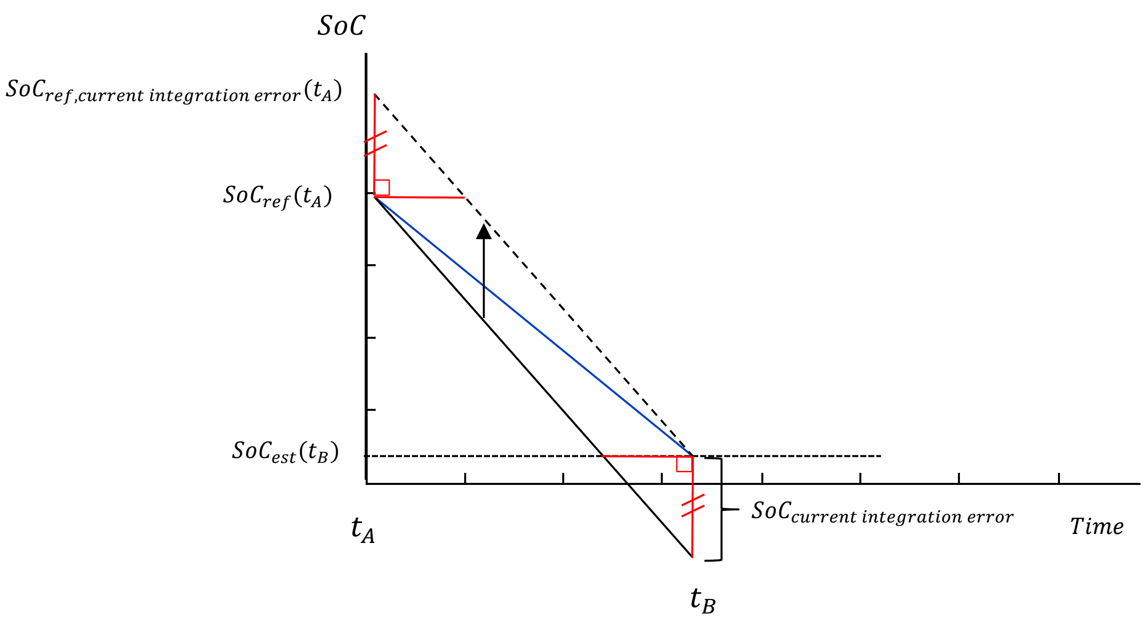


FIGURE 7.5 ILLUSTRATE SoC_{ref} AND $SoC_{ref,current\ integration\ error}$. THE SOLID BLACK AND BLUE LINES ARE THE REFERENCE SOCS WITH AND WITHOUT THE ERROR, RESPECTIVELY.

8. TEST RESULT IN VIRTUAL TEST BENCH

This section presents the test results that are carried out in the virtual test rig. The test rig is set up as discussed in Section 6 where the developed estimator and the provided battery model are simulated in parallel with and without measurement noise.

8.1.EVALUATION OF THE PROPOSED SoC_{ref} METHOD

Table 8.1 presents the results of the simulation tests that have been carried out. The purpose of the tests is to evaluate how well the proposed SoC_{ref} method performers with respect to the measurement noise. The virtual test rig is run with the specified load cycle HEV for two different time lengths, 4 hours and 10 hours.

The arithmetic mean of the determined errors $SoC_{ref\ error}$ with and without measurement noise is 0.002 and 0.01, respectively. Hence, it is shown from the tests that the proposed method works satisfactorily to determine the reference SoC. A simulation example of a HEV cycle and the proposed method is shown in Figure 8.1.

