STATE OF CHARGE ESTIMATION FOR LITHIUM-BASED BATTERIES

A Thesis

by

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STATE OF CHARGE ESTIMATION FOR LITHIUM-BASED BATTERIES

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To my family

ABSTRACT

This thesis proposes a new State of Charge (SOC) estimation method for lithium-based batteries, which offers a good trade-off between convergence and computation times. Lithium-based battery packages are quite common in the automotive industry and beyond because of their high-power density and dynamic response capabilities. Per a given volume, lithium-based battery cells have much more capacity, higher C rates, and lower internal resistance than other cell chemistries. However, this comes at a cost because of lithium's reactive nature. It is hard to preserve, monitor, cool, and control lithium in a pack within a safe state. For these reasons, battery control, or in other words, Battery Management Systems (BMS) is a major topic in the literature, and estimation of SOC, State of Health (SOH), and State of Power (SOP) are considered as core subfunctions of BMS. This thesis focuses on improving SOC estimation for lithium-based batteries. SOC estimation determines the remaining charge level on the battery and is very critical for battery-powered devices. This process is relatively straightforward when the battery is in the resting state. However, it can be difficult while the battery-powered device is operating, due to process disturbances and model uncertainties. The best performing SOC estimation methods in the literature are based on Kalman Filtering, and they are specifically Extended Kalman Filter (EKF) and Adaptive Dual Extended Kalman Filter (ADEKF). While EKF offers the shortest computation time, it results in a long convergence time. On the other hand, ADEKF offers short convergence time and long computation time. We propose PID-controlled EKF, which offers a mid-point in terms of convergence and computation times. The importance of convergence characteristics are also articulated in this thesis, especially from an automotive perspective.

ÖZETÇE

Bu tez Lityum tabanlı piller için yakınsama performansı ve hesaplama karmaşıklığı dengelenmiş yeni bir SOC kestirim algoritması sunmaktadır. Lityum bazlı piller yüksek enerji yoğunluğuna ve dinamik tepkilere sahip olduğu için endüstride oldukça yaygın olarak tercih edilmektedir. Bu piller, belirli bir hacimde diğer hücre kimyalarına göre daha yüksek kapasite, yüksek C oranlar ve düşük iç direnç sunmaktadır. Fakat lityumun reaktif yapısı çeşitli problemlere yol açmaktadır. Bu kimyasal maddeyi bir paket içerisinde muhafaza etmek, soğutmak, kontrol etmek ve takibini sağlamak oldukça zordur. Bu sebeplerden ötürü Batarya Yönetim Sistemleri hakkındaki akademik çalışmalarda pilin şarj, ömür ve güç durumunun takip edilmesine önemle yer verilmitir. Bu tezde lityum tabanlı pillerin şarj durumunun yüksek hassasiyet ile takibine odaklanılmştır. Bir pilin açık devre konumunda iken şarj durumu tespiti yapılması oldukça kolaydır fakat yük altındaki bir pilin şarj durumunun kestirilmesinde çeşitli zorluklar ortaya çıkar. Literatürde Kalman tabanlı filtreler, özellikle EKF ve ADEKF, en iyi SOC kestirimi performansını sağlamaktadır. EKF düşük hesaplama karmaşıklığı sunar fakat yakınsama zamanı uzundur. Diğer taraftan, ADEKF kısa yakınsama zamanı sunarken yüksek hesaplama karmaşıklığına sahiptir. Bu tezde bu iki algoritmanın güçlü yönlerini dengeleyen yeni bir PID kontrollü EKF algoritması sunulmuştur. Ayrıca bu tez, yakınsama performansının önemini de vurgulamaktadır.

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CHAPTER I

INTRODUCTION

Lithium-based battery demand is rising in the last years especially after the electric vehicles become popular. It can be seen in the daily life that lots of devices become lithium-based battery powered. Due to the high energy density of lithium, it is highly advantageous to use lithium as an energy source in mobile devices.

A lithium-based battery pack should be used with a Battery Management System for optimizing the performance and life of the battery. Safety reasons are also considered for lithium-based battery packs. The position of lithium in the periodic table is one above the sodium in the alkali metal column which means this chemical has a reactive nature which can lead to critical failures while it is processed.

Increasing demand for lithium-based batteries leads fast developments in the Battery Management System research area. Lots of academical and industrial work is done in this area to make sure that lithium-based batteries are used optimally in a safe way.

A BMS can have lots of different functionalities depends on the application area. State of Charge estimation is one of the important functions of a BMS. For electric vehicle manufacturers, it is very important to estimate SOC accurately. To know how long a device can be powered with the remaining charge, SOC should be known precisely. However, it can not be directly measured with a sensor but, it can be estimated with some mathematical approaches. This work is focused on improving the performance of SOC estimation.

In the following sections, fundamentals of batteries and BMS are explained for the next chapter topics.

1.1 Battery Cell Chemistries

Storing energy is a critical problem in the design process of devices especially for mobile ones. This problem causes some design limitations for engineers. Once the power and energy requirements of a system is calculated, a satisfying energy source should be determined to meet the demand. Volume, mass, and thermal properties are some of the important concerns in this process. If the device is powered by a battery like a drone, mobile phone, or an electric vehicle (EV) then some alternative chemicals should be considered like lead-acid, nickel-cadmium (NiCd), nickel-metal hydride (NiMH), lithium-ion (Li-ion), lithium-ion polymer, etc. as an energy source. Even a supercapacitor can be considered as a main or secondary energy source in a device. All these alternatives come with their pros and cons.

Differing from capacitors, in batteries, a chemical reaction should be triggered to gather energy. According to the characteristics of these reactions, the dynamic response of the battery cell takes form. Generally, chemical bond energy is exposed in metal-based electrochemical cells while it is under load.

Four different rechargeable battery chemistries are used commonly in the industry.

1.1.1 Nickel-Cadmium Batteries (NiCd)

Comparing with other chemistries this type has much more life-time, higher instant power release capabilities, and low prices. However, from an energy density point of view, it is relatively weak and cannot store a high amount of energy in a given volume. They are often used in alkaline AAA batteries.

1.1.2 Nickel-Metal Hydride (NiMH)

NiMH cells have much more capacity than NiCd. It can store up to two times more energy than NiCd at the same volume. It also doesn't contain toxic metals so that it is more environmentally friendly. However, it has a reduced lifetime compared with NiCd.

1.1.3 Lead-Acid Batteries

Lead-Acid battery is one of the oldest types of battery but it is still very common especially in automotive and renewable solar-panel energy storage (Fig. 1) [1]. It has high instant power capability and lifetime with its low prices. However, it has a very weak energy capacity in a given weight.

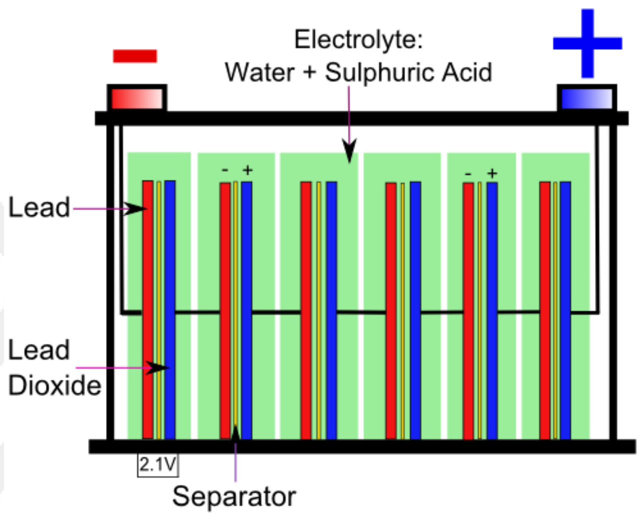


Figure 1: Lead-Acid Battery Diagram

1.1.4 Lithium-Based Batteries

Lithium-Based batteries are the most common type in Electric Vehicles. They can store much more energy in given volume and mass than other chemistries. They also have wide power bandwidth. A Li-ion cell can supply energy to low and high power applications with a robust efficiency. However, well-designed protection hardware and software should be used with these cells. Battery Management Systems are developed for this reason.

18650 battery cell is very common in the industry (Fig. 2). Different versions of this battery are used in wide product range like laptop batteries to electric vehicles.

Figure 2: 18650 Li-ion Battery Cell

1.2 Lithium-ion Battery Packs

Li-ion battery packs are consist of individual cells. A cell, which can provide 3.3 V nominal, is the smallest unit of a battery pack. To reach the required voltage level cells are connected in series and to reach the required capacity and maximum current they connected parallel. The reason for not producing the battery as a single cell is to provide a modular design possibility. For example in an electric vehicle battery can be divided and located at different positions for mechanical reasons. The production and recycling process is also simplified. These cells are usually connected with a nickel strip over spot welding (Fig. 3). Each module contains parallel cells and modules are connected in series (Fig. 4). With this design, modules balance their self and balance between the modules is done by BMS. Cell balancing is explained in Section 1.3.

Figure 3: Connected Cells via Spot Welding

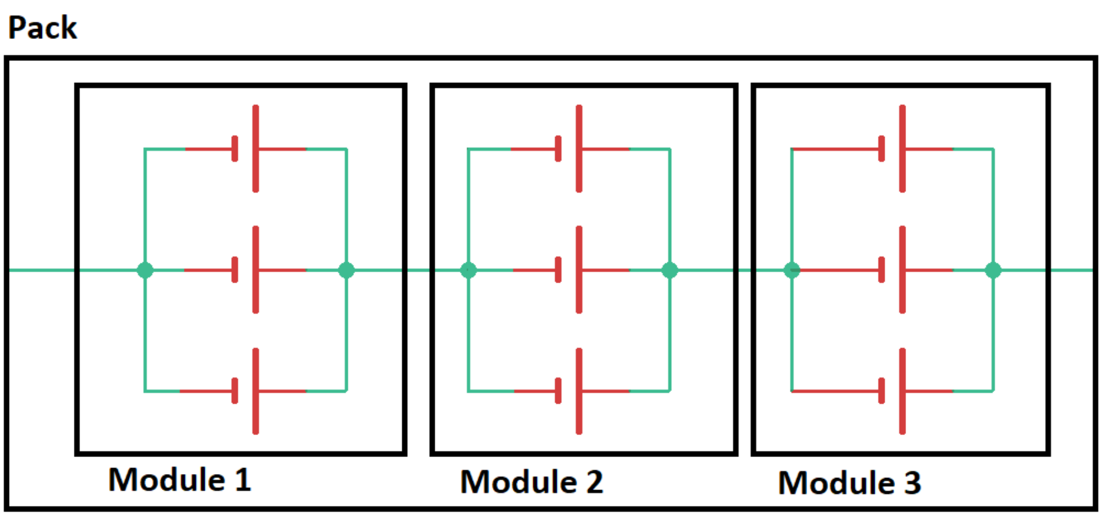


Figure 4: Circuit Diagram of a Battery Pack

1.3 Battery Cell Terminologies

This section explains the basic concepts and terminology about batteries.

1.3.1 C Rate

C rate defines the maximum current that a battery cell can give.

$$MaxCurrent = CRate * Capacity \tag{1}$$

A battery with 2C discharge rate and 2 ampere-hour capacity can give 4 amperes maximum and it will last in a half-hour if it is used in 2C. A battery will last in 1 hour if it is used in 1C according to equation (1).

The discharge rate is not a physical limitation. A battery with a 1C discharge rate may be discharged with 10C but it can cause serious problems and failures. The discharge rate is determined by the manufacturer and the battery can be used safely within this limitation.

1.3.2 Capacity

The capacity of a battery is measured with ampere-hours. A battery with 50Ah will be finished after giving 50 amperes for 1 hour. The capacity of the same battery can be changed in different conditions like C-rate, temperature, and the age of the battery.

With a direct proportion, it can be said that 50Ah battery will last in a half-hour if it is discharged with 2C which means 100 ampere instant current consumption. However, it will last before a half-hour. In higher discharge rates the usable capacity of a battery is reduced because of chemical reasons. The performance of a battery is always reduced when limits are pushed. Datasheet of the Samsung 18650 cell shows how cell capacity affected by the discharge rate (Fig 5).

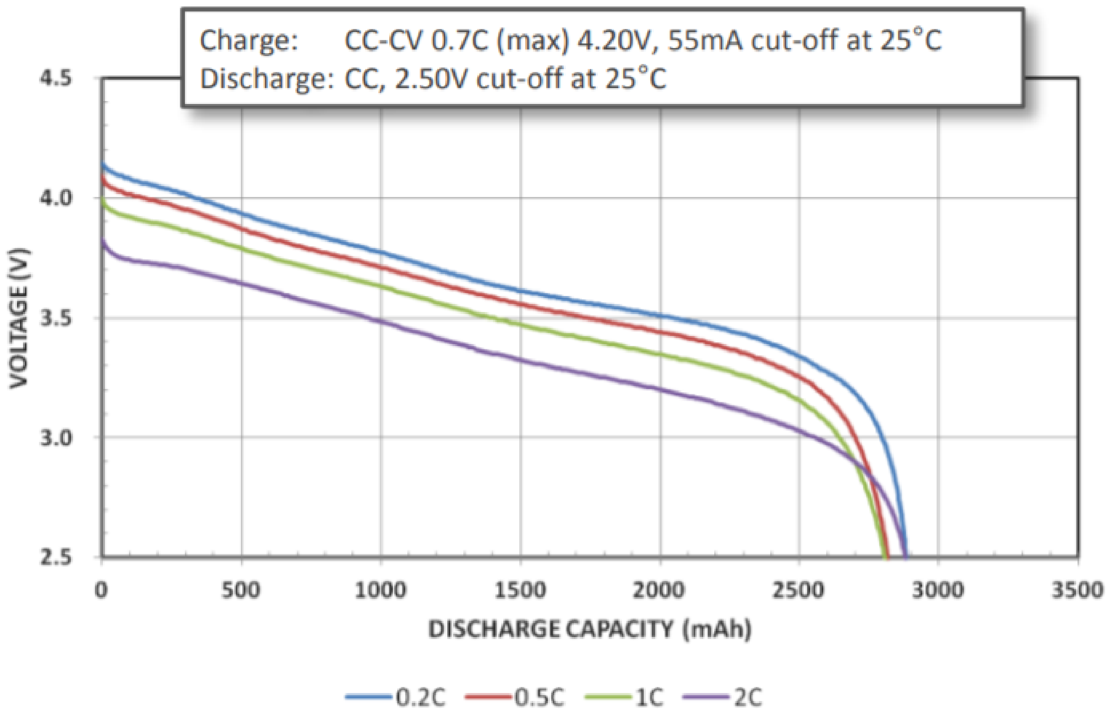


Figure 5: Capacity Characteristics by Discharge Rate

Temperature is one of the most important variables that affect capacity. When a cell has connected to a load, a chemical reaction starts between the anode and cathode labels of the cell. Environment temperature has a catalytic effect on this reaction. At lower temperatures capacity decreases by up to 20%. For these reasons, electric vehicle manufacturers cover the batteries with heating pads of the vehicles which are produced for north countries like Norway. Datasheet of the Samsung 18650 cell shows how cell capacity affected by the temperature (Fig. 6).

