Selection of three *RC* Branches in Equivalent Circuit Model of Lithium-ion Batteries for Improved Accuracy

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Abstract: Battery management system (BMS) comprises of an electronic circuitry that monitors the battery operation to ensure temperature regulation, cell balancing, protection against overcharging and deep discharging, etc. This results in increased battery life, prevents degradation of the health of battery, prevention of fire hazards and increased safety. BMS is critical to the performance and wider acceptance of electric vehicle (EV) technology. Accurate estimation of the state of charge (*SOC*) of the battery is necessary for the precise operation of BMS. Kalman filters can be employed for *SOC* estimation. This paper presents unscented Kalman Filter (UKF) based *SOC* estimation for a 3100mAh, 3.7V lithium iron phosphate cell, which is employed for developing a battery pack for EVs. Four different Thevenin models of the cell, using (i) zero *RC* branch, (ii) one *RC* branch, (iii) two *RC* branches, and (iv) three *RC* branch, are considered in this work. With the increase in the number of *RC* branches, the accuracy of the model increases. However, consequently the computational burden also increases. The UKF based *SOC* estimation with the four different *RC* model is analysed with the help of the model developed in MATLAB/SIMULINK. The analysis reveals that the root mean square error in *SOC* estimation is lowest with three *RC* model, resulting in more accurate *SOC* estimation. This is achieved without significant increase in the execution time as recorded with the Raspberry Pi based implementation of the UKF algorithm for each model.
Keywords: Battery Management System, Battery Modelling, Thevenin Model, *RC* Model, State of Charge, Unscented Kalman Filter

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1. Introduction

The climate change concerns and the global warming issues mandate a marked reduction in greenhouse gas (GHG) emissions. Transportation sector is one of the major sources of GHG emissions resulting from combustion of fossil fuels like petrol and diesel(Lu, Iyer, Mukherjee, Ramkumar, & Kar, 2015). To reduce the contribution of transport sector towards GHG emissions, it is necessary to have more and more battery powered electric vehicles (EVs). The activation of Corporate Average Fuel Economy standards in 2016, has strengthened the case for shifting to EVs(Sant, Khadkikar, Xiao, & Zeineldin, 2015). Moreover, the increasing prices of petrol and diesel have resulted in increased adoption of EVs. Along with this, the recent advancement in electrochemistry of battery and standardization of manufacturing techniques also compliments the EV revolution.

An EV battery comprises of cells connected in series and parallel to obtain required current and voltage rating. The algorithms used to estimate states for a cell can be translated to a battery. Battery management system (BMS) is an integral part of any EV. With an electronic circuitry, BMS monitors the battery operation to ensure temperature regulation, cell balancing, and protection against overcharging and deep discharging. This supports in improving the battery life, preventing degradation of battery health and increase safety against fire hazards. BMS necessitates the instantaneous estimation of state of charge (*SOC*) of battery, which in turn requires mathematical modelling of the battery. Battery models are also a key aspect of a dynamic EV simulator(Wipke, Cuddy, & Burch, 1999).

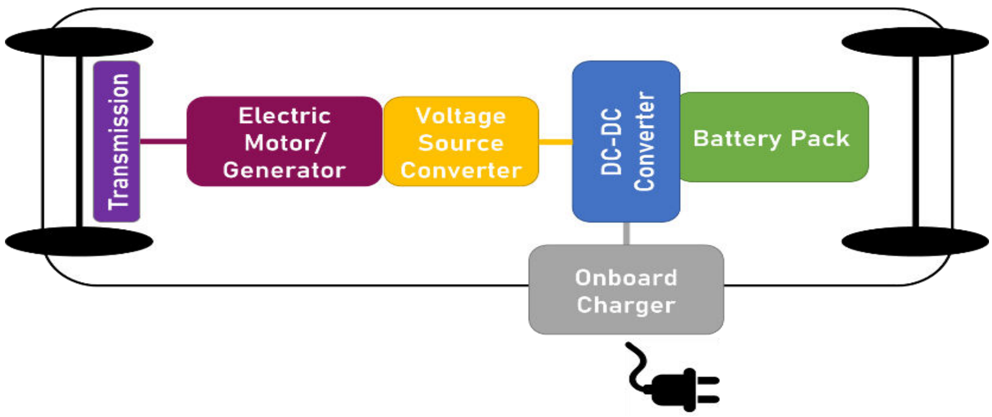
The techniques used for modelling of batteries can be divided into (i) analytical method. (ii) electrochemical method, and (iii) equivalent circuit method. Analytical method when used to develop battery models does not correctly interpret the electrochemical processes taking place in the cell (Rakhmatov, 2009). Electrochemical models require a huge amount of computational power to solve the time-varying differential equations. Also, it is difficult to directly connect this model to the rest of the electronic system (Safari, Morcrette, Teyssot, & Delacourt, 2009). The equivalent circuit model uses different circuit elements to replicate battery characteristics. It would suffice to say that the equivalent circuit models can model the nonlinear behavior of the battery in an EV system and they also can easily integrate it with the rest of the electronic system(Liaw, Nagasubramanian, Jungst, & Doughty, 2004).