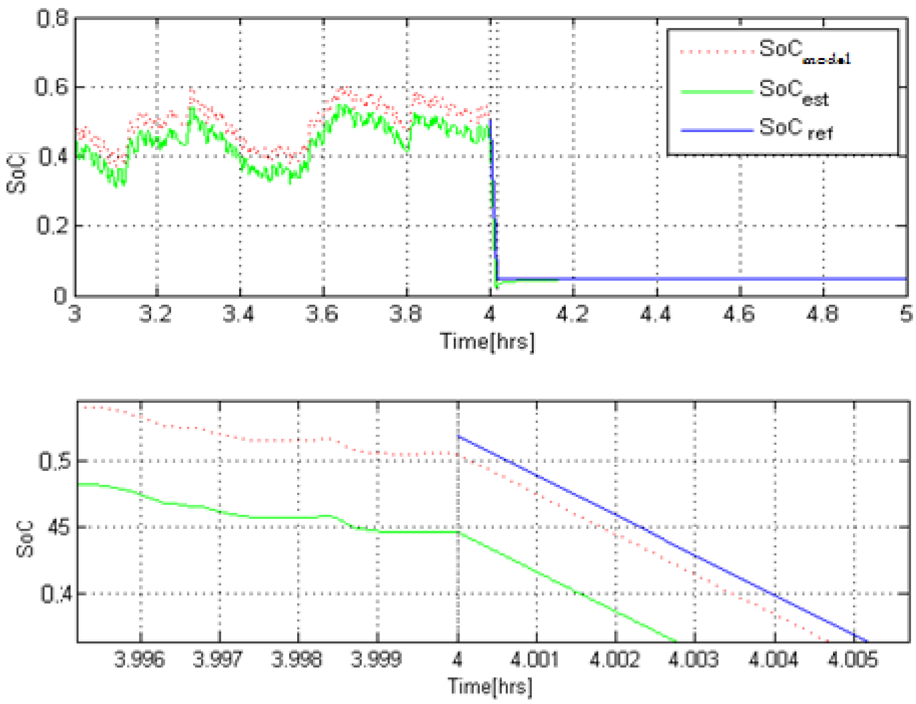
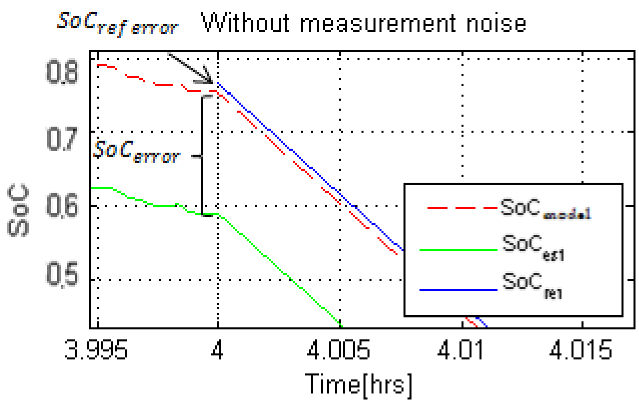
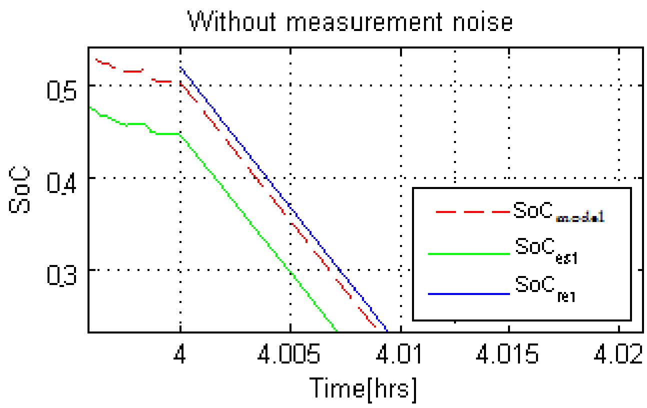
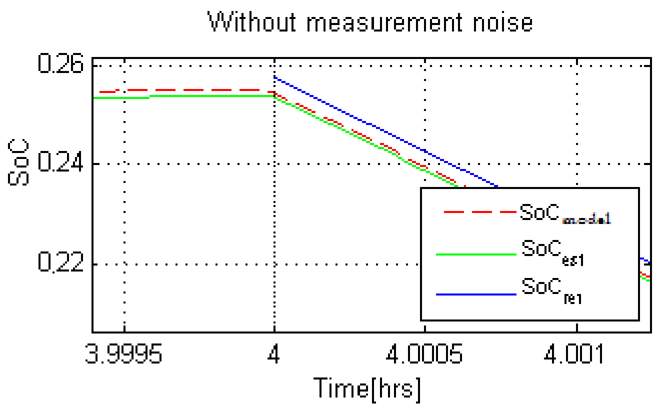
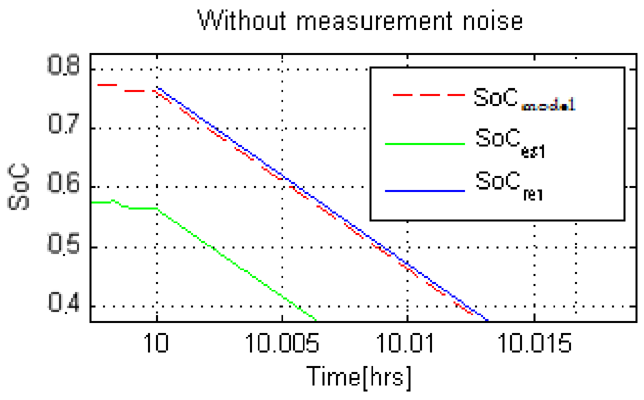
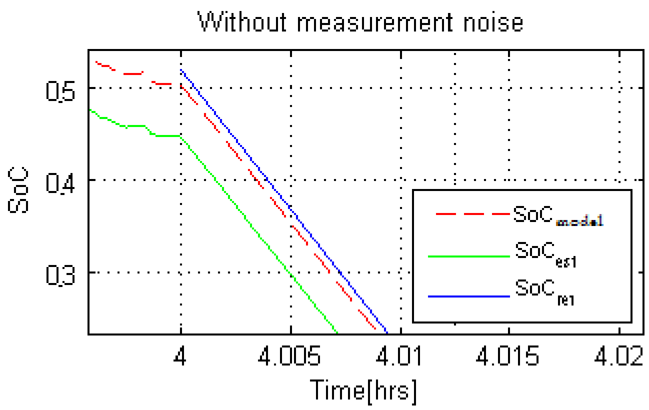
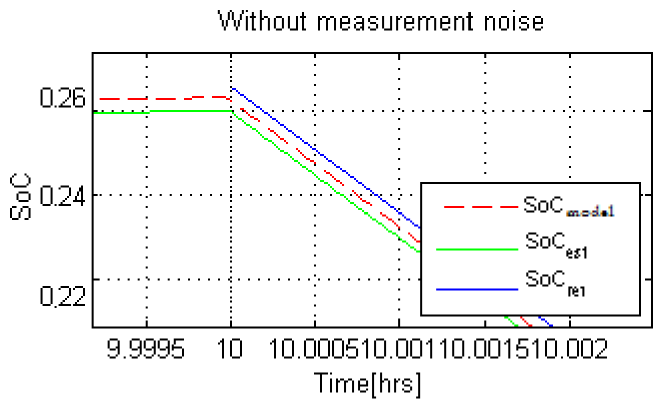