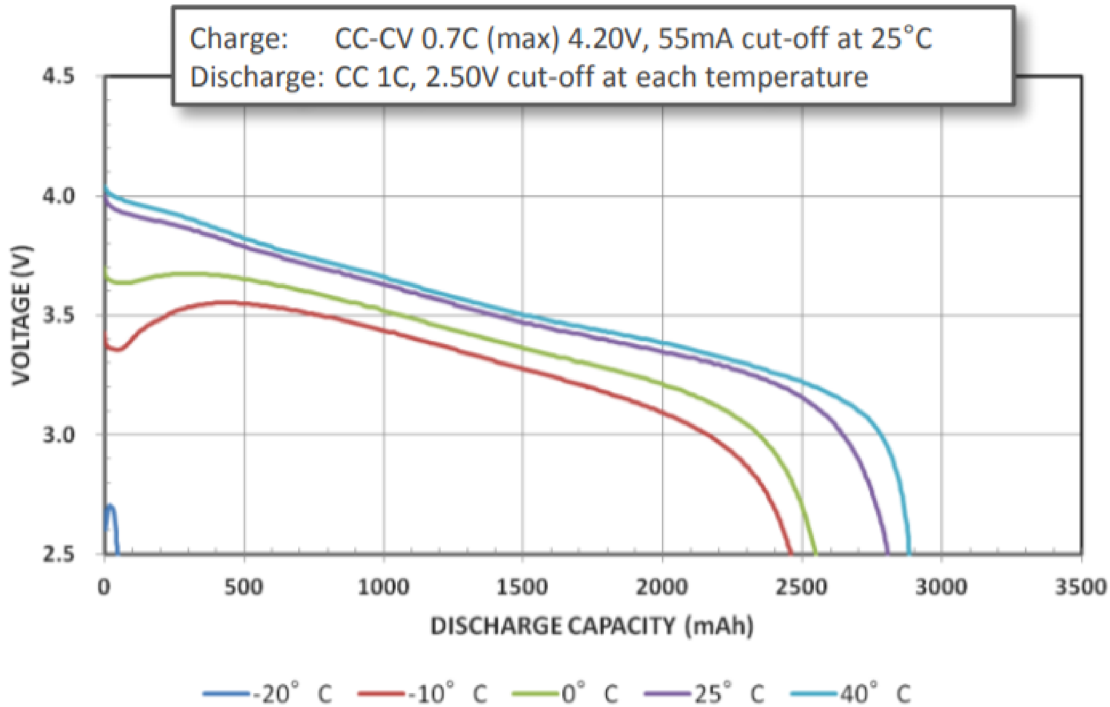


Figure 6: Capacity Characteristics by Temperature

The characteristics of a battery always change because of the aging effect. The simplest way of tracking the age effect is cycle counting. Every charging and discharging period is counted as a cycle and the age of the battery is assigned by this count. While a cell is aging capacity is reduced. Datasheet of the Samsung 18650 cell shows how cell capacity affected by the aging effect (Fig. 7).

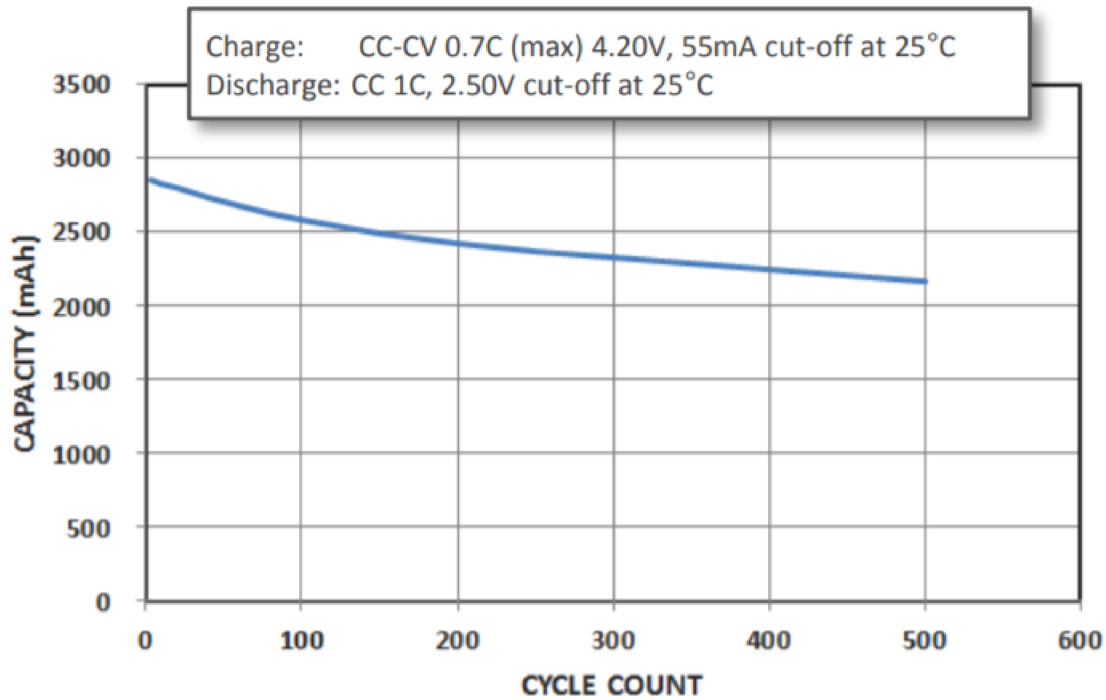


Figure 7: Capacity Characteristics by Aging

1.3.3 Open Circuit Voltage

Open circuit voltage (OCV) is a function of State of Charge (SOC), temperature, and State of Health(SOH). Like a capacitor, terminal voltage decreases as available charge decreases in a lithium battery (Fig. 8) [2]. Similarly, OCV decreases at low-temperature levels. This is the reason that the performance of an electric vehicle is reduced perceptibly in winter. OCV is important because if temperature and SOH are known, SOC can be exactly known if the battery is in open circuit condition. For open-circuit condition, the battery should be rested for a while and cooled down after an excitement.

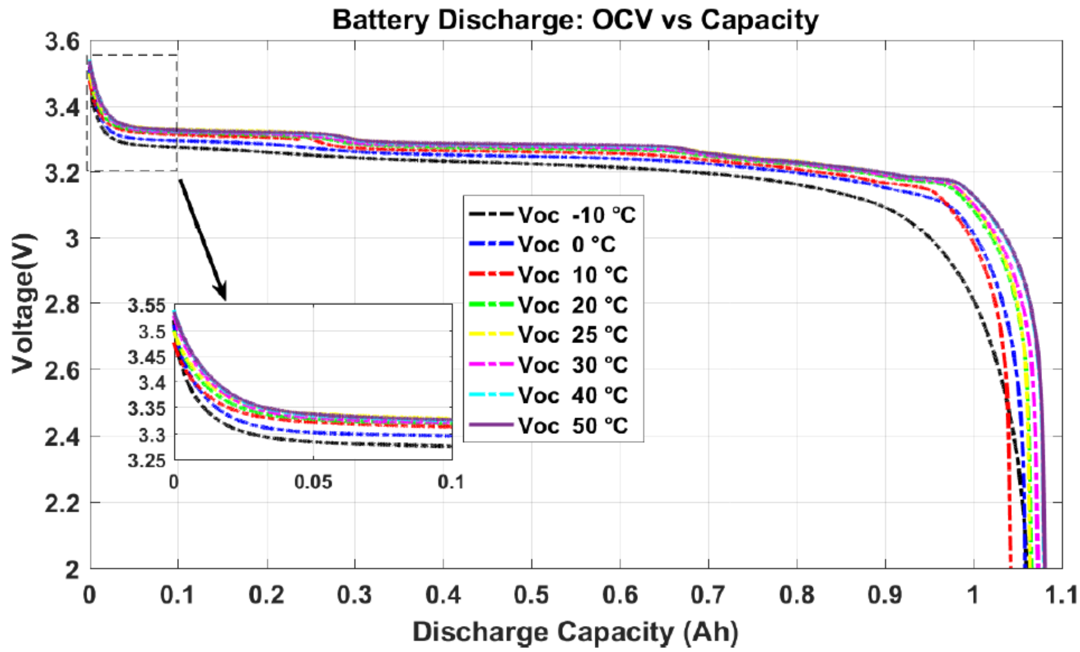


Figure 8: OCV vs Discharge Capacity.

1.3.4 Internal Resistance

Like every other power source, batteries also have internal resistance. A simple cell model can be constructed from a voltage source and a series resistance (Fig. 9). Because of internal resistance, under higher loads, there will be a huge amount of voltage drop across the internal resistance. This drop may affect the performance of the system so that it should be considered in the design process. SOH and temperature also have an impact on this resistance. Under extreme cases, internal resistance increases and according to ohms law maximum current that a cell can give decreases. Also, it should be considered that generally cell producers write AC impedance to datasheets. In this work, internal resistance refers to DC series resistance.

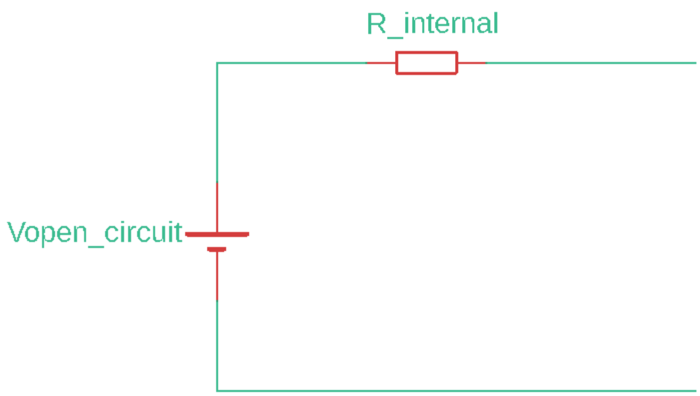


Figure 9: Cell Model with Internal Resistance

1.3.5 SOC

State of charge indicates how much charge remains in the battery. It is very critical for electric vehicles to obtain that vehicle can go to a charge station with the remaining charge. SOC should be distinguished from remaining energy. For energy consumption both voltage and current should be considered however in SOC estimation, only electric charge is evaluated. It indicates how much current capacity that the battery can provide.

SOC is also important for tracking the balance between individual cells in a battery pack. Cells that are close to the package are a bit cooler than the centrally located ones because they can radiate their heat to the environment. That's why middle cells have higher temperatures and lower SOC. This situation should be detected and protection functions like balancing and cooling should be activated.

In a battery cycle, generally, cells are not fully charged and discharged. This is important for safety reasons and the lifetime of the cell. Pushing the limits is not a good idea for a reactive chemical. Also in an unbalanced battery, some cells can be degraded early from the other ones and discharging more in such a battery can lead to current requests from a zero SOC cell (Fig. 10). To avoid unsafe situations generally, cells are charged up to 90% and discharged to 10%.

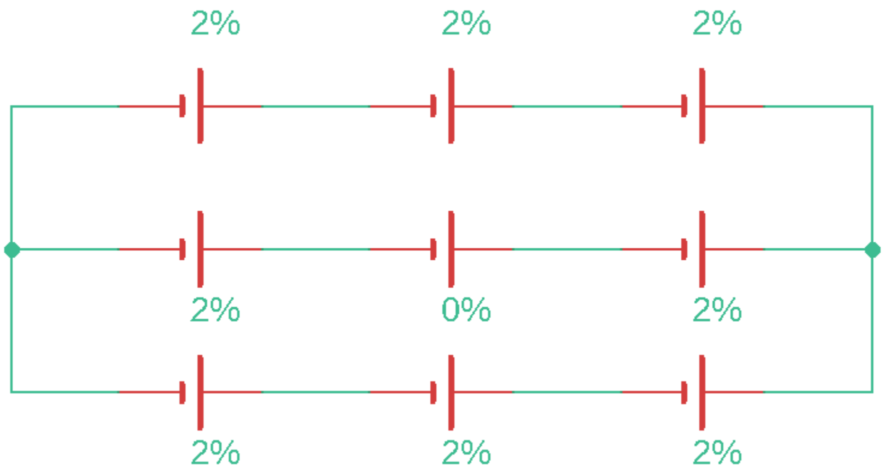


Figure 10: An Unbalanced Battery Pack

1.3.6 SOH

State of health indicates how much life does battery still has. A brand-new battery has 100% SOH and a dead cell has 0% SOH. A battery with 80% SOH has 20% less capacity from its initial state and it has 80% available capacity. Other than the capacity loss internal resistance of the cell also increases while the cell is aging and according to ohms law maximum current that the cell can provide is decreased. Open circuit voltage is also reduced and because of the voltage and current drop, the power that the cell can provide decreases.

In electric vehicles generally, after 80% SOH, battery cant satisfy the vehicle's power demand and it should be changed. Before recycle these batteries are using in power plants and other applications.

The simplest SOH estimation method is cycle counting, however, it should be considered that every cycle does not affect the battery the same. A cycle with a higher C rate and temperature can decrease more than 1 cycle from a battery.

Capacity monitoring is another conventional method that is used in electric vehicles. The BMS monitors the battery and waits for a complete cycle that SOC is decreased to 0% from 100%, by this way available capacity can be determined. Model-based SOH estimation methods are also explained in the literature

1.3.7 Charging Procedure

Charging a lithium-based battery can be challenging. Other than different cell chemistries, lithium cells cant be charged with a simple voltage source. Normally a constant voltage source connected to a battery and because of the internal resistance, battery doesn't take huge amounts of current at reasonable voltage levels. However, lithium batteries have quite small resistance and a little voltage difference between charger and battery leads to huge current flow. That's why current control needed in the charging procedure. Generally, lithium batteries charged with a 1C charge rate and the charger's voltage should be increased gradually according to satisfy 1C charge rate because of the voltage rise of the battery while it is charging. After the maximum charge voltage level which is determined by the supplier reached, increasing the voltage may cause serious failures. After that point voltage should be fixed until the cut-off current reached. This method is called constant current, constant voltage charging procedure (Fig. 11) [3].

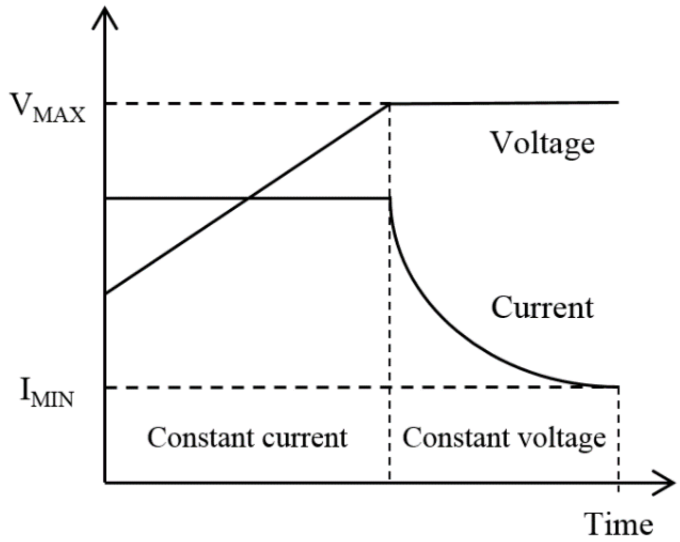


Figure 11: Constant Current Constant Voltage Charging

1.4 Battery Management Systems

The purpose of BMS depends on the application but generally, it protects the battery and the battery-powered system. A BMS (Fig. 12) should prevent potential accidents and failures by detecting risky events like short-circuit, reverse polarity, overcharge, over-discharge, over-voltage, over current and over temperature. Regulation of charge and discharge procedure also maximizes the life and performance of the battery. In electric vehicles, generally, BMS provides an interface over CAN-BUS for other vehicle control units. At the following section monitoring, thermal management, balancing, and SoX estimation functions are explained.

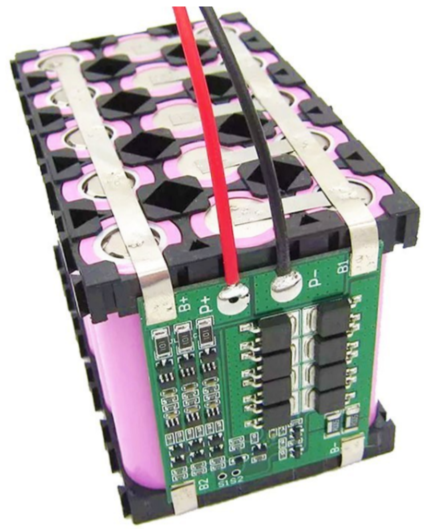


Figure 12: BMS with a Battery Pack

1.4.1 BMS Functions

A BMS has a wide range of functionality variations. However, monitoring, thermal management, cell balancing, and SoX estimation are basic and common functionalities of a BMS.