Most of the equivalent circuit-based models are categorized as impedance-based models or Thevenin models. The impedance-based model requires a method called electrochemical impedance spectroscopy (EIS) to determine the electrical circuit components. The circuit components represent the electrochemical processes occurring within the cell. In Thevenin-based models the values of different circuit components, such as resistors, capacitors and voltage sources, are determined based on the measured voltage response. The benefit of using Thevenin models is that, using various parameter estimation algorithms the circuit components can be determined from voltage measurements without any additional equipment for an EV(Lam, Bauer, & Kelder, 2011). Various algorithms such as Coulomb counting, Kalman filter, extended Kalman filter, unscented Kalman filter, artificial neural network, fuzzy logic, genetic algorithm, etc. can be used for estimating battery *SOC*. All the algorithms have their own merits and demerits. Depending on the requirement of accuracy, availability of data, quality of data, computational time, etc. the selection of appropriate methods for a particular application can be done.

1.1. Electric Vehicle Drivetrain Configuration

The EV drivetrain is very elementary when we compare it with the drive train of Internal Combustion Engine Vehicle (ICEV). There are thousands of moving parts in engine of ICEV whereas there are very few moving parts in an EV. The reduction of moving parts results in lower wear and tear during operation of vehicle thus enables smooth functioning of the vehicle. As shown in Figure 1, EV drivetrain basically comprises of onboard charger, *dc-dc* and *dc-ac* converters, traction battery pack and electric motor. The battery is charged from the power outlet. If *ac* charger is used then only the onboard charger comes into picture and *ac-dc* conversion is implemented. On the other hand, if *dc* charger is employed then the onboard charger is not required. The battery stores electricity to run the vehicle. The *dc-dc* converters adjust voltage level requirement of battery pack and electric motor. The variable voltage variable frequency supply required by the electric motor is supplied by *dc-ac* converter. This converter ensures that the EV performance requirements, such as starting, accelerating, climbing and other driving demands, are met. The power input to the electric motor and subsequently the mechanical power output of motor is controlled based on the driving requirement. Electric motor works equivalent to engine in ICEV and generates the necessary tractive effort as per the driving requirement. The positive point for electric motor as compared to engine is that the engine works optimally only at a certain range of r/min whereas an electric motor works efficiently over a wide range on r/min. Thus, the efficiency of an EV is much higher as compared to ICEV. Other advantage of having an electric drivetrain is the feature of regenerative breaking, wherein the kinetic energy generated during braking is converted into electric energy for charging the battery. During regenerative braking, the electric motor acts as an electric generator. In cars significant amount of kinetic energy is generated while breaking and gets wasted as heat and friction. However, with the feature of regenerative breaking in EVs this energy is not wasted and is converted in electric energy for charging the battery pack. This in turn contributes to extending the driving range of the battery.

Figure 1. EV drivetrain

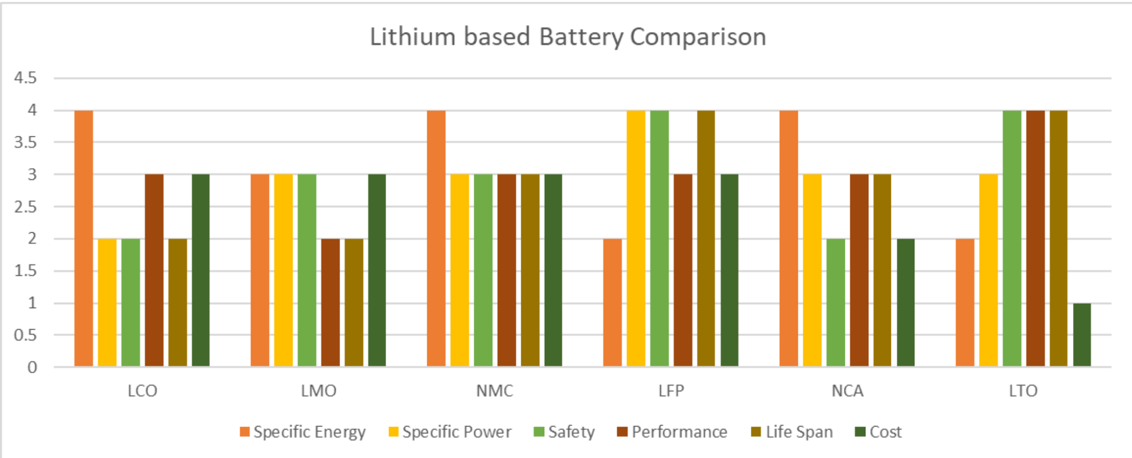


1.2. Energy Storage for Electric Vehicles

Batteries are reliable, stable, have longer life, less hazardous, provide higher energy density and specific energy when compared to other energy storage systems. There are many battery chemistries available in market such as lead-acid based battery, lithium-based battery, nickel-based battery, sodium-based battery, etc. Out of all the chemistries commercially available, the most preferred choice among EV manufacturers is lithium-based battery chemistry (Ali et al., 2019). One of the biggest hurdles in increasing the size of battery pack in an EV is the lack of available space and weight of the battery. Higher the weight of battery more energy is required to propel the EV, which in turn will reduce the overall driving range of the vehicle. With lithium-based battery for the same weight and size for a battery, higher range can be obtained due to its higher energy density. Additionally, higher life cycle, nominal voltage and lower cost are also critical factors in selection of lithium-based battery for EV application.