FIGURE 8.1 THE LOWER PLOT SHOWS HOW CLOSE THE BACKTRACKED SOC (PROPOSED METHOD) IS TRACKING THE REFERENCE SOC.

TABLE 8.1 SIMULATION TESTS OF THE PROPOSED METHOD.

HEV	Comment
	<u>Settings:</u> SoC_{init}=0.75 Simulation time = 4hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 <u>Result without measurement noise:</u> $SoC_{ref\ error}$ = 0.014 SoC_{error} = 0.18 <u>Result with measurement noise:</u> $SoC_{ref\ error}$ = 0.0003 SoC_{error} = 0.15
	<u>Settings:</u> SoC_{init}=0.5 Simulation time = 4hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 <u>Result without measurement noise:</u> $SoC_{ref\ error}$ = 0.015 SoC_{error} = 0.07 <u>Result with measurement noise:</u> $SoC_{ref\ error}$ = 0.0001 SoC_{error} = 0.054
	<u>Settings:</u> SoC_{init}=0.25 Simulation time = 4hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 <u>Result without measurement noise:</u> $SoC_{ref\ error}$ = 0.0003 SoC_{error} = 0.00041 <u>Result with measurement noise:</u> $SoC_{ref\ error}$ = 0.0001 SoC_{error} = ~0.0