1.4.1.1 Monitoring

Monitoring is the basic functionality of the BMS. Voltage, temperature, and current should be observed for other functions. BMS evaluates all modules as a single cell. In a module, cells are connected parallelly (Fig. 4) and each module is separately balanced and each cell has the same voltage in the same module because of the parallel connection. In a battery pack cables should be connected from every battery module pole head to BMS (Fig. 13) [4]. Generally, a multiplexer circuit is used for switching between cells for cell voltage measuring. For temperature sensing generally, sensors mounted to the middle cell which is the hottest one, of each module. For current sensing generally, hall effect sensors are connected to the main bus of the battery.

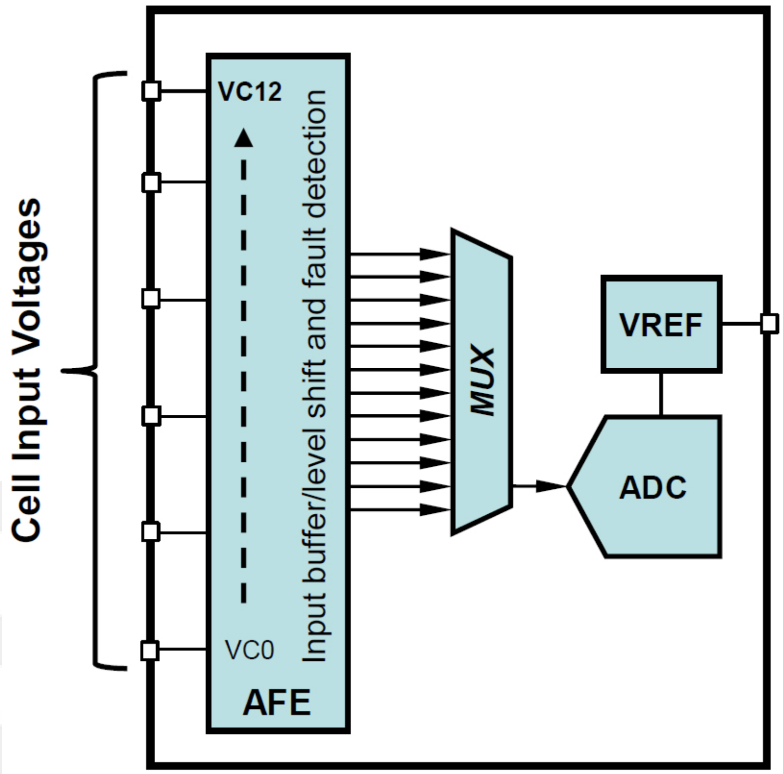


Figure 13: Basic Cell Monitoring Hardware Diagram for a BMS

1.4.1.2 Thermal Management

While charging and discharging a battery cell, chemical reactions make them heat up. After a temperature offset cell stars to release poisonous gas. After that offset, if it continues to heat up, it can be deflagrated or blow-up. Once these failures happen battery should be completely cooled and discharged to stop this unwanted reaction. It is very hard for a firefighter to extinguish these reactions. To prevent this a well designed cooling system should be integrated into the battery if it is necessary. BMS should track pack temperature to activate the cooling system or even completely shut down the battery by opening contactors if it is needed. It is also important that using the battery at the optimal thermal band for improving performance and lifetime.

1.4.1.3 Cell Balancing

Because of production errors and environmental effects, two different battery cell cannot be identical even they are produced in the same production line. These differences lead to some unbalanced conditions in a battery pack. SOC levels for cells are diverse from each other over time. In charging procedure if a cell reaches full charge before other cells, charging should be stoped to prevent overcharge. In this situation, unused capacity occurs in other cells. Likewise, if a cell completely discharged while other cells have some charge, battery cant used to prevent over-discharge and even pack has the energy it is not available (Fig. 14) [5] . To maximize the capacity and lifetime of a pack, cell balance is required. There are two common balance techniques which are passive and active balancing used in the industry.

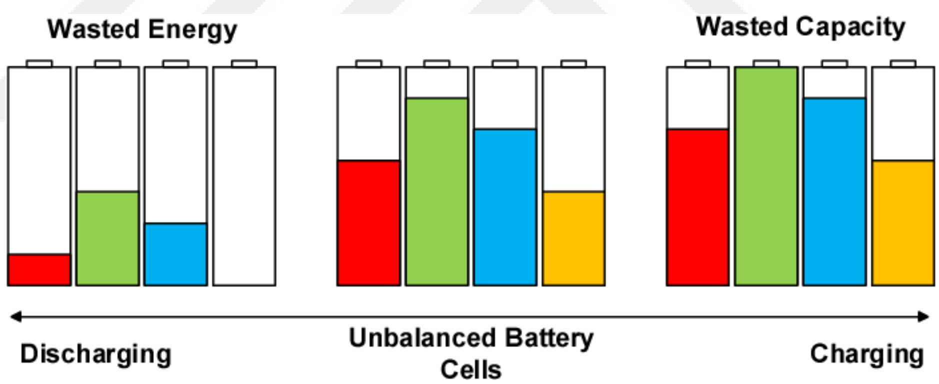


Figure 14: Unbalanced Cells

Passive balance is more common because of its simplicity. Cells that have more charge, simply discharged over a resistor until the pack reaches to balance (Fig. 15) [6]. This function can be activated on charging time to not waste the mobile energy but this will increase the charge time. If it is activated on discharging, charge time is not affected but mobile energy is wasted. This function can also be activated on idle time.

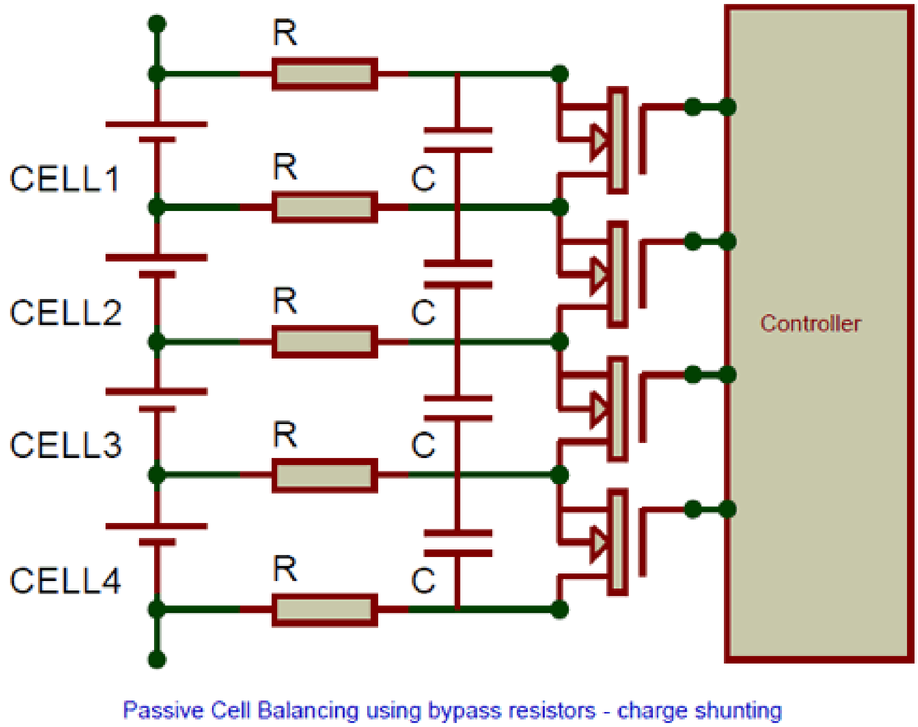


Figure 15: Passive Cell Balancing Diagram

Even active balancing is a smarter method it is not common as passive balancing because of its manufacturing and maintaining complexity. In this method, a super-capacitor or an extra battery module added to battery in order to transfer extra capacity between cells.

1.4.1.4 SoX Estimation

SOC and SOH estimation is critical for battery-powered systems. It can be challenging because they cant be measured with a sensor directly. Somehow SoX should be calculated or estimated because other BMS functions need SOC and SOH as an input. It is also critical for electric vehicle drivers to know when to charge and obtain the remaining range that the vehicle can go. Other than some conventional methods, model-based approaches and machine learning algorithms used for estimation.

CHAPTER II

MODELING

A mathematical representation is needed for model-based observers. Basically, measured and calculated states will be compared to figure out system uncertainties. A model is also necessary for simulation purposes.

Even a battery pack contains multiple cells, modeling a single cell is enough for simulations and observer algorithms. BMS algorithms generally track the cell that has minimum and maximum SOC in a pack. In this work, the cell model is instantiated over different cells in a pack.

2.1 Cell Modeling

In the literature, there are 3 main different modeling techniques which are electrochemical cell , neural network and equivalent circuit model are available.

Wei et al. [7], has modeled the reactions between anode and cathode terminals (Fig. 16). This is a quite comprehensive and sophisticated model that can be used from battery cell manufacturers in the design progress. Ahmad et al. [8] point out, other than some corner cases equivalent circuit model is almost accurate as an electrochemical model with lower complexity. A neural network, which has a reasonable performance, is constructed by Wei et al. [9] for cell modeling. Inputs of this network are temperature, voltage, and current (Fig. 17). Jiani et. al. [10] proposed a machine learning algorithm that is reinforced with a model-based method, which has high accuracy. They modeled the cell with a neural network that drives a Kalman-based filter. However, training such a network requires a lot of data from a battery that is not time and cost-effective. Therefore in this work machine learning algorithms are not considered.

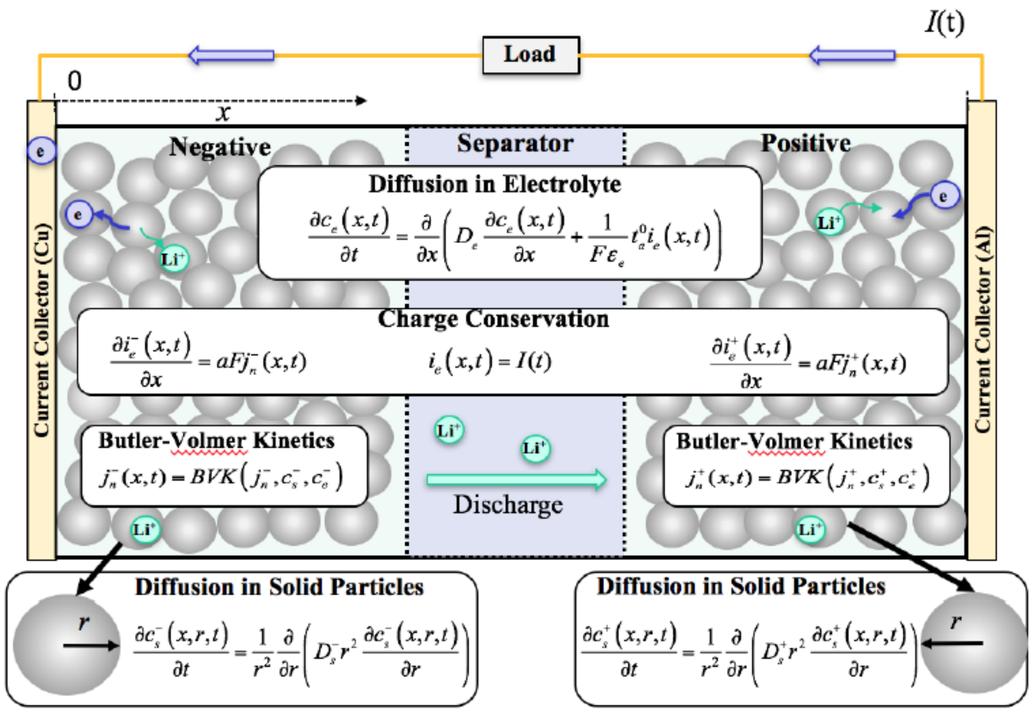


Figure 16: Electrochemical Model

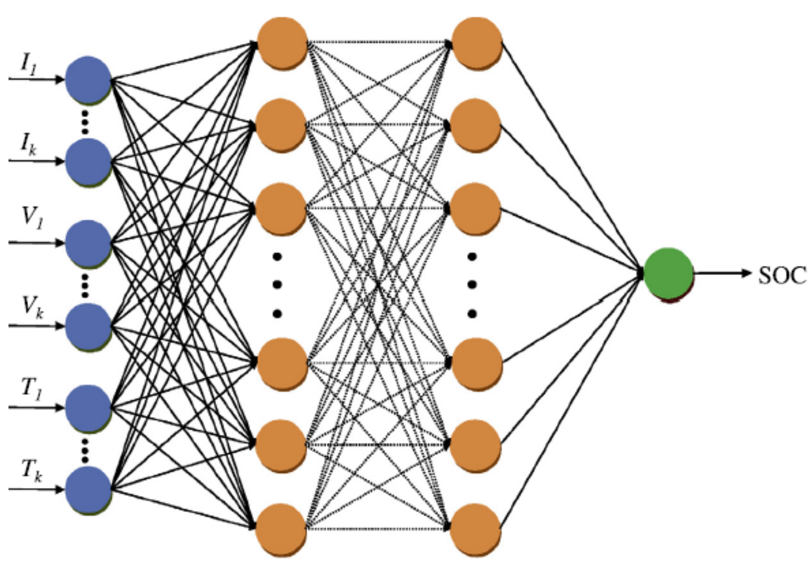


Figure 17: Neural Network for Cell Modeling

2.2 Equivalent Circuit Modeling

In this work equivalent circuit modeling is used for it is simplicity (Fig. 18). This equivalent circuit does not exist in the cell but it simulates the behavior of a cell which helps to estimate system states in Kalman Filtering. All parameters are a function of SOC, temperature, and SOH. Table 1 explains the meanings of the parameters.

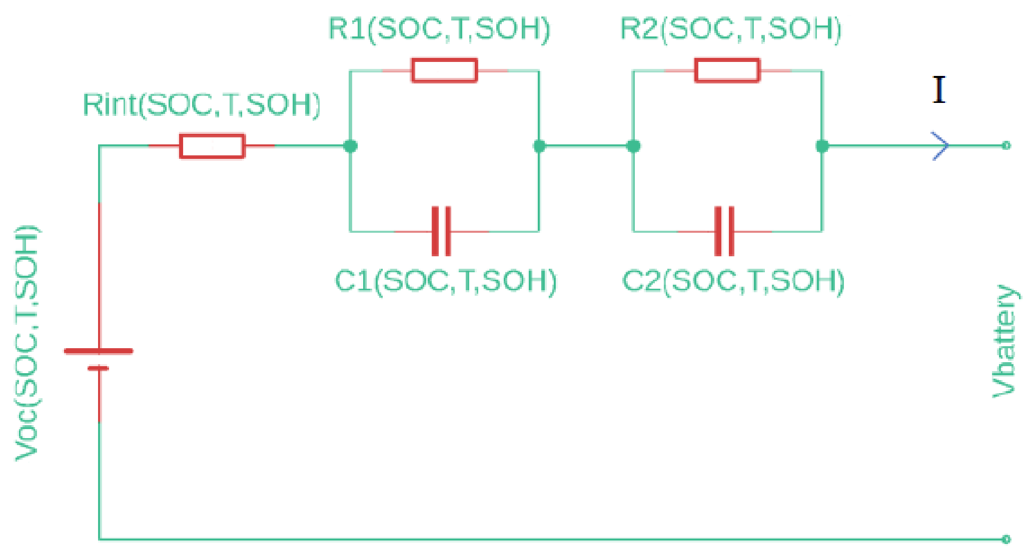


Figure 18: 2RC Equivalent Circuit Model

Voc	Open circuit voltage.
Rint	Internal resistance of the cell.
Vbatt	Terminal voltage of the cell.
C values	Capacitance values that simulates delayed voltage response of the cell.
R values	Leakage resistances of the capacitors
I	Charge or discharge current

Table 1: Equivalent Circuit Model Parameters

2.2.1 State Space Model of the Equivalent Circuit

$$\begin{bmatrix} \dot{V_{C1}} \\ \dot{V_{C2}} \\ \dot{SOC} \end{bmatrix} = \begin{bmatrix} \frac{-1}{R_1C_1} & 0 & 0 \\ 0 & \frac{-1}{R_2C_2} & 0 \\ 0 & 0 & 0 \end{bmatrix} \begin{bmatrix} V_{C1} \\ V_{C2} \\ SOC \end{bmatrix} + \begin{bmatrix} \frac{1}{C_1} \\ \frac{1}{C_2} \\ \frac{1}{BatteryCapacity} \end{bmatrix} I \tag{2}$$

$$V_{battery} = V_{oc} + R_{int}I + V_{C1} + V_{C2} \tag{3}$$

2RC equivalent circuit equations were derived from Kirchhoff's law and capacitor voltage formula. Equation (2) shows the state matrix equation of the model and equation (3) indicates the measurement function.