In all the lithium-based battery the negative electrode comprises of some form of graphite composition and different chemistries of lithium is used for positive electrode(Ali et al., 2019). The naming of battery is done based on the chemical composition of positive electrode. Different lithium-based batteries are Lithium Cobalt Oxide (LCO), Lithium Manganese Oxide (LMO), Lithium Nickel Manganese Cobalt Oxide (NMC), Lithium Iron Phosphate Oxide (LFP), Lithium Nickel Cobalt Aluminum Oxide (NCA) and Lithium Titanate Oxide (LTO). All these battery types are compared for their specific energy, specific power, safety, performance, life span and cost in Figure 2. Based on requirement of application, the selection of battery chemistry can be done. For example, in EVs, the parameters of focus are specific power, user safetyand life span, hence the most preferred choice of manufacturer is LFP battery.

Figure 2. Lithium based Battery Comparison



Lithium-based batteries are sensitive to overcharging as well as deep discharging. Hence, they require BMS for protection. Apart from protection BMS has various functionalities such as sensing and high voltage controls, works as an interface between battery pack and controller, performance management and diagnostics. Essentially, BMS makes sure that battery is safe from abusive behavior. ICEV has a fuel gauge for estimating remaining fuel and thus driving range. Similarly for EV, BMS performs this task through performance management and diagnostics. In performance management and diagnostics, BMS estimates *SOC* and state of health (SOH) of a battery. *SOC* indicates the remaining energy in a battery. The range anxiety concern of EV users could be addressed only by accurately estimating remaining driving range of an EV. This is possible through accurate estimation of *SOC* of a battery. Algorithms used for *SOC* estimation requires efficient battery model. Thus, an efficient battery model eventually results in accurate *SOC* and remaining driving range estimation. I this paper a thorough study has been performed to develop a battery model which not only replicates battery performances efficiently but is also computationally simpler.

2. Background

Reference(Madani, Schaltz, & Kær, 2019) investigated a second order equivalent circuit model for a 13Ah lithium titanate oxide cell. The proposed method was based on a comprehensive characterization experiments performed to operate battery on a wide range of operating conditions. The outcomes from the experiments were used to parameterize the dynamic model of the cell. An experimental study on intermittent discharge and hybrid power pulse characterization to identify the parameters of the battery was presented in(Su et al., 2019). Also, MATLAB/SIMULINK based study on splice equivalent circuit model for a lithium-ion battery pack for an EV is also presented.

Parameter identification for a lithium-ion battery in SIMULINK model for a hybrid power system was investigated in(Knauff et al., 2007). Additionally, a procedure for obtaining battery cell model parameters using the experimental data was developed. To validate the experimental data, it was compared to the simulation outcomes and a high degree of efficiency were observed by author in(Knauff et al., 2007). Reference (Schweighofer, Wegleiter, Recheis, & Fulmek, 2012)presents a battery model that accurately simulates the current-voltage response of the battery. The complexity of the model is low and can be used as a quick simple parameter identification method. The author provided values for power loss for use in design and optimization of cooling system for the battery.

The work presented in(Moss, Au, Plichta, & Zheng, 2008) has an equivalent electrical circuit model of a Li polymer battery using MATLAB/SIMULINK, ac Impedance method was used for parameter identification. The model developed in this paper considers the non-homogeneous behaviors of the battery, such as geometry of pores and cell's particle size. A fast and computationally simple method for the electrical equivalent circuit modelling of a Lithium-ion battery was proposed by the author in(Saxena, Raman, Saritha, & John, 2016). No lookup tables were involved in this proposed method. Reference(Mehta, Sant, & Sharma, n.d.) proposed an advanced equivalent circuit model for a battery with three *RC* branches. A charge and discharge curves analysis for Li-ion batteries was developed. A comparative study for *SOC* estimation using extended Kalman filter and UKF was presented. From the simulation study, it was deduced that with the increase in age of battery the internal resistance of the battery increases and the capacity of the battery decreases.

The general notion in developing battery model is to use Thevenin model with one or two *RC* branches. This is because the battery model developed using Thevenin model can be easily integrated with other electronics of the BMS. The method widely used for *SOC* estimation in the literature is UKF. Hence in this paper, battery model with different *RC* branches is developed and compared using UKF based *SOC* estimation.

In this paper a new three *RC* model of battery is proposed. Moreover, this paper presents unscented Kalman Filter (UKF) based *SOC* estimation for four different battery models (i) zero *RC* branch, (ii) one *RC* branch, (iii) two *RC* branches, and (iv) three *RC* model. The UKF based estimation of *SOC* for each model is analyzed considering the estimation accuracy and computational intensity. A 3100mAh, 3.7V LFP cell is considered, which can be employed for developing a battery pack for EVs. This work implements the Thevenin model for a battery using different *RC* branches. The accuracy of the model increases with the increase in the number of *RC* branches. Theoretically, this number can be increased to any number to improve accuracy. However, in terms of practical implementation increasing this number after a certain level greatly adds computational burden and execution time, while having little or negligible impact on the accuracy. Based on the root mean square error in *SOC* estimation, the three *RC* branch battery model is selected as it provides the most accurate estimation. From implementation perspective, the computational time taken for all the three models is also compared with Raspberry Pi based implementation of the UKF algorithm for different *RC* models. Based on analysis performed in the study it was observed that the root mean square error is lowest for the battery model with three *RC* branches. The delayed estimation for application like battery modelling, because of increased computational time may lead in estimations which are not in accordance with the present state of the battery. EV application is highly dynamic and it is required to get the instantaneous results for better performance of battery management system. This can be achieved with UKF *SOC* estimation using 3-*RC* model to have the necessary accuracy and computational simplicity.

