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Estimating the Optimal State of Charge for Electric Car Batteries Using an Extended Kalman Filter

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Abstract: - The efficient management of battery state of charge (SOC) is crucial for maximizing the performance, range, and longevity of electric vehicle (EV) batteries. This paper presents a novel approach for estimating the optimal state of charge of electric car batteries using an Extended Kalman Filter (EKF). The EKF is a recursive algorithm that combines measurements from various sensors with a dynamic battery model to estimate the current SOC and predict future SOC values with high accuracy. The paper provides a detailed explanation of the EKF algorithm and its application to battery SOC estimation, highlighting its ability to handle nonlinearities, uncertainties, and measurement noise inherent in battery systems. Furthermore, this research presents a simulation-based validation of the proposed EKF approach using real-world driving data from electric vehicles. The simulation results demonstrate the effectiveness of the EKF algorithm in accurately estimating the SOC of electric car batteries under various operating conditions, including different driving patterns, temperatures, and battery degradation scenarios.

Keywords: Battery state of charge (SOC),Electric vehicle (EV) batteries, Extended Kalman Filter (EKF),Battery management systems, Dynamic battery model

Introduction

When it comes to resolving global environmental issues, electric vehicles (EVs) are essential. Most wealthy and developing nations have included electric cars (EVs) into their policies to reduce carbon emissions and provide affordable, zero-emission vehicles as a response to climate change, innovations in renewable energy, battery chemistry, fast urbanization, data collection and analysis, and energy security. The all-electric battery electric vehicle (BEV), which can be recharged by plugging it into an electrical outlet, is a convenient one-stop solution for this[1][2]. Among the several battery types available, lithium-ion batteries provide the most benefits for electric vehicle applications, including a long service life, minimal maintenance requirements, and a high energy density. The Li-ion battery has many benefits, but it is very vulnerable to overcharging and deep discharging, which may shorten its life and potentially trigger an explosion or fire[3]. Because of this, a SOA is required while using the battery. Nevertheless, a BMS is required to ensure a safe charging and discharging level. Hardware and software are the two primary categories into which BMS's operational components fall[4]. Figure

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1 shows the overall structure of BMS. The software is the brains of the operation, as it manages the hardware and uses input from sensors to make choices. Online data processing is going to catch most of the errors. Intelligent data analysis is necessary for the delivery of battery problem notifications[5]. In order to uncover the pre-alarm before the defect occurs, data collecting is of utmost importance. The hardware parts carry out their functions in accordance with the instructions provided by the software. Using sensors, one may measure the voltage and current of a battery. In order to avoid thermal runaway, detect defects, and analyze and monitor battery performance, a reliable battery model is required[6][7]. It is also important to monitor State of Charge (SOC) using accurate estimate techniques because of the critical role it plays in controlling battery functioning. A battery's charging pattern may be optimized by using an appropriate optimization algorithm once the algorithm has learned the battery's behaviors[8]. Because it affects battery accessibility and protection directly, battery charging is an essential component of BMS. A well-planned charging procedure reduces stress on the battery, keeps temperature fluctuations to a minimum, and maximizes the efficiency with which energy is converted. Then, a data collecting system may save all the battery's parameters[9]. The system controller then checks the recorded data against the battery's safe operating limits. A safety module safeguards the battery from potential harm in the event of an unexpected operating state. An efficient communication network connects the battery to the BMS and serves as a user interface[10].