2.3 Parameter Identification

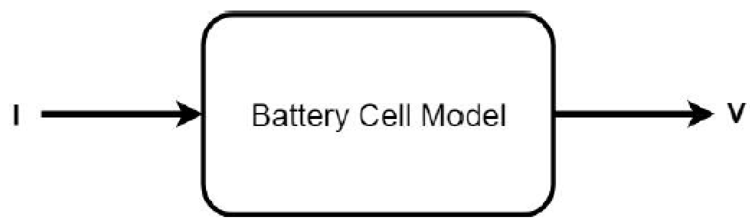


Figure 19: Cell Model I/O

Current is directly controllable and voltage changes according to current and system states in a battery cell (Fig. 19). Shortly current is the input and voltage is the output of the system. Model parameters should be identified for a specific cell in order to compute the model.

A commercial battery that is used in hybrid vehicles with 51Ah capacity is used for parameter identification to use reasonable values for simulations. Least squares method is used to estimate system parameters. The battery is connected to a current source to perform charge and discharge cycles. Hybrid Pulse Power Characterization (HPPC) drive cycle is used for parameter identification (Fig. 20). This cycle is developed for battery characterization progresses. Battery is excited with constant current to charge and discharge capacitors at the cell model. After constant current periods, idle time periods performed. At that period battery is released and current flow is stopped. Only measurement functions are performed to collect data to fit curves and identify parameters at the idle time. Constant current and idle periods are repeated to figure out parameters in different SOC, temperature and SOH conditions. Equation (4) is the cost function that is minimized to find cell parameters. MATLAB/SIMULINK parameter identification toolbox is used to converge to the real parameter values.

$$J = \sum (V_{measured}(t) - V_{simulated}(t, I))^2 \tag{4}$$

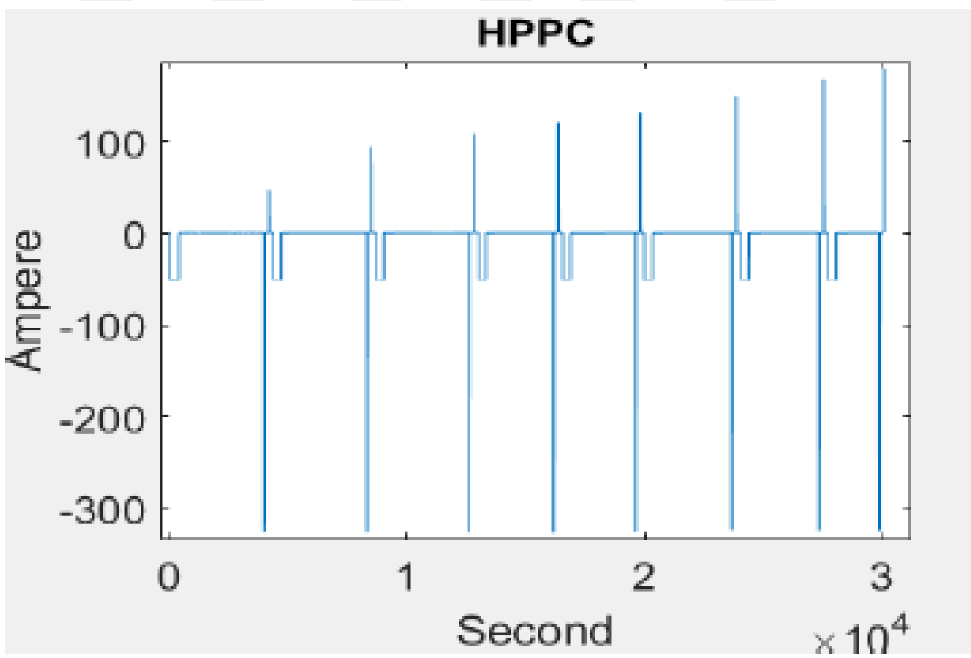


Figure 20: HPPC Drive Cycle

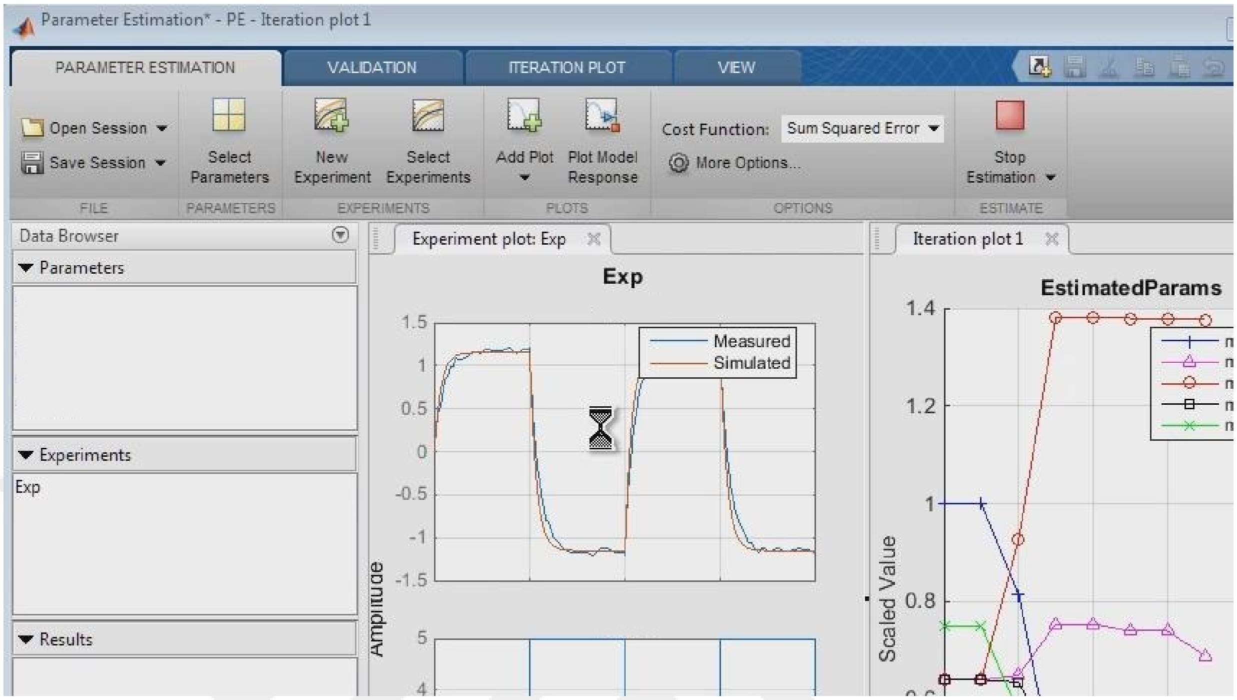


Figure 21: MATLAB/SIMULINK Parameter Identification Toolbox

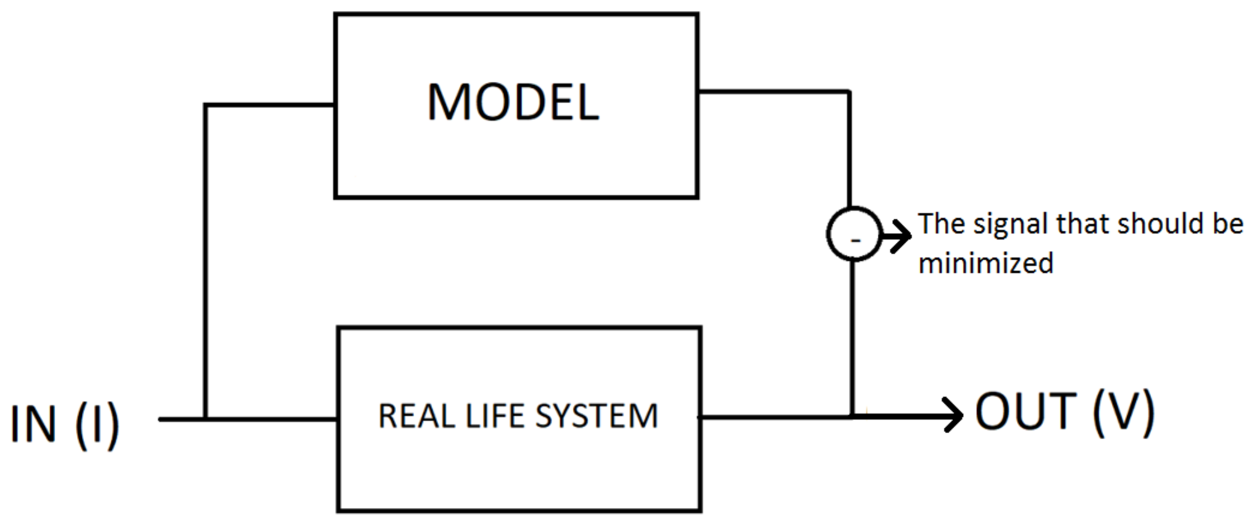


Figure 22: Parameter Identification Block Diagram

Parameter identification toolbox computes the model (2RC cell model for this work) with initial parameters and given input profile (Fig. 21). Then it computes an error value with subtracting real-life measurements and simulated outputs (Fig. 22). According to this error, parameters are updated iteratively. In this work, battery is excited under the HPPC cycle and the voltage of the battery is logged. For initial parameters, different cell parameters are used. Model is simulated with the HPPC drive cycle and voltage error is minimized iteratively.

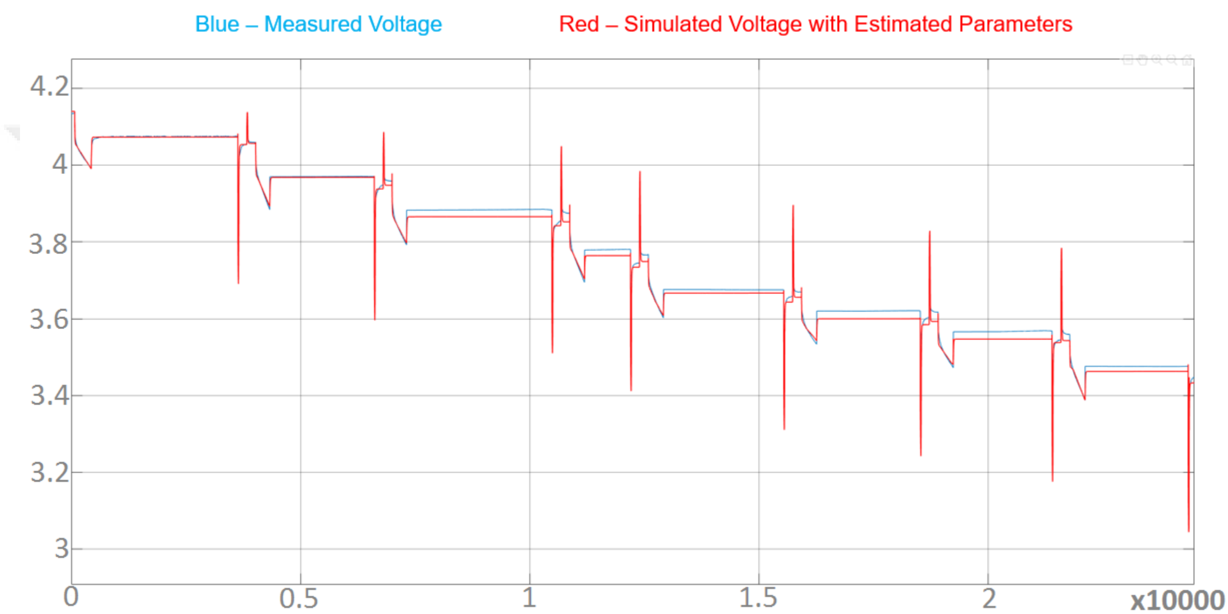


Figure 23: HPPC Voltage Profile at 40 degrees (Volt vs Second)

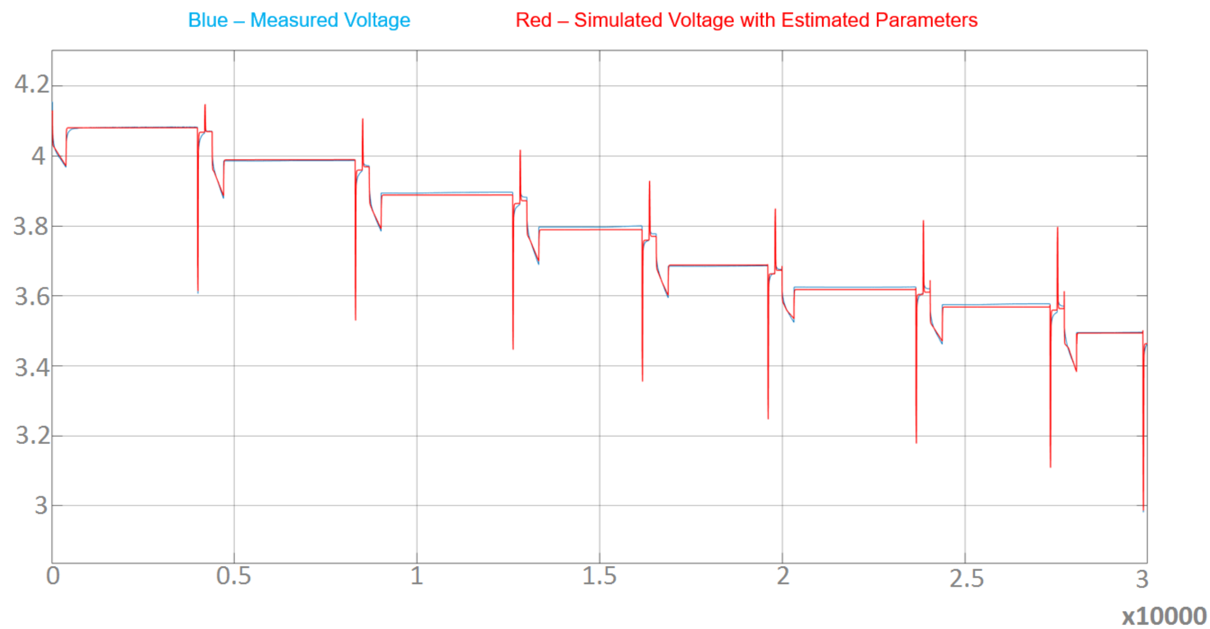


Figure 24: HPPC Voltage Profile at 25 degrees (Volt vs Second)