3. Battery Model

To monitor various battery parameters, like *SOC*, health, cell balancing, etc., the mathematical model of battery is essentially required. Thevenin models are largely used for battery modelling in EV applications (You, Bae, Cho, Lee, & Kim, 2018). Thevenin models essentially comprises of a voltage source to simulate the open circuit voltage of the battery, a resistor for instantaneous voltage drop effect when load is connected across the battery terminals and several *RC* networks to imitate delayed voltage drop effect of a battery(Ahmed et al., 2015) By increasing the number of *RC* networks, a better estimation of battery's internal working can be obtained. Theoretically, the number of *RC* branches can be increased to a larger number to get exact model of battery(Lam et al., 2011). The downside to this is, increasing the number of *RC* branches increases the computational load on BMS, this effects in increase in computational time. Determining the number of *RC* branches for a battery model involves trade-off between accuracy and computational speed.

Figure 3. Ideal Battery Model

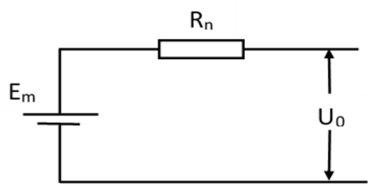


Figure 4. Thevenin Battery Model

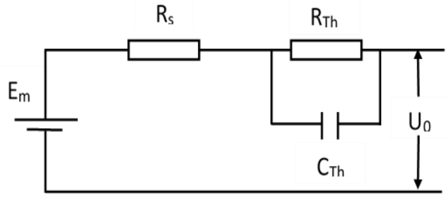


Figure 3. shows the ideal battery consisting of internal voltage E_m, internal resistance, R_n, and terminal voltage U_0. The drawback for this model is that it does not take into account the delay in voltage response of the cell and consequently the battery. Figure 4. shows the most basic form of Thevenin model. The model uses an OCV E_m, and internal resistance, R_S, a parallel RC network comprising of R_{Th} and C_{Th} to predict battery response under different loads. Based on this model, different models have been developed by adding additional components so as to have increased accuracy in terms of predicting the runtime and dynamic response of the cell and battery.

3.1. State of Charge

SOC of a battery indicates how much charge can be extracted from the battery at that particular time instant. The Coulomb counting method, which is one of the widely used method for SOC estimation, involves integration of current being supplied by the battery(Mehta et al., n.d.). When the battery is supplying the load the SOC reduces and with the direction of current being reversed during the charging operation SOC increases. The mathematical representation of SOC estimation with Coulomb counting method shown in Equation 1 as:

$$SOC_t = SOC_{t-1} + C^{-1} \int I \, dt \tag{1}$$

where, SOC_t is existing state of charge, SOC_{t-1} is the initial or previous state of charge, C is the ampere-hour capacity of the battery, I is the current being supplied by the battery. There is an error in measurement of current at any instant or determination SOC_{t-1} can not only result in incorrect estimation of SOC_t at that instant. This error would keep accumulating and result in erroneous estimation of SOC_t. This would result in degradation of the performance of the BMS and may end up harming the battery life. A battery is said to be out at end of life when the initial capacity of the battery is reduced to 80% (Moss et al., 2008).

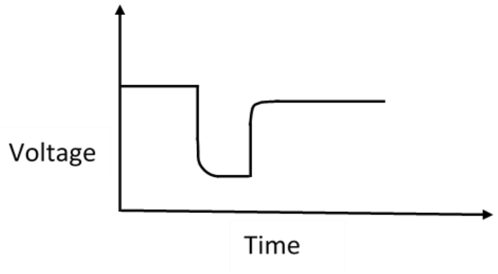
Battery SOC is one of the key states to properly control the EV. It can also be used to response the changes in bower requirement for an EV as a result of change in operating conditions. Battery SOC reflects the performance of a battery therefore, precise estimation of battery SOC will protect battery from abusive operating condition, improve life and performance of battery. It also provides protection against overcharging and deep discharge. Precise battery SOC estimation also helps in cell balancing and realistic control strategies. This solves the purpose of efficient energy saving through BMS in EV.

3.2. Open Circuit Voltage

OCV is the potential measured across the terminals of the battery when it is disconnected from the load. OCV is one of the many parameters that needs to be determined while modelling a battery. In this paper, a 2-D lookup table is used to determine various model parameters such as voltage, internal resistor and RC branches. This 2-D lookup table gives values for the model parameter as a function of SOC vs temperature. OCV is considered as a function of temperature, current and SOC. OCV for the cell was determined over the whole range of SOC.