	Settings: SoC_{init}=0.75 Simulation time = 10hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 Result without measurement noise: $SoC_{ref\ error} = 0.001$ $SoC_{error} = 0.21$ Result with measurement noise: $SoC_{ref\ error} = 0.0007$ $SoC_{error} = 0.19$
	Settings: SoC_{init}=0.50 Simulation time = 10hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 Result without measurement noise: $SoC_{ref\ error} = 0.015$ $SoC_{error} = 0.08$ Result with measurement noise: $SoC_{ref\ error} = \sim 0.0$ $SoC_{error} = 0.07$
	Settings: SoC_{init}=0.25 Simulation time = 10hrs Discharge current =3C $SoC_{est}(t_B)$=0.08 Result without measurement noise: $SoC_{ref\ error} = 0.0033$ $SoC_{error} = 0.0059$ Result with measurement noise: $SoC_{ref\ error} = \sim 0.0$ $SoC_{error} = 0.006$

8.2. EVALUATION OF THE SOC ESTIMATOR IN A VIRTUAL TEST RIG

The aim of this section is to evaluate the SoC estimation accuracy by first investigating the SoC_{error} measures that are presented in Table 5.1. All the tests are carried out in a virtual test rig (second figure in Figure 6.5) with the specified load cycles (HEV and PHEV) for two different time lengths, 4 hours and 10 hours. The measured errors SoC_{error} after each test is presented in Figure 8.2 and Figure 8.3 (without and with measurement noise, respectively).

It can be seen in Figure 8.2 and Figure 8.3 that the measures give similar SoC_{error} values with minor differences, especially between mean, final error and RMSE. Due to the similarities the final error is considered to be a more efficient measure, since it can easily be used for a real battery system. The main reason is that this measure only requires a reference at the end of each test run, see Table 5.1. The reference can either be determined by measuring the OCV after a rest period as discussed in (Mao, et al., 2011) or by utilizing the SoC_{ref} method proposed in Section 7. From a real battery system point of view, the proposed SoC_{ref} method will give a more accurate SoC_{ref} than directly measuring the OCV, see Section 2.3 on page 5.

The weighted mean and weighted standard deviation[1] of the measured errors SoC_{error} without (with) measurement noise (using the Final error measure + proposed SoC_{ref} method) is 0.04 ± 0.005 (0.03 ± 0.001), means that the SoC estimation accuracy is 0.96 ± 0.005 (0.97 ± 0.001).

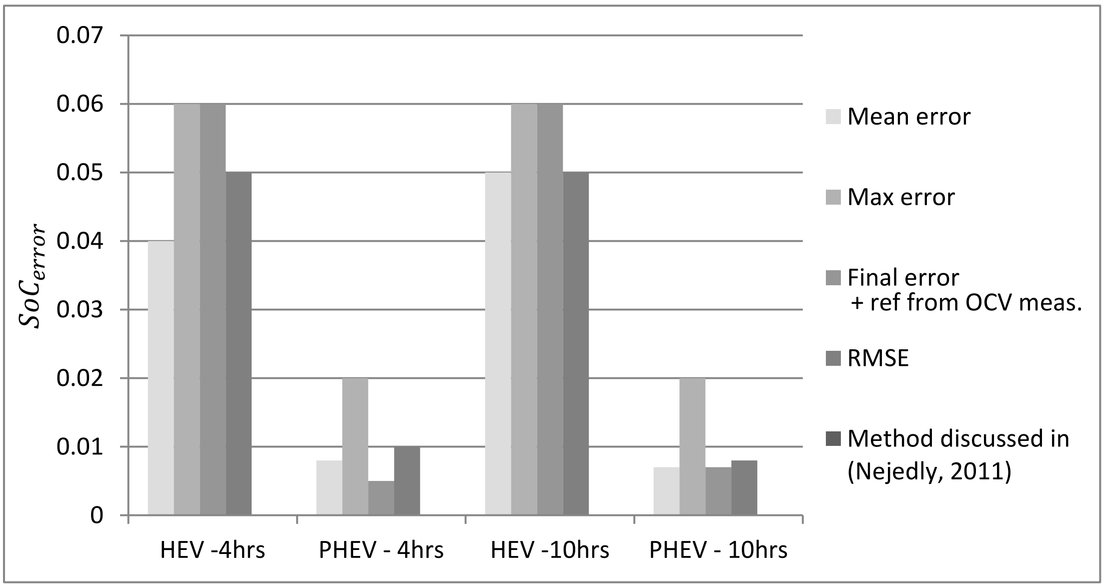


FIGURE 8.2 MEASURED SoC_{error}S WITHOUT MEASUREMENT NOISE IN THE VIRTUAL TEST RIG. NOTE THAT THE METHOD DISCUSSED IN (NEJEDLY, 2011) IS NOT APPLICABLE. THIS IS MAINLY BECAUSE THE REFERENCE SOC AND ITS ESTIMATE NEVER MERGE AT THE END, SEE SECTION 3.