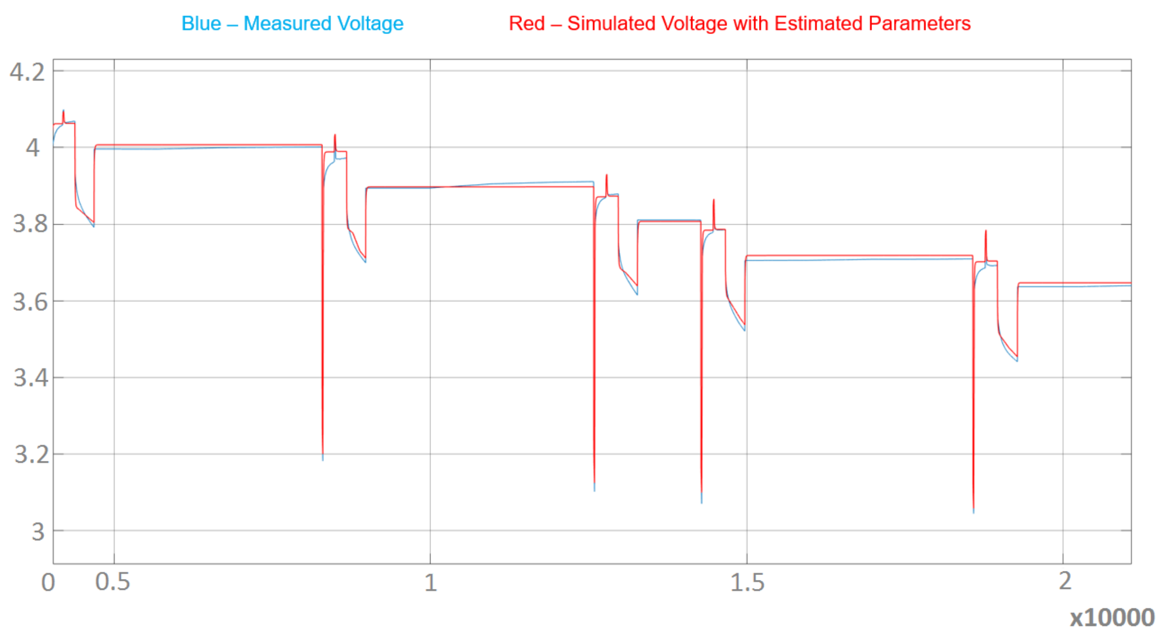


Figure 25: HPPC Voltage Profile at 0 degree (Volt vs Second)

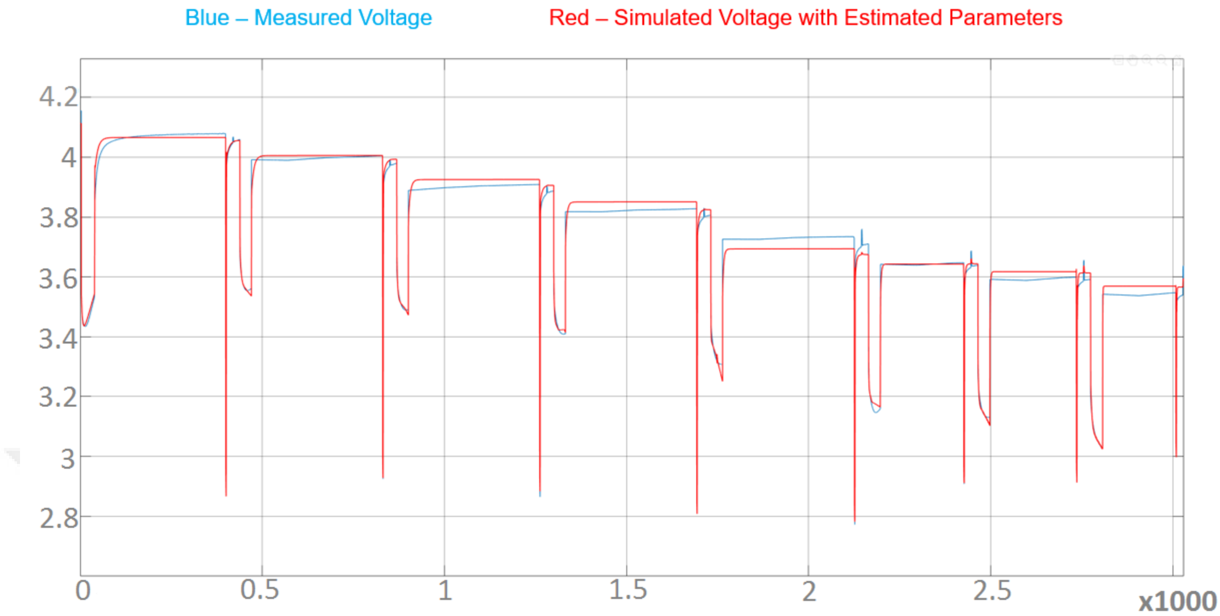


Figure 26: HPPC Voltage Profile at -20 degrees (Volt vs Second)

Voltage profiles under the HPPC cycle at 40, 25, 0, and -20 degrees after parameters are optimized (Fig. 23-26). Simulated voltage is converged to measured one with 2% maximum error and Voc, Rint, R1, C1, R2, C2 parameters are identified.

2.4 Model Validation

For model validation, a new drive cycle should be used which is not used at the parameter identification process. Worldwide Harmonised Light Vehicles Test Procedure (WLTP) drive cycle (Fig. 27) is performed at real-life battery and simulation with identified parameters at 25 and 40 degrees (Fig. 28-29).

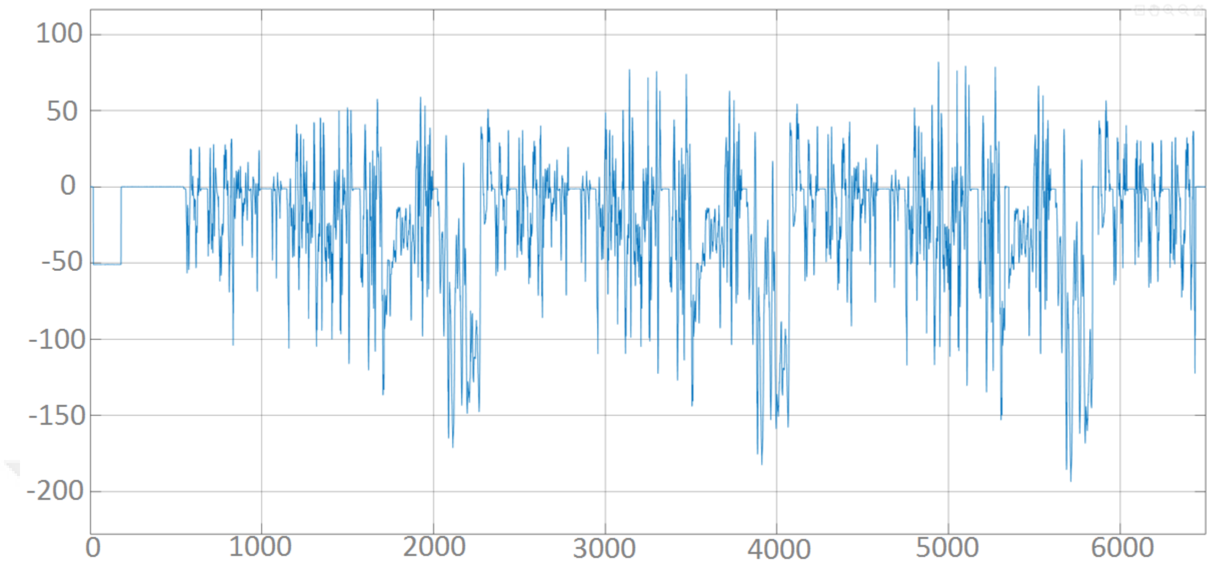


Figure 27: WLTP Drive Cycle Current Profile (Ampere vs Second)

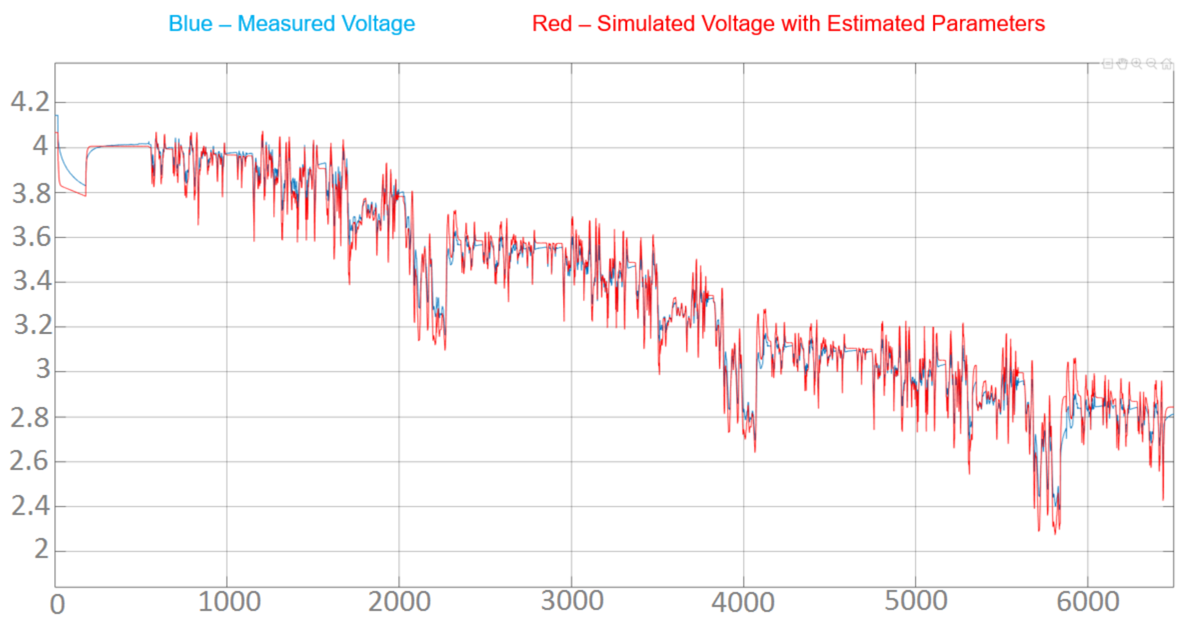


Figure 28: WLTP Drive Cycle Voltage Profile at 25 degrees (Volt vs Second)

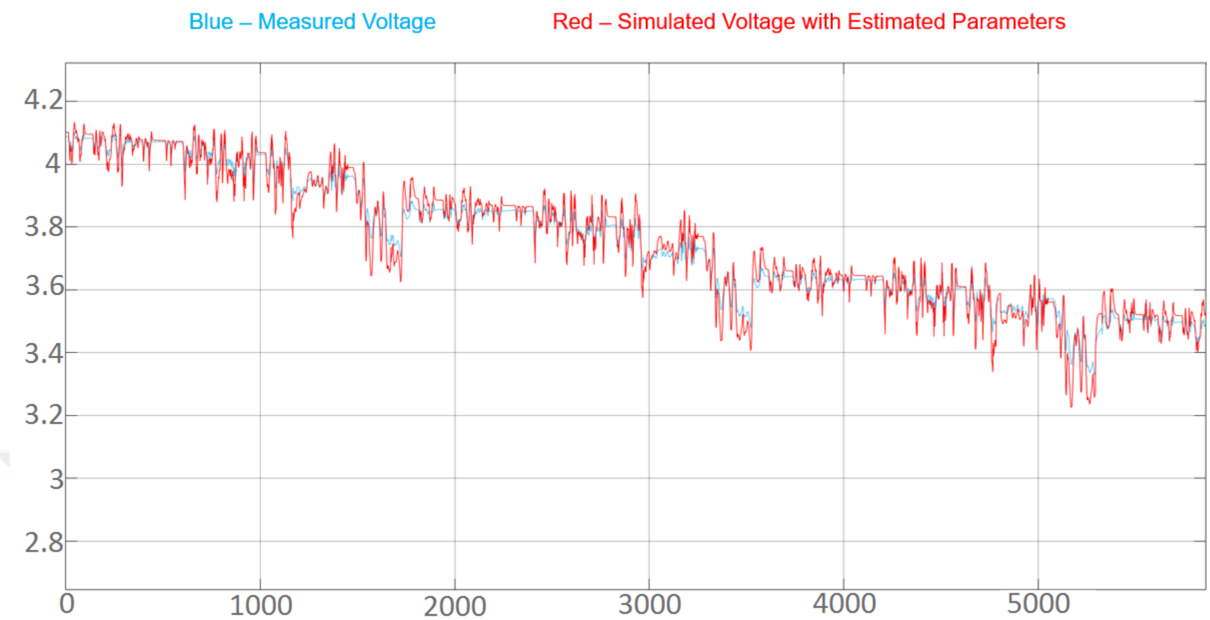


Figure 29: WLTP Drive Cycle Voltage Profile at 40 degrees (Volt vs Second)

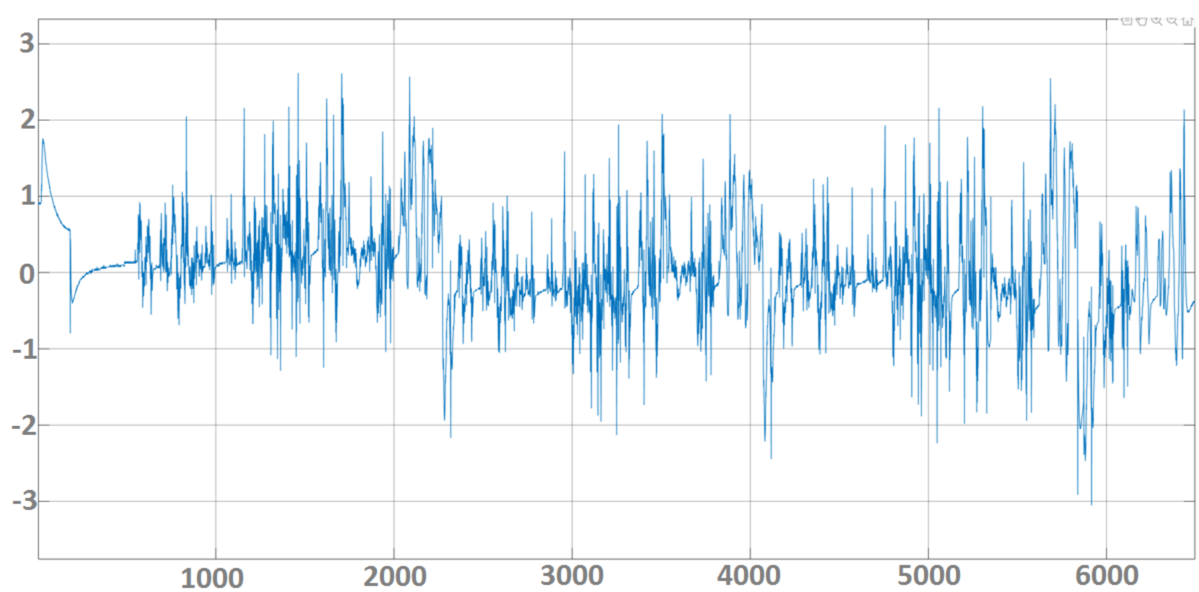


Figure 30: WLTP Voltage Error at 25 degrees (Error% vs Second)

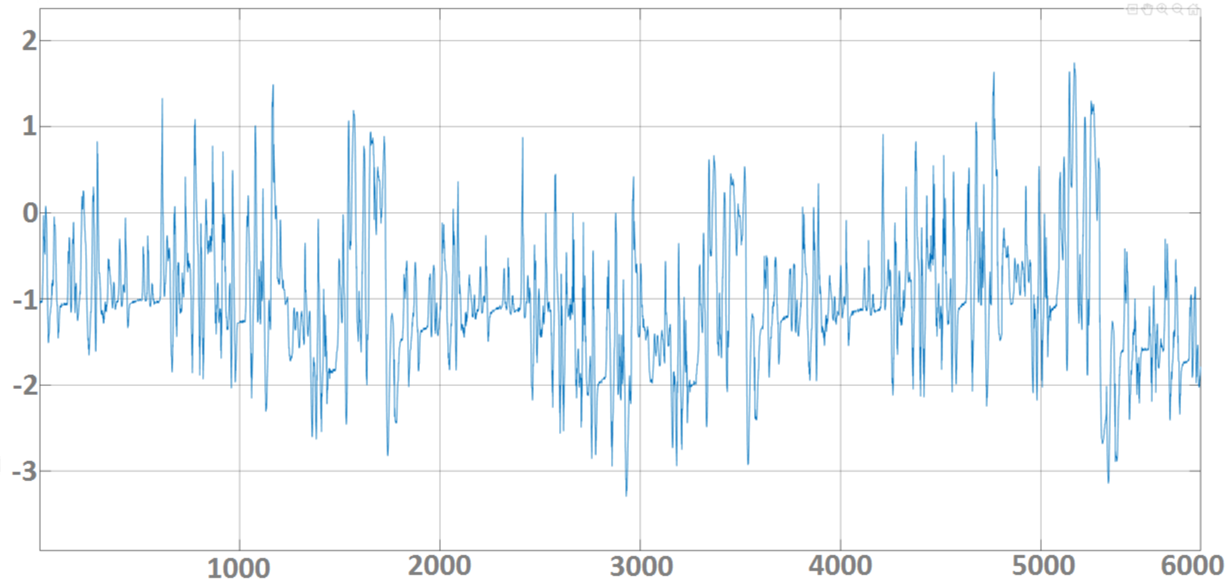


Figure 31: WLTP Voltage Error at 40 degrees (Error% vs Second)

The model is validated with a maximum 3% error which is good enough for simulations and further algorithms (Fig. 30-31).