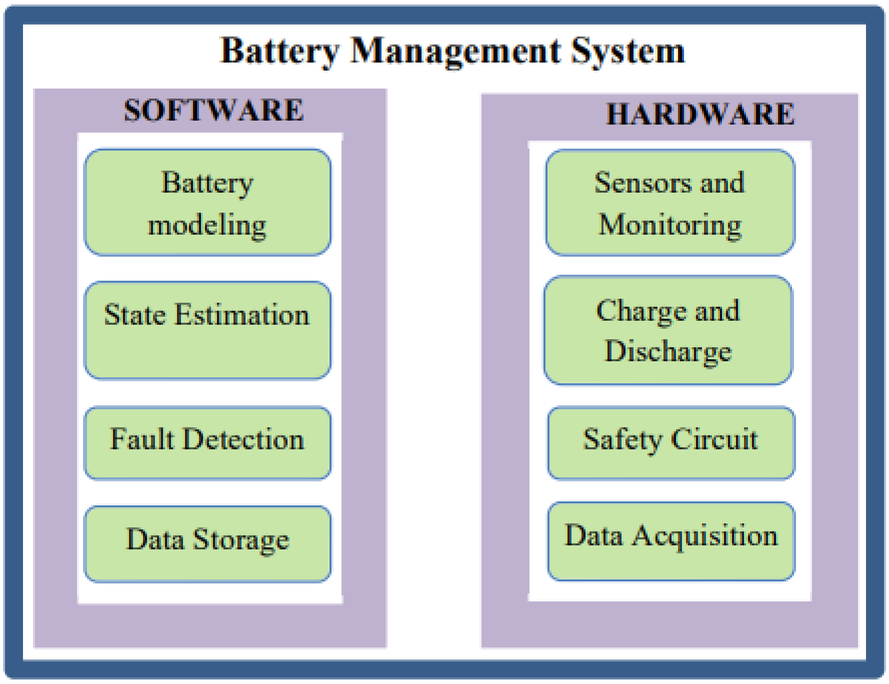

Figure 1. Overview of the software and hardware components of BMS

Although they are simple in concept, the majority of cell balancing circuits that rely just on voltage end up underperforming. Active cell balancing is set up for improved performance based on an average SOC. Before implementing a cell balancing approach, it is crucial to estimate the single cell SOC. This is because fault detection relies on the cell balancing strategy that is based on SOC and voltage. Consequently, the SOC is fed into processes that determine power consumption, balance cells, and identify problems. Electric vehicle (EV) battery life forecast, cell balance, power demand, energy management, thermal management, and driving range calculation all rely on each condition[11]. There is a strong correlation between SOC and other states, making it the most crucial parameter to detect and regulate in most research estimating SOC of a battery cell. Also, capacity fading, temperature, internal resistance, and SOC are all factors that are gradually altering the State of Health (SOH). Charging method, heat transmission, and electrochemical battery characteristics all contribute to intermediate-scale variations in the State of Temperature (SOT)[12]. Despite the fact that SOE and SOP may change rapidly, SOC is a major determinant of both. Hence, while estimating other states, SOC estimate is crucial.

Importance Of State Of Charge Estimation

There are a variety of estimating techniques employed, but model-based approaches have recently been recognized as the gold standard. Since the accuracy of the model has a direct impact on state prediction, building a battery model should be the first order of business. Thus, to accurately predict a battery's SOC, one needs a well trained battery model in addition to an appropriate SOC estimation method. Because of this interdependence, it is critical to choose an appropriate battery model and state-of-charge estimate method when designing a BMS. In order to avoid thermal runaway, detect defects, and analyze and monitor battery performance, a reliable battery model is required[13]. The behavior of the battery is shown by analyzing and describing the standard models and the parameters linked to them.

Therefore, model-based methods for estimating SOC often make use of Electrochemical Models (EMs) and Equivalent Circuit Models (ECMs). While EMs outperform ECMs in terms of accuracy, they still fail to provide an optimal balance between complexity and precision. For real-time BMS operations including state estimation, cell equalization, and charging management and optimization, ECMs are often used models instead of EMs due to their simpler parameterization and implementation requirements[14]. Because of its great precision, simplicity, and outstanding modeling needs, Two RC-ECM is a suitable model for web-based applications. At each stage, SOC updates the time-variant parameters since the model parameters are highly reliant on SOC. Both online and offline methods have been used to identify the model parameters for online SOC estimation. Because online SOC estimate algorithms are computationally difficult and time-consuming to conduct, most researchers choose offline identification approaches. To improve the model-based SOC estimate technique's accuracy for real-time EV applications, however, the model parameters need to be determined online. Consequently, in order to estimate SOC, the parameters of the battery model are determined using the VFFRLS method[15].