[1] See Table 5.2 in section 5 for explanation. The calculated value is absolute.

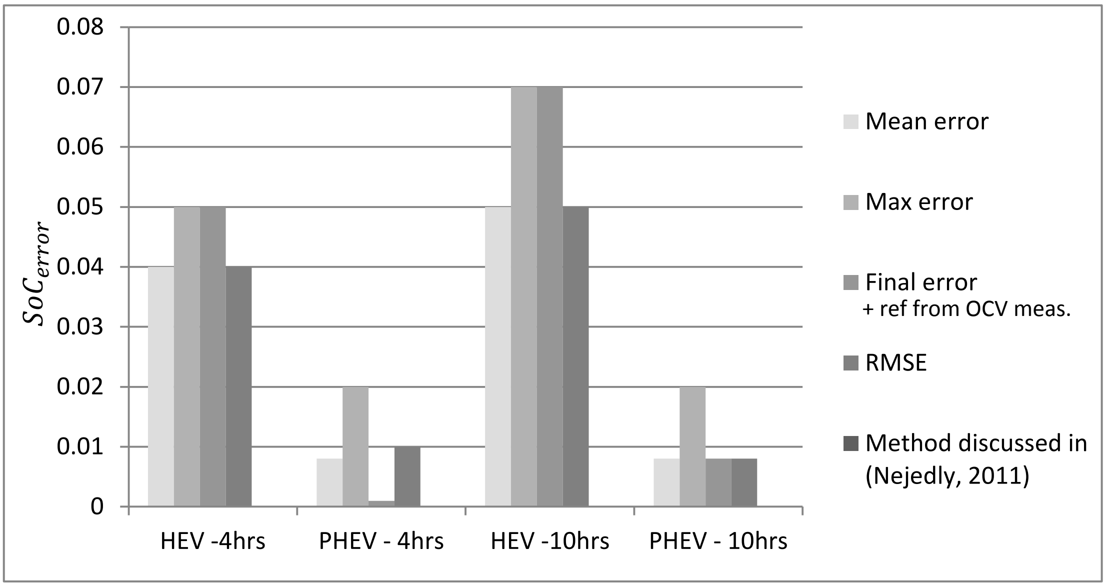


FIGURE 8.3 MEASURED SoC_{error}S WITH MEASUREMENT NOISE IN THE VIRTUAL TEST RIG. NOTE THAT THE METHOD DISCUSSED IN (NEJEDLY, 2011) IS NOT APPLICABLE. THIS IS MAINLY BECAUSE THE REFERENCE SOC AND ITS ESTIMATE NEVER MERGE AT THE END, SEE SECTION 3.

9. DISCUSSION AND CONCLUSION

It has been shown that the proposed SoC_{ref} method works satisfactorily in the tests with, and without, measurement noise and sensor uncertainties. From the tests presented in previous section, it can be concluded that the method is robust to measurement noise and gives a very accurate SoC_{ref}. However, it cannot be concluded that the method is the best one, due to the limited testing data available, such as load cycles. On the other hand, it has been shown here that the method performs well.

It has also been concluded in the thesis that the weighted mean is the most suitable measure to weight the determined errors SoC_{error}, see Table 5.2.

The proposed evaluation method for the battery system is as uses the final error measure, presented in Table 5.1, in combination with the proposed SoC_{ref} to determine the SoC_{error} after each test run. In addition, to determine the SoC estimation accuracy, denoted $SoC_{accuracy}$, using the weighted mean and standard deviation.

10. BIBLIOGRAPHY

Andersson, B., 2012. *Internal* [Interview] 2012.