CHAPTER III

SOC ESTIMATION

If observing the status of chemical bonds in a battery is possible in a feasible way than SOC estimation is much more simpler however, SOC can not directly measured with a sensor. It is also not possible to calculate the exact SOC because of the system uncertainties. This chapter explains how to estimate SOC under these challenges.

3.1 Conventional Methods

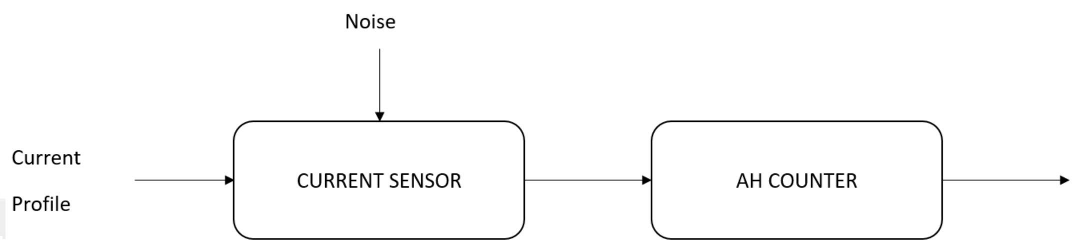
Open Circuit Voltage - SOC Mapping and Ampere Hour Counter are basic approaches for SOC estimation. They are commonly used because they are straightforward and computationally cheap.

3.1.1 Open Circuit Voltage - SOC Mapping

The most reliable SOC estimation method is OCV - SOC mapping in the literature [11, 12, 13]. OCV value is chemically related to SOC variance. Once the OCV value of the cell is measured, SOC can be called from a look-up table which contains OCV values for SOC labels (Fig. 8). However, this method cannot calculate precise SOC value after excitation of battery or while the battery cell is under load. OCV-SOC mapping is optimal for SOC estimation validation when essential conditions are fulfilled.

3.1.2 Ampere-Hour Counter

Ampere-hour counter is very common for SOC estimation in the industry because of its simplicity [14] . Output of the current sensor which is located one of the terminals of a battery is integrated to calculate the consumed capacity. Then consumed capacity is subtracted from the initial capacity to find SOC. However, while the current sensor is integrated, sensor noise drifts and after a while, estimations can become useless (Fig. 32). This method can be reinforced with the OCV-SOC map to update SOC while the battery is resting. In this way, sensor noise drift can be controlled.



$$SOC = InitialSOC - \frac{(\int(I(t) + Noise(t)) * dt}{Capacity}$$

Figure 32: Ampere-Hour Counter

3.2 Model-Based Algorithms

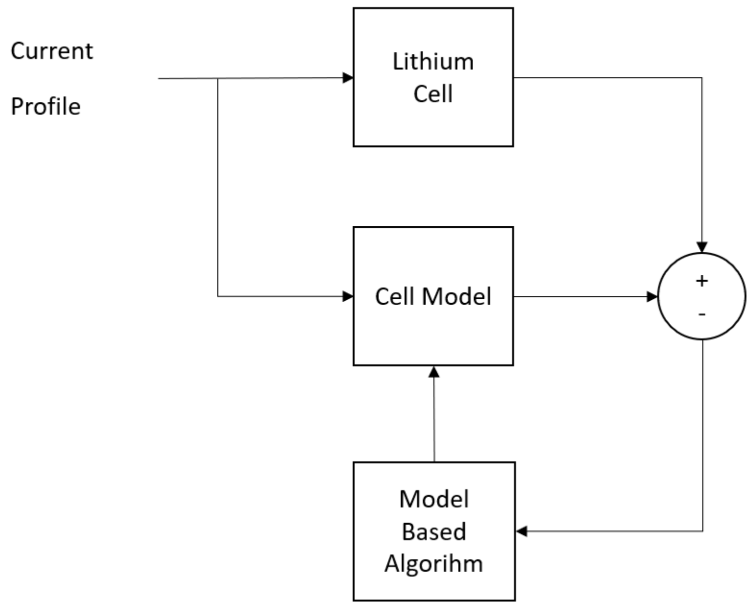


Figure 33: Model-Based Algorithm Block Diagram

Model-based methods like Kalman Filter, H-infinity Filter, Luenberger Observer, Sliding Mode Observer and Proportional Integral (PI) Observer can preserve their performance over temperature and SOH changes if they are implemented with adaptive modeling features to handle cell parameter changes. These methods generally, compare measurements with calculated states then updates filter parameters accordingly (Fig. 33). Zou et al. [15], proposed a PI Observer with a 3% SOC estimation error. This error can be reduced by combining model information and sensor data.

3.3 Kalman Filtering

Kalman Filter (KF) combines two data which have errors and tries to find a new estimate with less error (Fig. 34) [10]. It has 2 stages with 5 equations (Fig. 35) [16]. Kalman gain (K) changes adaptively according to the state covariance matrix.

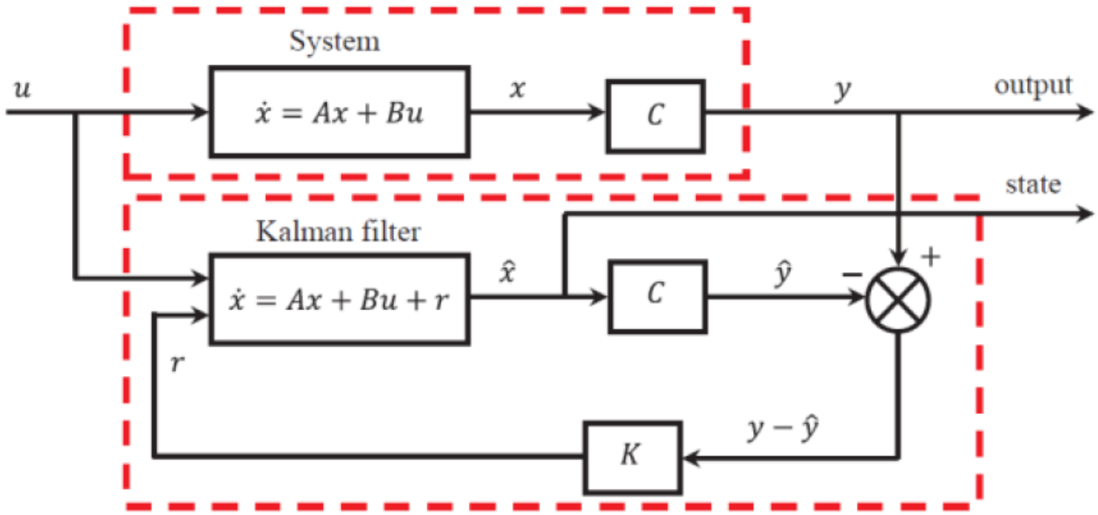


Figure 34: Kalman Filter Block Diagram

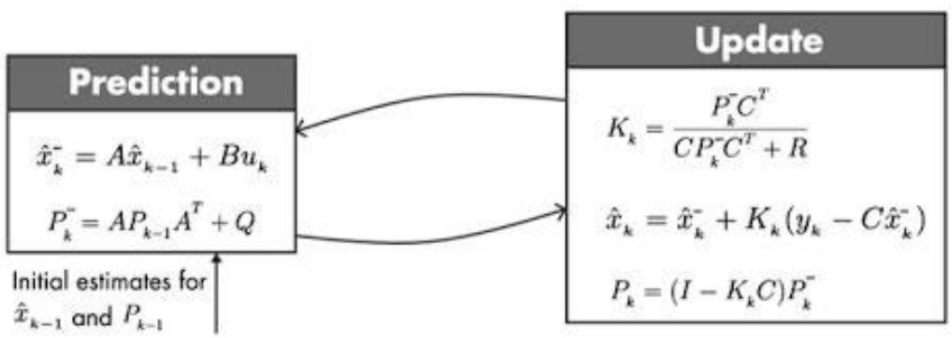


Figure 35: Kalman Filter Equations

P matrix (state covariance matrix) is updated iteratively and holding state uncertainties. It is assumed that states are varying in the range of the P matrix with a Gaussian distribution.

Q matrix (process noise covariance matrix) holds modeling, discretization, approximation errors, and disturbances. It is adding to P Matrix at each time step. Also, it forces the P to not become 0. P = 0 means that the system doesnt have any uncertainty and the algorithm will only depend on the model and do not use measurements.

R matrix (measurement noise covariance matrix) holds average measurement errors which can be easily obtained from the datasheet of the sensor.

First prediction equation simply computes the state equation.

Second prediction equation is simply Pnew = Pold + Q. A and A transpose comes from the models matrix formation. Process noise covariance matrix is added to the state covariance matrix at each step.

In the first correction equation, Kalman Gain is calculated. If this matrix was constant, then this filter will become a state observer, but it is changing dynamically in KF Equation (5) is the simplified form of the first correction equation.

$$\frac{StateUncertainty}{StateUncertainty + MeasurementUncertainty} \tag{5}$$

This ratio shows, what to depend on. If it is close to 1 then model uncertainty is increased and measurements are more reliable. If it is close to 0 then measurements are more reliable from the model. If it is exactly 0, then 2nd correction equation will ignore measurements.

Second correction equation calculates the final states for the current time step. Equation (6) is the simplified form of the second correction equation.

$$State = PredictedState + KalmanGain(Measurement - PredictedMeasurement) \tag{6}$$

If Kalman Gain increases, then the effect of the measurement will also increase. Otherwise, the algorithm will depend more on the model.

Equation (7) is the simplified form of the third correction equation.

$$P_{new} = (1 - KalmanGain)P_{old} \tag{7}$$

If Kalman Gain is close to 1, then KF depends on the measurement, which fixes the uncertainties quickly, and error in the estimate decreases faster. If Kalman Gain is close to 0, then K.F uses the model for estimation more and do not let the measurement change states.

3.3.1 Extended Kalman Filter

KF does not work with nonlinear models because of the Gaussian assumption, which is made in the state covariance matrix. If Gaussian function takes linear input, then the result is still Gaussian. If it takes nonlinear input, then the output will be corrupted (Fig. 36) [17].

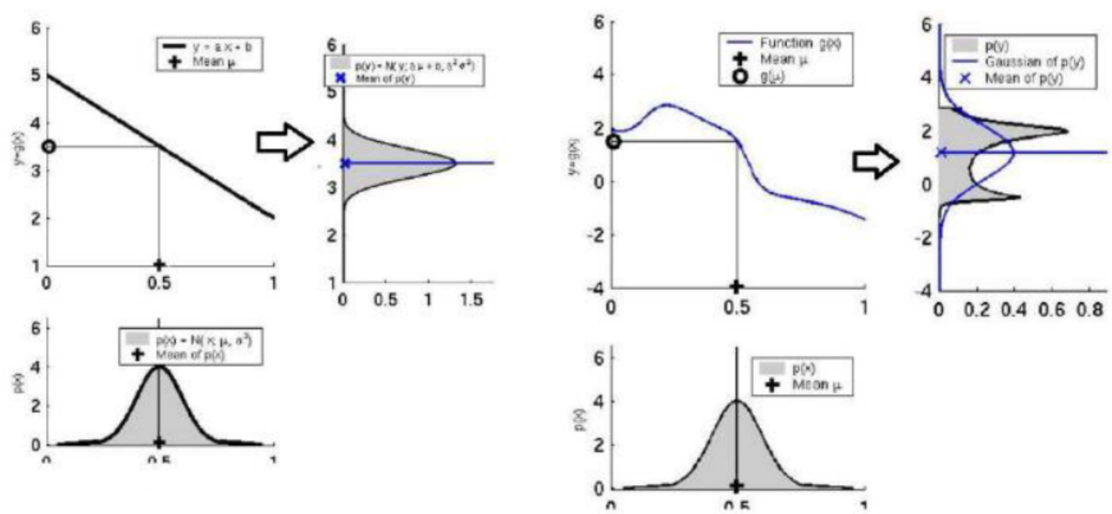


Figure 36: Gaussian Function

Extended KF adds a linearization stage to KF For SOC estimation open-circuit voltage at equation 3 is linearized with central difference approximation. Discretization is done by the following equation;

$$X[k] = x(k-1) + x(k)dt \tag{8}$$

EKF is commonly used in the literature for SOC estimation[18, 19, 20, 21, 22, 23].

3.3.2 Simulation Environment and Results

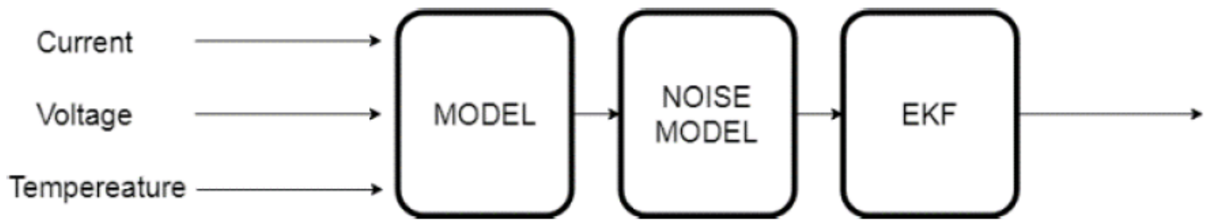


Figure 37: Simulation Block Diagram

A noise model is adapted between cell model and EKF (Fig. 37). In the MATLAB-SIMULINK environment voltage, current and temperature sensors are modeled according to their datasheets. Cell model takes input profiles directly and EKF. takes input profiles and model output after the noise model. Comparing model outputs and E.K.F output will indicate the performance of the algorithm. Worldwide Harmonized Light Vehicles (WLTP) drive cycle was used for this simulation. 20% initial condition error was compensated at 300 second , maximum SOC estimation error was 3.5% and the estimated voltage error was a maximum of 20 mV (Fig. 38-40).