Significance of Kalman Filter

Since the battery model and state-of-charge estimate approach are interdependent, it is important to choose the correct one when designing a BMS. Because of its accuracy, robustness, self-correction capability, and convergence rate, the Kalman Filter (KF) family algorithm is superior than Artificial Neural Network (ANN) for SOC estimation. A state-space model of the battery must be first created before a KF-based approach can be employed for SOC estimation. The model ties SOC to quantifiable factors like voltage and current by using SOC as a state variable. An improved version of KF that accounts for the battery's nonlinear nature shows great promise for state-of-charge estimation. The EKF is chosen because of its balance between complexity and accuracy, even if the Particle Filter (PF) and the Unscented Kalman Filter (UKF) have been created and provide excellent results for SOC estimate. Just because other sophisticated filters increase computing complexity while also improving accuracy[16]. An accurate but not too complex technique is required for the severe operating conditions of an electric vehicle.

The filter performance is affected by specified settings of the system noise, even though EKF has its benefits. So, it's worth investigating how the process noise covariance matrix (Q) and the measurement noise covariance matrix (R) affect SOC estimation with the use of Kalman filter techniques. To examine the impact of these matrices on SOC estimation, several combinations of noise covariance matrices are used. Poor convergence rate and estimate mistakes might be caused by inaccurate battery modeling and noise covariance matrices. The noise covariance matrices (Q & R) are often fine-tuned by hand using the time-consuming trial-and-error technique. It gets more difficult to manually tune these matrices as the system order grows[17]. In order to address this, SOC estimation makes use of adaptive filtering techniques such as the Adaptive Unscented Kalman Filter (AUKF) and the Adaptive K-Filter (AEKF). These strategies, however, increase both the computing complexity and the amount of initial predictions that need to be made. Additionally, an optimization technique is required for these approaches to choose the size of the moving window, which is crucial. In order to focus only on state estimation, one needs be familiar with process and measurement noise, according to Kalman theory[18]. The adaptive approach or filter tuning aims to collect the filter statistics Q and R by running a filter on measurement data. Consequently, adjusting the filter is crucial for accurate and fast SOC estimate of Li-ion batteries. The suggestion of filter tuning is explored for every possible formulation or version of the Kalman filter, including EKF, UKF, and PF. In order to get near-ideal solutions, the best tuning that is practically possible is needed. Without correct tuning, it is hard to determine whether the performance of Kalman filter variants is a result of their formulation. Therefore, independent of the battery model and filtering approach, filter tweaking is crucial for improved state estimation[19].

Modeling And State Of Charge Estimation Of Lithium-Ion Battery In Electric Vehicle

Electric vehicle (EV) models must prioritize extending the driving range and optimizing the run time of the batteries. This opinion holds that BMS is crucial for the reliable and secure functioning of batteries, particularly when it comes to electric vehicles employing Lithium-ion (Li-ion) batteries. Estimating SOC is a crucial function of BMS. If you want an accurate state estimate, you need a battery model that is well-parameterized. Why? Because avoiding thermal runaway and other issues with a well-modeled battery requires constant monitoring and analysis of the battery's activity. It is also important to monitor State of Charge using accurate estimate techniques because of the critical role it plays in controlling battery functioning. Consequently, for accurate SOC estimation, it is necessary to use a well trained battery model in conjunction with the appropriate SOC estimation approach. This study examines the merits and shortcomings of popular battery models by concentrating on these characteristics. These models include the electrochemical model, the equivalent circuit model, and the data-driven model. Also included are the usual procedures for estimating a battery's state of charge, including direct and model-based approaches. In order to create an appropriate BMS for EVs, we thoroughly examined the three most different battery types and categorized the various SOC estimate methods, paying close attention to details like accuracy, setup effort, computing complexity, implementation simplicity, and real-time applications. Battery modeling and state-of-charge (SOC) estimation for Li-ion battery cells are the primary areas of emphasis in this study.