A voltage source is used to replicate the open circuit voltage of battery, whereas the other components model the internal resistance and time dependent behavior of battery cell. The internal resistance replicates instantaneous voltage drop response and the RC branch models the delayed voltage drop response. Figure 5 shows the voltage response of a typical lithium-ion cell when supplying a load(Ahmed et al., 2015).

Figure 5. Typical Voltage Response of Lithium-Ion Battery



4. Unscented Kalman Filter

Kalman filter is a method for extracting parameters that cannot be accessed or measured directly, from inaccurate, indirect and uncertain data(Wan & Van Der Merwe, 2000). In contrast to any processing algorithm which processes on batch of data, Kalman filter works on the instantaneous data for extracting the necessary information. Hence, Kalman filter is ideally suited for estimating the SOC of the battery during each sampling instant based on the data sampled during that instant. The recursive nature of Kalman filter also helps in reducing mean square error between estimated and measured value. This is because the error can be corrected based on the available data, which results in precise parameter estimation. Kalman filter is implemented in two steps (i) predict step and (ii) measurement step (Marelli & Corno, 2021). In the predict step the states are predicted using previously measured values and previously predicted states. The measurement step in UKF calculates Kalman gain, updates state estimates and error covariance based on measured value. These steps are repeated at each sampling instant.

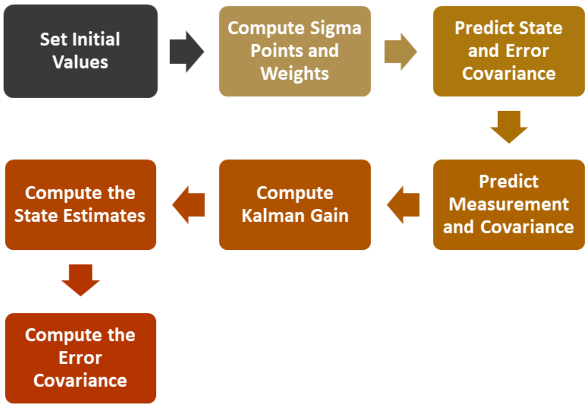
Kalman filters are applied to estimate states for a linear model. However, this filter is not suitable for nonlinear models. The mathematical model that replicates the electrochemical nature of battery is highly nonlinear. Hence, the conventional Kalman filters are not preferred for SOC estimation of cell or battery. Alternately, extended Kalman Filter (EKF) can be employed for SOC estimation. In EKF, the state distribution is approximated by Gaussian random variable (GRV) that are propagated through first order linearization function. This linearization can add large error in mean and covariance of the transformed function. This can be overcome with the use of UKF, a variant of Kalman filter that can handle higher nonlinearities. UKF gives better result than extended Kalman filter when it comes to battery modelling and SOC estimation(Konatowski, Kaniewski, & Matuszewski, 2017).

UKF involves approximation of the probability distribution, rather than to approximation of a random transformation function or nonlinear function(Julier & Uhlmann, 2004). In UKF sigma points are chosen which have mean and covariance exactly equal to state space X_{k-1}^{a} and covariance P_{k-1}. Each sigma point is then passed through the nonlinearity giving a collection of transformed points. The new mean and covariance are calculated after this, based on the statics of transformed points. This technique for calculating the statistics of random variable that has undergone a nonlinear transformation is termed as unscented transformation (Wan & Van Der Merwe, 2000). The number of sigma points are calculated based on the dimension of the state space. Suppose n is the dimension of the state space then number of sigma points are $2n + 1$. The UKF was selected to estimate battery SOC as the filter does not make use of linearization to calculate state parameters, predictions, covariance matrices. This helps in providing accurate Kalman gain.

4.1. Algorithm for Unscented Kalman Filter

UKF is an extension of unscented transform to the recursive estimation, where random variable is redefined as the concentration of the original states and noise variables. Figure 6 shows flow chart for UKF. First the unscented transform is performed.

Figure 6. Flow Chart for UKF



In Prediction Step, first the sigma points are generated and then the state and error covariance are predicted. First the states, X_{k-1},P_{k-1}, are predicted as

$$\gamma = f(x, \Delta t) \tag{2}$$

Where, γ is the set of sigma points, $f(x, \Delta t)$ is the function through which sigma points passes.

$$x = \sum W^m \ \gamma \tag{3}$$

Where, w^m is the weight and x is the state space.

$$P = \sum W^c \ (\gamma - x) \ (\gamma - x)^T + Q \tag{4}$$

Where, $w^c$is the weight function, P is the error covariance and Q is the process noise. This is followed by update step. In update step conversion of previously calculated sigma points are done using measurement function $h(\gamma)$ that is defined as

$$\mathrm{Z} = h(\gamma) \tag{5}$$

The mean and covariance of sigma points are calculated using unscented transform as,

$$\mu_z = \sum W^m Z \tag{6}$$

$$P = \sum W^C (Z - \mu_z)(Z - \mu_z)^T + R \tag{7}$$

Where, μ_z is the mean of sigma points using unscented transform, Z is the measurement function of sigma points and R is the sensor noise. Using $\mu_z$the residual of measurement function can be calculated,

$$\Upsilon = \mathrm{z} - \mu_z \tag{8}$$

Where, ϒ is the measurement state and z is the noise in measurement. To computer Kalman gain, the cross covariance of state and the measurement needs to be calculated,