Avago-Technologies, 2011. *Automotive High Precision DC Voltage Isolation Sensor,* United States: AvagoTech (Specification).

Ceraolo, M., 2011. *Modeling Test Matrices for Li Batteries and SC cells,* Italy: Universita Pisa, Hybrid Commercial Vehicle (Report No: D.3100.5).

Chiang, Y.-H., Sean, W.-Y. & Ke, J.-C., 2011. Online Estimation of Internal Resistance and Open-Circuit Voltage of Lithiu-Ion Batteries in Electric Vehicles. *Journal of Power Sources,* 196(8), pp. 3921-3932.

Conte, F., 2006. Battery and Battery Management For Hybrid Electric Vehicle: A Review. *Elektrotechnik & Informationstechnik 123,* 10(10), pp. 424-431.

Gelso, E., 2012. *Li-ion Battery Demonstrator p2 - Algorithm Development,* Gothenburg, Sweden: Volvo Group Truck Technology (Internal Report).

Groot, J., 2012. *State-of-Health Estimation of Li-ion Batteries: Cycle Life Test Methods,* Göteborg: Chalmers University of Technology (Licentiate Thesis).

Groot, J. & Lunden, M., 2006. *Energy Storage Project, Restarted Program A,* Gothenburg, Sweden: Volvo Group Truck Technology (Internal Report).

Hellgren, J., 2012. *Internal* [Interview] 2012.

Howell, D., 2010. *Battery Test Manual For Plug-In Hybrid Electric Vehicles: Revision 2, (Manual No: INL/EXL-07-12536).* [Online]
Available at: http://avt.inl.gov/energy_storage_lib.shtml
[Accessed 12 Oct 2012].

Lee, S.-J., Kim, J.-h., Lee, J. & Cho, B., 2008. State-of-Charge and Capacity Estimation of Lithium-ion Battery Using A New Open-Circuit Voltage Versus State-of-Charge. *Journal of Power Sources,* 185(2), pp. 1367-1373.

LEM, 2007. *Automotive Current Sensor (Specification).* [Online]
Available at: http://www.lem.com/
[Accessed 12 Oct 2012].

Mao, X., Tang, X., Lin, J. & Koch, B., 2011. *Li-Ion Battery Parameter Estimation For State of Charge.* San Francisco, CA, USA, AACC, pp. 941-946.

MIT, 2008. *A Guide to Understanding Battery Specifications - MIT Electric Vehicle Team.* [Online]
Available at: http://mit.edu/evt/summary_battery_specifications.pdf
[Accessed 29 07 2012].

Nejedly, A., 2011. *Evaluation and Test of A Battery Management Unit for Hybrid Electric Vehicles.* Stockholm, Sweden: Royal Institute of Technology (Master's Thesis).

Plett, G. L., 2004. Extended Kalman Filtering For Battery Management Systems of LiPB-based HEV Battery Packs - Part1. *Journal of Power Sources,* 134(2), pp. 252-261.

Pop, V., Bergveld, H. J., Notten, P. P. & Regtien, P. P., 2005. State-of-Art Of Battery State-of-Charge Determination. *Measurement Science and Technology,* 16(12), p. 12.

Wang Z et al, 2011. *The Comparative Study of SoC Estimation Based on EKF and ANFIS Algorithm IPCSIT vol.4.* Singapore, IACSIT.

APPENDIX

A. BATTERY MODEL SPECIFICATION

The accuracy of the battery model is presented in Table 1. The model is optimized for two specified regions of the operating conditions, the *optimized region* and the *extended region* are described in detail in Table 2.

TABLE 1 THE BATTERY MODEL

Battery model	Optimized region	Extended region
Voltage accuracy (mean)	< 0.01	< 0.05
Temperature accuracy	± 3°C	± 6°C
SoC, SoH and REL accuracy	< 0.1	< 0.1
Power limit accuracy	< 0.05	0.15

TABLE 2 THE OPTIMIZED REGION AND THE EXTENED REGION

	Optimized region	Extended region
State of Charge region	0.20 … 0.80	0.05 … 0.95
Temperature region	$\pm 0 \ldots \pm 40$°C	$-30 \ldots 50$°C
Current region	$1A \ldots 100\%\ of\ rated\ max.current$	$1A \ldots 110\%\ of\ rated\ max.current$

B. K-CURVE

A procedure to define $SoC_{est}(t_B)$ with respect to the OCV measurement error (denoted as c in Figure 1) and a desired accuracy of $SoC_{ref}(t_A)$ is presented in this section.