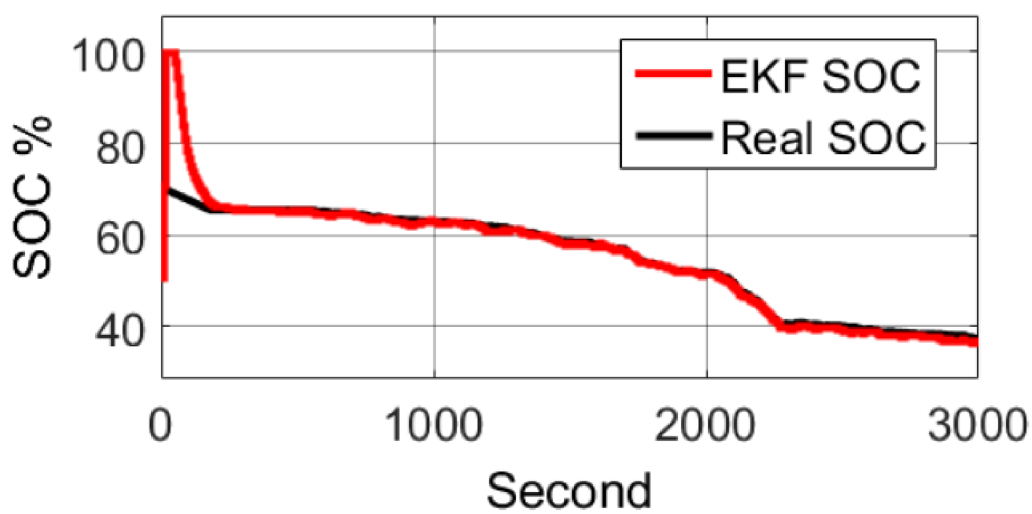


Figure 38: Real and Estimated SOC with 20% Initial Error

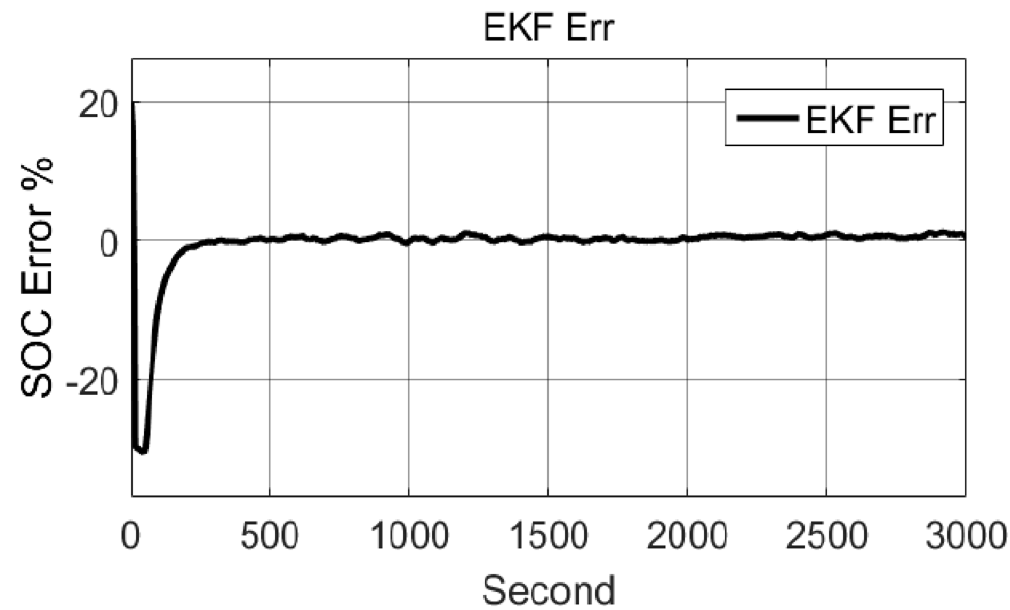


Figure 39: SOC Estimation Error

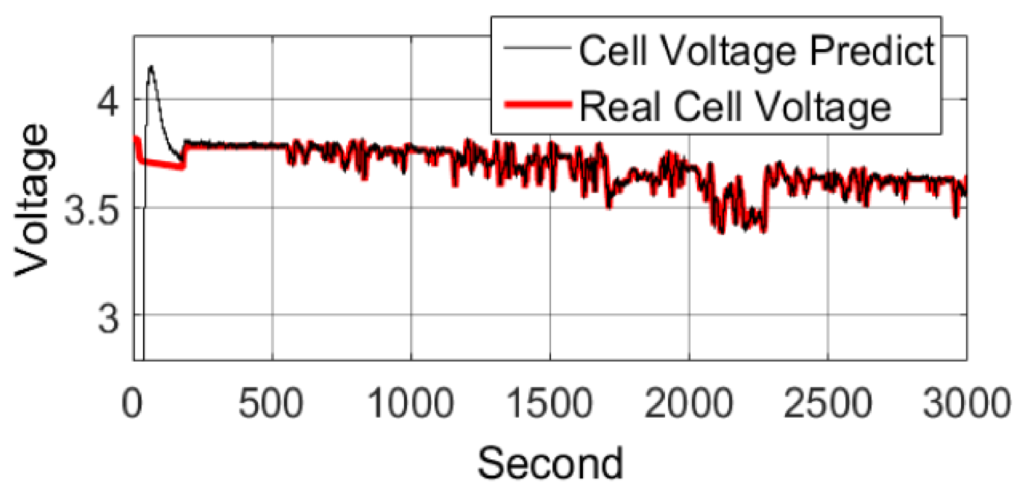


Figure 40: Real and Estimated Voltage with 20% Initial Error

3.4 PID Controlled EKF (PEKF)

It can be seen from results that Kalman Filtering can handle initial condition errors with model information (Fig. 38). In BMS point of view, SOC should be estimated without initial SOC and open circuit condition knowledge. In electric vehicles, microcontroller of BMS should write the current SOC to the permanent memory to know the initial conditions at the next startup. However, these memories have limited writing cycle number so that BMS can only write the SOC at the shutdown procedure. If there is an electrical failure like voltage fluctuation at vehicles low voltage line, then BMS could be shut down without writing the final SOC to the memory. Under this condition, BMS should figure out the initial condition. Even without failure, this procedure is required for diagnostic purposes. For these reasons, it is important to increase convergence performance of the SOC estimation.

3.4.1 EKF with PID Controlled Process Noise Based-On Voltage

From equations 2 and 3, system states are SOC and voltage. SOC cant be measured directly with a sensor but voltage is observable. A new method [24] which increases the performance of the SOC estimation by using the difference between measured voltage and estimated voltage is published within the scope of this thesis.

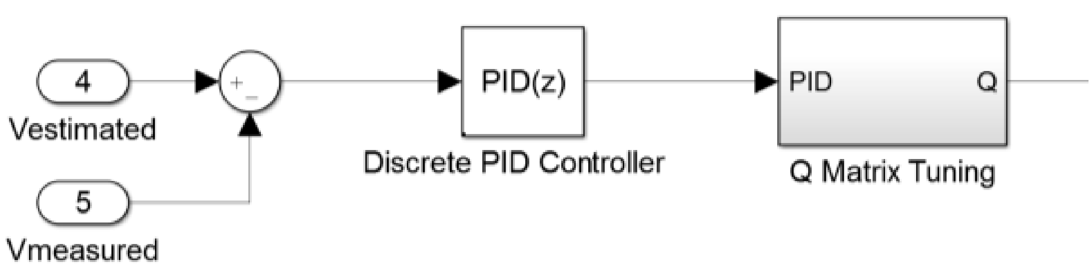


Figure 41: Q Matrix Adaptation

A PID controller is driven by the voltage error and the Q matrix (process noise covariance matrix) is adapted according to the PID signal (Fig. 41). In KF this matrix is constant. With changing this matrix adaptively SOC estimation converges faster. This method also compensates modeling errors and provides disturbance rejection ability.

3.4.2 Results

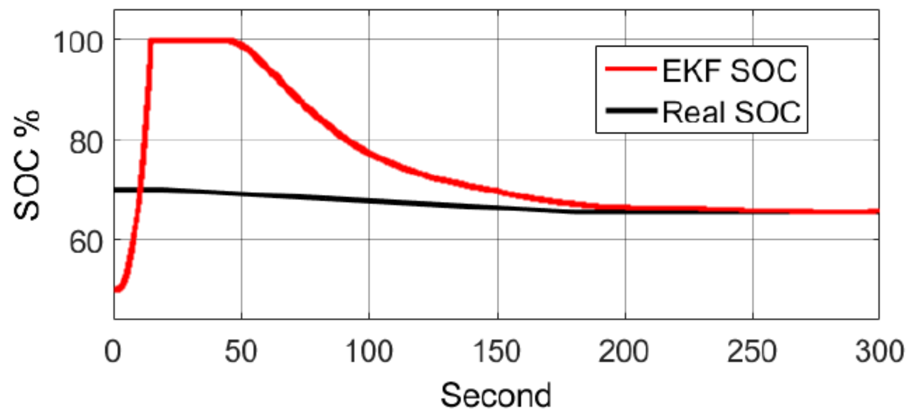


Figure 42: SOC Estimation Convergence with Constant Q Matrix

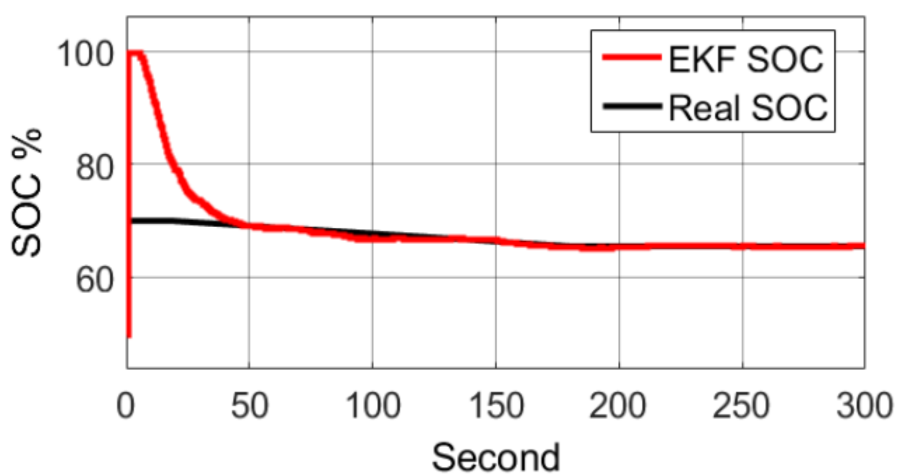


Figure 43: SOC Estimation Convergence with Adaptive Q Matrix

The convergence time of EKF was 300 seconds (Fig. 42). With Q matrix adaptation convergence time was decreased to 50 seconds (Fig. 43).

3.5 Adaptive Dual KF vs PEKF Comparison

Hou et al. [25], proposed a sophisticated algorithm for the SOC estimation which is Adaptive Dual Extended Kalman Filter (ADEKF). This algorithm computes two Kalman-based filters, one for SOC estimation and one for online cell model parameter estimation. For EKF implementation literature is scanned for papers that considered computational and convergence time. According to these papers, EKF was implemented. Table 2 shows a comparison between EKF, ADEKF, PEKF which is the proposed method under constant current discharge with the same process noise covariances and measurement noise variances.

	Max. SoC Error	Convergence Time	Computation Time
EKF [17]	3.5%	300 s	400 μs
ADEKF [24]	1.28%	10 s	400 + 400 = 800 μs
PEKF	3%	50 s	400 + 50 = 450 μs

Table 2: EKF & PEKF & ADEKF Comparison

Computation times in Table 2 are determined on an HP EliteBook laptop with an i5 processor. PEKF provides better SOC estimation and convergence time than EKF with a little extra computational time. For example, if a BMS designer cant uses ADEKF because of computational complexity, this designer can use PEKF instead of EKF with PEKF's improved convergence performance.

CHAPTER IV

CONCLUSION

In this thesis, battery terminology is explained in the BMS point of view. For BMS functions a battery cell is modeled with 2RC equivalent circuit and its parameters are identified according to the HPPC drive cycle with a 2% maximum error. This model and parameters are validated according to the WLTP drive cycle with a 3% maximum error.

A new Adaptive Extended Kalman Filter implementation which is called PID Controlled EKF, proposed in this paper for SOC estimation. With a simple add-on PID controller, convergence time is reduced 6 times compared with EKF. The importance of convergence behavior is explained from the automotive point of view in this work.

This method has better estimation performance from EKF and lower computation time from ADEKF contributed to the literature. In BMS controllers, PEKF can be used instead of EKF to improve convergence performance without increasing the computational power a lot. Also in some cases BMS hardware cost can be reduced if complicated algorithms should be used like ADEKF. Instead of ADEKF, PEKF can be used if system requirements are satisfied.

Online parameter estimation is future work for this study. With Dual EKF method parameters can be identified dynamically on the run time and this will reduce SOC estimation error. However, this should be done in a computationally effective way to not sacrifice the computation time advantage of the PEKF. SOH estimation is also critical for a battery. To know the exact capacity of the cell SOH should be known. For this reason, SOH estimation should be estimated accurately to estimate SOC.