$$P_z = \sum W^c \ (\Upsilon - x) \ (Z - \mu_z)^T \tag{9}$$

And the Kalman gain K is simply the ratio of belief in state and belief in measurement and it is calculated as,

$$\mathrm{K} = P_z \ P^{-1} \tag{10}$$

Finally, the new state estimates and covariance matrix are calculated using Kalman gain,

$$\mathrm{x} = \bar{x} + K \ \Upsilon \tag{11}$$

$$\mathrm{P} = \mathrm{P} - \mathrm{K} \ P_z K^T \tag{12}$$

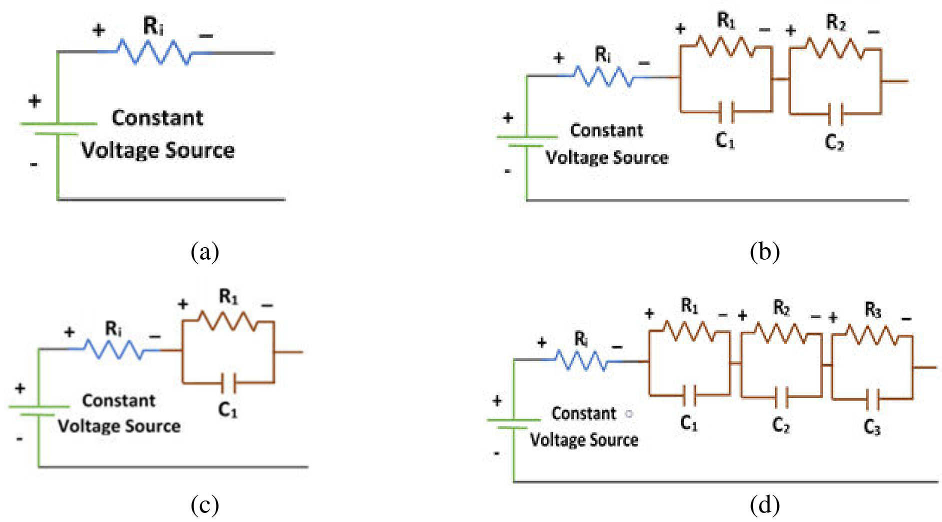
5. Simulation Study

The UKF based *SOC* estimation of LFP cell was carried out on MATLAB/SIMULINK. LFP18650 LFP cell with the respective capacity and nominal voltage of 3100mAh and 3.7V is considered in this work. Four different Thevenin models of LFP18650 LFP cell using (i) zero *RC* branch, (ii) one *RC* branch, (iii) two *RC* branches, and (iv) three *RC* branch are developed. The *SOC* estimation with UKF is developed on the simulation platform for these four models.

Figure 7a to 7d shows different models used for the comparison. Here constant voltage source is used to replicate the open circuit voltage of the battery. Internal resistor represents the instantaneous voltage drop when a load is applied to the battery. The different numbers of *RC*, branches depending on the type of the models represent the time dependent voltage drop response of the battery. The parameters of the equivalent circuit model used for simulation studies were derived as a function of *SOC*, current and temperature. Lookup tables were used for battery modelling.

In this study, the discharge current is controlled by selecting the load. Based on the *SOC* of cell, the load resistances were selected.

Figure 7. Equivalent Circuit Models (a) battery model with zero *RC* branch, (b) battery model with one *RC* branch, (c) battery model with two *RC* branch, (d) battery model with three *RC* branch



In this paper, different discharging currents corresponding to the C-rate are considered. The Table 1 shows the discharge current at different *SOC*. The range of *SOC* for the cell is considered with cut-off *SOC* at 30% and upper limit is 90% *SOC*. The starting point of the simulation is considered as 50% *SOC*. In practical application of battery in EV, it is observed that when battery is fully charges the power output from the battery is higher as compared to battery being partially charged. This concept was kept in mind while designing the *SOC*based discharging current. Initially the discharge current was kept higher than gradually with decreased *SOC* of battery the discharge current was also reduced. First discharge current is applied to the system to reach cut-off *SOC*. And then constant current is applied for charging. Measurement noise is considered in the simulation studies by adding white noise to the current being measured.

Table 1. Discharge Current

SOC	Discharge Rate	Discharge Current
100% to 80%	1C	31A
80% to 65%	0.8C	24.8A
65% to 50%	0.6C	18.6A
50% to 30%	0.4C	12.4A

5.1. Computational Time

Execution of any instruction on CPU requires finite time. The computational time of an algorithm is time required to perform the set of instructions for the completion of the task for which it has been designed. This time is computed as the time duration from the instant when the input signals are received to the instant when the final outcome is provided by the algorithm for further processing. Computational time for an algorithm depends on many factors, such as size of the data to be processed, mathematical functions employed and limitations of the processor. In the case of UKF based *SOC* estimation of LFP18650 LFP cell using different *RC* models, the computational complexity increases with the increase in the number of RC branches and consequently the computational time increases. The computational time can be calculated as

$$CPU_{Time} = I * CPI * T \tag{13}$$

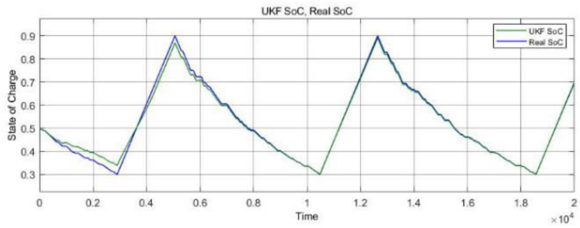
where, CPU_{Time} is the time taken by CPU to perform a certain operation, I is the number of instructions in the algorithm, CPI is average CPU cycle per instruction and T is clock cycle time. To calculate the computational time for an algorithm, the time for executing each of the mathematical and logical operations involved is required to be calculated(Assimakis, Adam, & Douladiris, 2012).