Assume the lower part of the OCV curve (0.0-0.5 SoC) has a shape as shown in Figure 1 and $SoC_{ref}(t_A)$ with an absolute accuracy, $SoC_{ref\ accurate}$[1], is required. Due to the shape of the curve and the measurement error (discussed in section 6), the accuracy of $SoC_{ref}(t_A)$ depends mainly on $SoC_{est}(t_B)$[2].

Assume further $SoC_{est}(t_B)$ with an error $[SoC_{lower\ error}, SoC_{upper\ error}]$ is found and

$$SoC_{upper\ error} - SoC_{est}(t_B) = SoC_{ref\ error}$$

,see the depicted figure. Hence, a line can be drawn between the points $\left(SoC_{est}(t_B), OCV(SoC_{est}(t_B))\right)$ and $\left(SoC_{upper}, OCV(SoC_{est}(t_B)) + c\right)$ with slope,

$$k = \frac{\left(OCV(SoC_{est}(t_B)) + c\right) - OCV(SoC_{est}(t_B))}{SoC_{upper} - SoC_{est}(t_B)} = \frac{c}{SoC_{ref\ error}}$$

If a k is calculated for every point on the lower OCV curve, then the k values can be plotted as shown in Figure 7.3. This figure can be used to determine $SoC_{est}(t_B)$ with respect to the required accuracy of $SoC_{ref}(t_A)$, see Section 7.

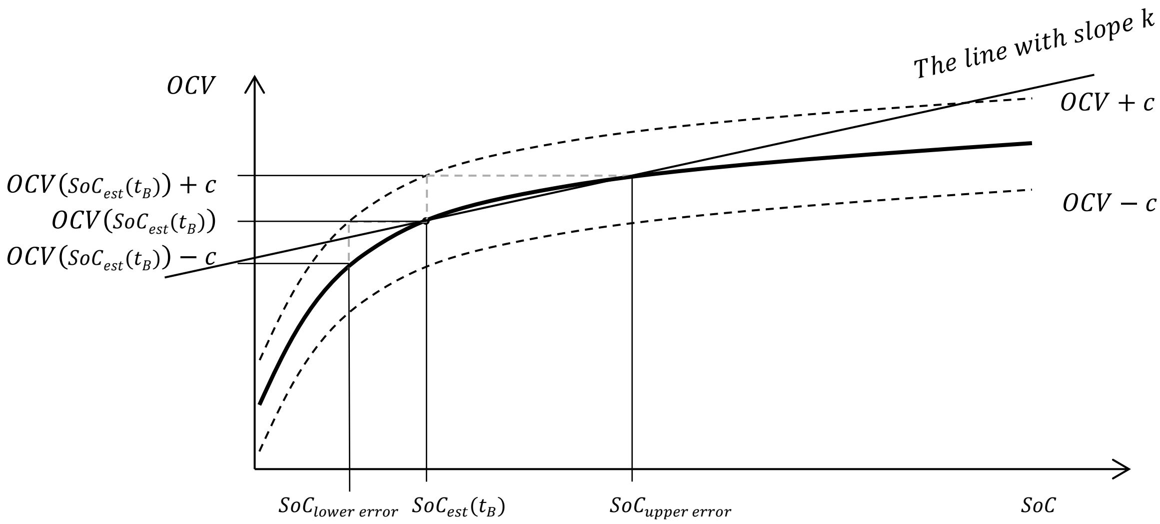


FIGURE 1 DEPICTS THE LOWER PART OF THE OCV CURVE. THE AFFINE LINE HAS SLOPE K.

---

[1] $SoC_{ref\ accurate}$=1- $SoC_{ref\ error}$. $SoC_{ref\ error}$ is the difference between the estimated reference SoC and the true SoC.

[2] SoC_{ref} is more accurate for lower $SoC_{est}(t_B)$. In fact, $SoC_{ref\ error} = SoC_{upper\ error} - SoC_{est}(t_B)$