APPENDIX A

SIMULINK MODEL

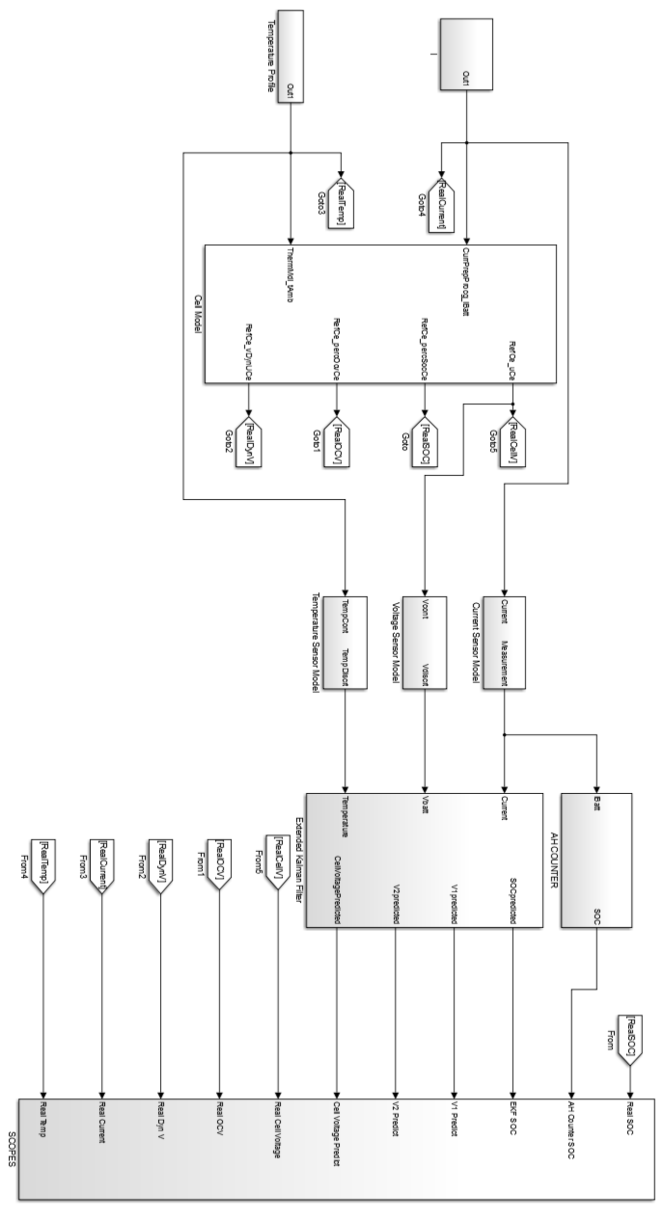


Figure 44: Upper Block

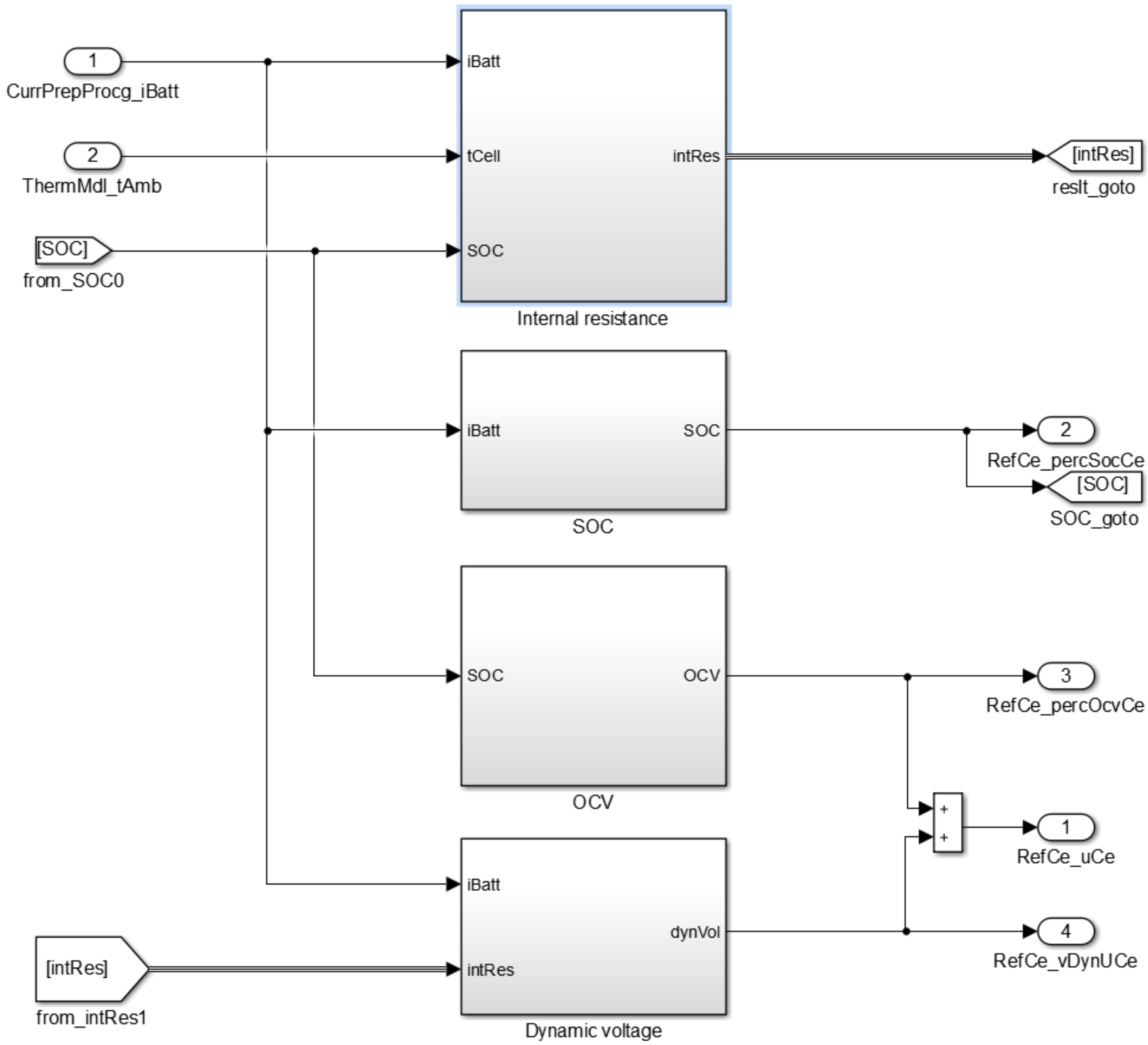


Figure 45: Cell Model

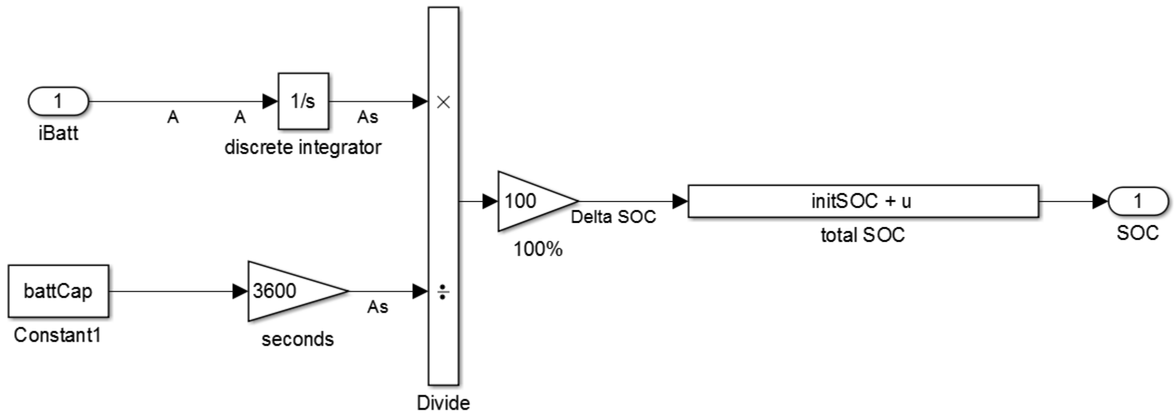


Figure 46: Ampere-Hour Counter

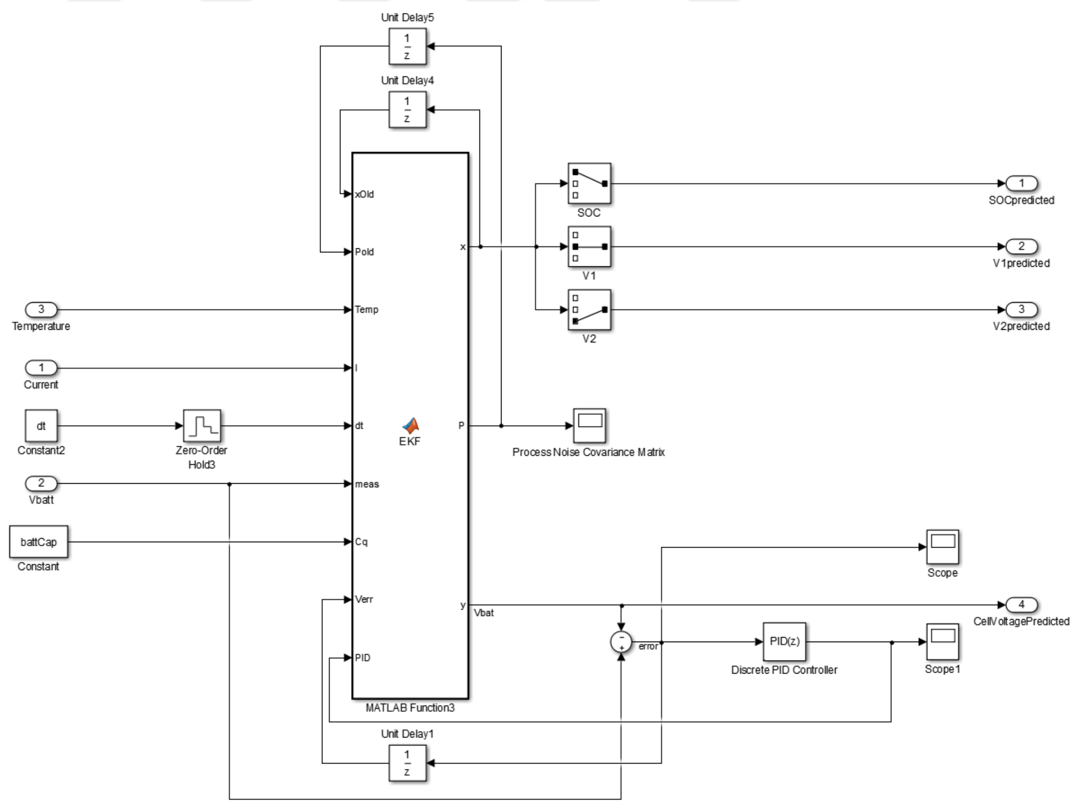


Figure 47: PEKF

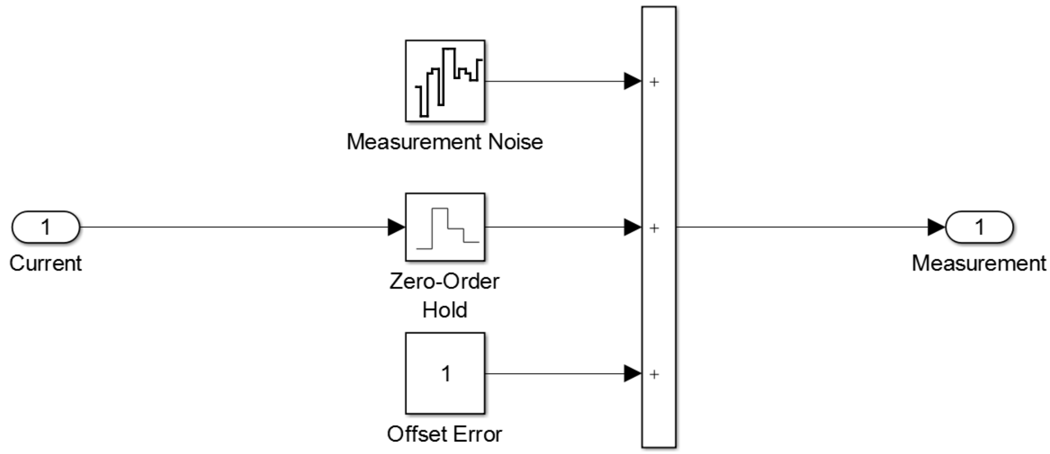


Figure 48: Sensor Model

Bibliography

[1] "Structure and operating principle of acid batteries." https://electrical-equipment-tao.blogspot.com/2019/08/structure-and-operating-principle-of-acid-batteries.html. Accessed: 2020-01-5.

[2] H. Hemi, N. M'Sirdi, A. Naamane, and B. Ikken, "Open circuit voltage of a lithium-ion battery model adjusted by data fitting," in *Proc. of International Renewable and Sustainable Energy Conference (IRSEC)*, pp. 1–5, IEEE, 2018.

[3] N. Leemput, *"Grid-supportive charging infrastructure for plug-in electric vehicles"*. PhD thesis, KU Leuven University, 2015.

[4] "Battery-monitoring IC reduces BMS cost by 80% in hybrid and electric vehicles." https://www.electronicspecifier.com/power/maxim-integrated-products-max11068-battery-monitoring-ic. Accessed: 2020-01-5.

[5] J. Qi and D. Lu, "Review of battery cell balancing techniques," in *Proc. of Australasian Universities Power Engineering Conference (AUPEC)*, pp. 1–6, IEEE, 2014.

[6] "Cell balancing techniques and how to use them." https://circuitdigest.com/article/cell-balancing-techniques-and-how-to-use-them. Accessed: 2020-01-5.

[7] W. He, M. Pecht, D. Flynn, and F. Dinmohammadi, "A physics-based electrochemical model for lithium-ion battery SOC estimation solved by an optimised projection-based method and moving-window filtering," *Energies*, vol. 11, 2018.

[8] A. Rahmoun and H. Biechl, "Modelling of lithium-ion batteries using equivalent circuit diagrams," *Electrical Review*, pp. 33–209, 2012.

[9] W. He, N. Williard, C. Chen, and M. Pecht, "SOC estimation for lithium-ion batteries using neural network modeling and unscented Kalman Filter based error cancellation," *International Journal of Electrical Power & Energy Systems*, vol. 62, pp. 783–791, 2014.

[10] J. Du, Z. Liu, and Y. Wang, "State of charge estimation for li-ion battery based on model from extreme learning machine," *Control Engineering Practice*, vol. 26, pp. 11–19, 2014.

[11] R. Zhang, B. Xia, B. Li, L. Cao, Y. Lai, W. Zheng, H. Wang, W. Wang, and M. Wang, "A study on the open circuit voltage and SOC characterization of high capacity lithium-ion battery under different temperature," *Energies*, vol. 11, 2018.

[12] Q. Yu, R. Xiong, L. Wang, and C. Lin, "A comparative study on open circuit voltage models for lithium-ion batteries," *Chinese Journal of Mechanical Engineering*, vol. 31, 2018.

[13] W. Yu, D. Huang, D. Feng, P. Guo, D. Dai, and W. Li, "An exact SOC estimate mathematic model of open-circuit voltage and parameters estimation," in *Proc. of International Conference on Mechatronics and Automation*, pp. 1302–1307, IEEE, 2012.

[14] D. Guo and L. He, "A novel algorithm for SOC using simple iteration and Coulomb Counting Method," in *Proc. of Student Conference on Electric Machines and Systems*, pp. 1–4, IEEE, 2018.

[15] Z. Zou, J. Xu, C. Mi, B. Cao, and Z. Chen, "Evaluation of model based SOC estimation methods for lithium-ion batteries," *Energies*, vol. 7, pp. 5065–5082, 2014.

[16] "Understanding Kalman Filters." https://www.mathworks.com/videos/understanding-kalman-filters-part-4-optimal-state-estimator-algorithm–1493129749201.html. Accessed: 2020-01-5.

[17] "Extended Kalman Filter: Why do we need an extended version." https://towardsdatascience.com/extended-kalman-filter-43e52b16757d. Accessed: 2020-01-5.

[18] Z. Gao, C. Chin, W. Toh, J. Chiew, and J. Jia, "SOC estimation and active cell pack balancing design of lithium battery power system for smart electric vehicle," *Journal of Advanced Transportation*, 2017.

[19] M. Paschero, G. L. Storti, A. Rizzi, F. M. F. Mascioli, and G. Rizzoni, "A novel mechanical analogy-based battery model for SoC estimation using a multicell EKF," *Proc. of Transactions on Sustainable Energy*, vol. 7, pp. 1695–1702, 2016.

[20] W. Wang, D. Wang, X. Wang, T. Li, R. Ahmed, S. Habibi, and A. Emadi, "Comparison of Kalman Filter based SOC strategies for lithium-ion batteries," in *Proc. of Transportation Electrification Conference and Expo (ITEC)*, pp. 1–6, IEEE, 2016.

[21] W. Wang, *Modeling, estimation and benchmarking of lithium-ion electric bicycle battery*. PhD thesis, MC Master University, 2016.

[22] K. Zhang, J. Ma, X. Zhao, X. Liu, and Y. Zhang, "Parameter identification and SOC estimation of NMC cells based on improved Ant Lion optimizer," *Mathematical Problems in Engineering*, pp. 1–18, 2019.

[23] S. Jung and H. Jeong, "Extended Kalman Filter based SOC and SOP estimation algorithm for unmanned aerial vehicle Li-Po battery packs," *Energies*, vol. 10, pp. 1237–1249, 2017.

[24] M. Celik, M. A. Gozukucuk, T. Akdogan, and H. F. Ugurdag, "SOC estimation for Li-Ion battery using Extended Kalman Filter with PID controlled process noise according to the voltage error," in Proc. of INTER. CONF. on ELECTRICAL and ELECTRONICS ENGINEERING (ELECO), 2019.

[25] J. Hou, Y. Yang, H. He, and T. Gao, "Adaptive Dual Extended Kalman Filter based on variational Bayesian approximation for joint estimation of lithium-ion battery SOC and model parameters," *Applied Sciences*, vol. 9, 2019.

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PRESENTATIONS

- 11th IEEE INTER. CONF. on ELECTRICAL and ELECTRONICS ENGINEERING (ELECO), SOC Estimation for Li-ion Battery Using Extended Kalman Filter with PID Controlled Process Noise According to the Voltage Error
- 11th IEEE INTER. CONF. on ELECTRICAL and ELECTRONICS ENGINEERING (ELECO), Electric Vehicle Model Parameter Estimation with Combined Least Squares and Gradient Descent Method
- 6th International Conference on Control Engineering Information Technology, Design and Simulation of an Optimal Energy Management Strategy for Plug-In Electric Vehicles