For UKF, scalar operations are involved in matrix manipulations. All the operations are performed on Raspberry Pi and the time taken to run these operations is calculated. A Python code was used for implementation. The configuration of Raspberry Pi used was 1.2 GHz, 64-bit quad-core ARMv8 CPU, 1 GB RAM. Raspberry Pi is a very good platform for implementing and testing models due to its ability to perform multi-tasking, online connection capabilities with systems that requires performing multiple activities simultaneously. As performed in this work, the computation time is determined by setting a software-controlled timer, executing the algorithm and noting the total time duration till the execution of last code statement (excluding timer functioning time). Table 2 summarizes the operation executed in the one iteration of UKF based estimation of SOC for the four different battery models. The computational time for the execution of one iteration of UKF based estimation of SOC for the four different battery models is shown in Table 3. In practice the number of iterations is in the multiple of thousands of operations for one charge-discharge cycle. The overall response time will be much higher when it comes to practical implementation of battery model with increased number of RC branches. From this analysis it is clear that the total number of computations is highest with the 3 RC model. In line with this finding, the computation time is also the highest with the 3 RC model. The consideration of computational time for developing any algorithm is essential as it is always desirable to obtain the results faster.

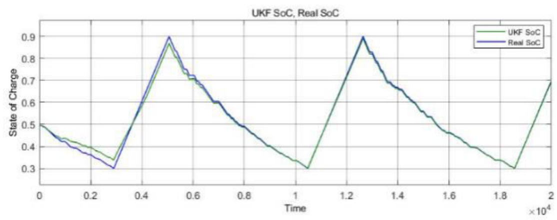
5.2. Results and Discussions

Four different types of battery models were developed in the SIMULINK and the accuracy of UKF based SOC estimation was analyzed for each model. The simulations are carried out on the set of measurements for LFP18650 LFP cell recorded at 20˚C. Figure 8 shows the comparison of UKF based SOC estimation for the four different RC models with the actual SOC. With increase in number of RC branches the estimated value of SOC is closer to the actual value and as a consequence the accuracy of estimation is also increases. As shown in Figure 8a, with no RC branch there is no way for the estimation algorithm to incorporate the time dependent voltage response of the battery. Figure 8b and 8c shows some improvement in SOC estimation of SOC but there exists a scope for improving the accuracy. In Figure 8d, with 3 RC model it can be seen that the estimated SOC virtually follows the actual value.

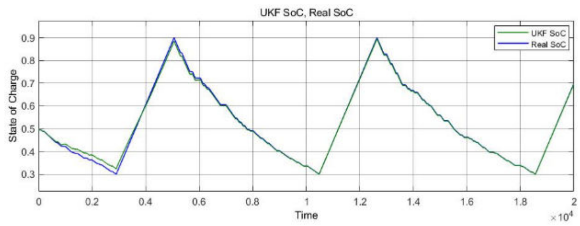
Figure 8. SOC estimation (a) SOC estimation for battery model with zero RCbranch, (b) SOC estimation for battery model with one RC branch, (c) SOC estimation for battery model with two RC branch, (d) SOC estimation for battery model with three RC branch



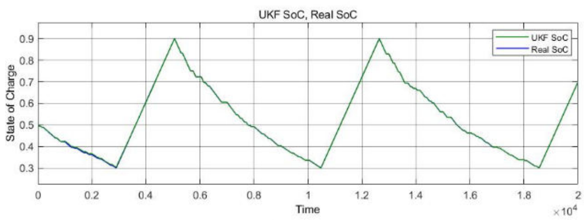
(a)



(b)



(c)



(d)

Table 2. Calculation Burden of UKF Algorithm

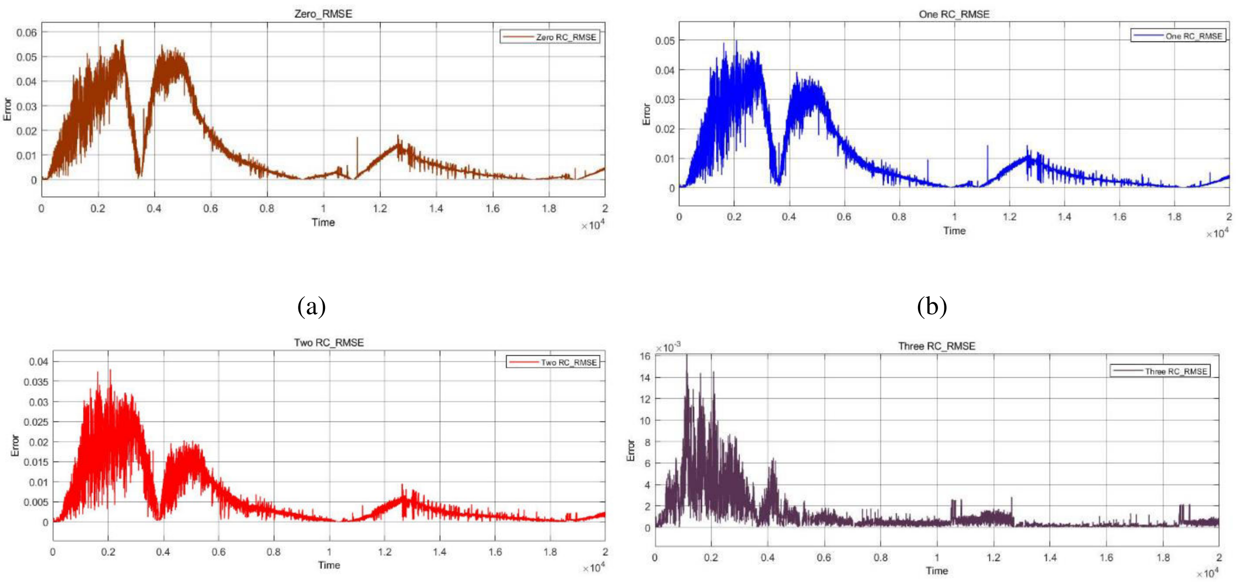
Operations	Number of Computation			
	No *RC* Branch Model	One *RC* Branch Model	Two *RC* Branch Model	Three *RC* Branch Model
Addition	10	11	12	13
Subtraction	14	14	14	14
Multiplication	11	12	13	14
Division	3	6	9	12
Transpose	3	3	3	3
Total	41	46	51	56

Table 3 Calculation Time for different models

Models	Computational Time
Zero *RC* Model	149 µs
One *RC* Model	160 µs
Two *RC* Model	196 µs
Three *RC* Model	216 µs

The root mean square error (RMSE) is calculated between estimated and real *SOC* values for the four battery models considered. RMSE is used for error calculation as it is standard deviation of the predicted values or residual values. Residual values are defined as how far from the actual line the predicted or estimated points are. From Figure 9 it can be observed that at the beginning of the simulation due to lack of training of the data for all the models the error is high as compared to later steps. Figure 9a shows RMSE for battery model with no *RC* branch in the equivalent circuit model. Here, error is the maximum. The peak error for this model is 5.7%. As shown in Figure 9b, the RMSE for battery model with one *RC* branch in the equivalent circuit model has the peak error of 5%. Whereas, the RMSE for battery model with two *RC* branches has the peak error of 3.5% as shown in Figure 9c. Figure 9d shown RSME for battery model with three *RC* branches with the peak error for this model as 1.6%.

Figure 9. Root Mean Square Error (a) RMSE for battery model with zero *RC* branch, (b) RMSE for battery model with one *RC* branch, (c) RMSE for battery model with two *RC* branch, (d) RMSE for battery model with three *RC* branch



(a) (b)

(c) (d)

In applications like EVs, where instantaneous state of charge estimation is a key to the reducing range anxiety, the increase in computational time will reduce the confidence of consumer in the segment. It is crucial to obtain a good tradeoff between model accuracy and computation time for execution of the UKF based *SOC* estimation. The peak error of 1.6% obtained with three *RC* branches provides the best choice in terms of accuracy. Table 4 shows the RMSE of UKF *SOC* estimation with the four different *RC* models. Though the execution time with three *RC* model is higher as compared to the other three models, it is to be noted that is higher by 45% as compared to the zero *RC* model. At the same time the RMSE with four *RC* model is lower as compared to the zero

RC model by 72%. Hence, three *RC* model is ideally suited for UKF based *SOC* estimation in terms of RMSE and computational time.

Table 4. Calculation Time for different models

Models	RMSE
Zero *RC* Model	5.7%
One *RC* Model	5%
Two *RC* Model	3.5%
Three *RC* Model	1.6%

6. Conclusion

Developing a reliable battery model is very crucial to estimate the *SOC* of any battery. In EVs, the remaining *SOC* is used to predict remaining driving range. For large scale adaptation of EVs accurate *SOC* prediction is a prime necessity. In the framework of this paper, four different types of battery models are studied and compared. These four battery models are developed in MATLAB/SIMULINK for 3100mAh, 3.7V LFP18650 LFP cell and UKF is employed to estimate the *SOC* in each case. As the delayed voltage response is directly associated with the number of *RC* branches used for battery model, with the increase in *RC* branches, *SOC* can be more accurately estimated with reduced RMSE. The peak error for the battery model with no *RC* circuit was 5.7% and for battery model with three *RC* circuit was least at 1.6%. Theoretically, we can further increase the number of *RC* circuit but practically this would be unnecessarily computationally intensive and would delay the results. The execution time for UKF based *SOC* estimation with each *RC* model is obtained through Raspberry Pi based implementation. The computational burden for one iteration of UKF used to estimate *SOC* for a battery model with three *RC* branches is 216 µs and peak value of RMSE is 1.6%. This seems to be a good compromise between computational burden and accuracy for an application like EVs.

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