With reliable SOC estimate, electric vehicle users may rest easy about their vehicles' range. Estimating the battery's status requires a reliable battery model. The creation of an accurate battery model is the first step in BMS design. Many battery models with varying degrees of accuracy have been created up to this point[19]. The electrochemical, equivalent circuit, and data-driven models of batteries are the most notable ones. Battery behavior may be described using electrochemical models that employ partial differential equations to account for variables such as electrolyte content, anode and cathode electrode size, and the electrochemical process occurring inside the battery. Finding a plethora of data—electrolyte potential, solid potential, open circuit potential, overpotential, electrolyte concentration, solid concentration, battery cell current, temperature, etc.—requires more computing power and time, despite the fact that EM delivers correct battery parameters. It also has a hard time finding a home in real-time apps. According to its physical mechanism, Optimal performance, range, and battery life in electric cars (EVs) are dependent on proper state of charge (SOC) management, which is becoming more important as EVs gain in popularity. To avoid wasteful deterioration and maximize battery life, an accurate SOC estimate is required[20]. Using an Extended Kalman Filter (EKF), this research presents a new method for determining the ideal battery charge level for electric vehicles. To accurately assess the present state of charge (SOC) and forecast future SOC values, the EKF recursive algorithm integrates data from several sensors with a dynamic battery model.
The effect that SOC estimate has on the general efficiency and performance of EVs is where its importance resides. By accurately estimating SOC, sophisticated battery management systems can maximize the vehicle's range while guaranteeing the health and life of the battery via optimized charging and discharging procedures. However, estimating SOC in EV batteries is difficult because of measurement noise, uncertainties, and nonlinearities that are unique to battery systems. This article explains the EKF method and how it is used to estimate the state of charge in batteries. We emphasize the EKF's capacity to efficiently manage these issues by repeatedly revising SOC estimations according to sensor readings in real-time and the battery's dynamic behavior. The EKF method ensures precise tracking of SOC changes over time by integrating data from several sources, such as battery voltage, current, temperature, and other pertinent factors.

In addition, we showcase a validation of the suggested EKF method using simulation, utilizing electric car driving data collected in the actual world. Electric vehicle battery state-of-charge (SOC) estimation using the EKF method was successful over a range of operating situations, including varying driving patterns, temperatures, and degradation scenarios, as shown in the simulation results. In real-world electric vehicle applications, our findings prove that the EKF-based SOC prediction method is reliable and resilient.

In electric cars, the energy storage devices that are housed in the batteries are closely monitored and controlled by the battery management system. Improving the efficiency of electric cars' battery management systems is crucial as it regulates the lifespan of the expensive battery, which is becoming more critical as battery technology continues to advance. Particularly in the areas of battery modeling and state of charge estimate, this chapter has addressed the most crucial facts of the battery management system. Battery modeling may be made more accurate and simpler by choosing the right model type and using a parameter identification approach. The literature on state of charge estimation suggests that, with the right choice of battery model, parameter type, and parameter identification technique, an adaptive filter-based approach to SOC estimate may produce accurate findings. To provide a balance between accuracy and complexity, state-of-charge estimation based on artificial intelligence requires a proper training approach, a large amount of data collection, normalization, and an algorithm for tuning hyperparameters. The majority of the battery management system's critical technologies, however, were developed and proven in controlled laboratory settings. However, it is impossible to extend the guarantee since real-world performance differs from laboratory findings. Customers of electric vehicles need a simple and precise technique for state of charge estimate if the manufacturers are serious about calming their fears about the battery pack's range and avoiding cell inconsistencies. Validation of the method under the dynamic settings of an EV is essential.

Battery Modeling and Parameter Identification Using Variable Forgetting Factor Recursive Least Square Algorithm

The transportation industry's huge drive for hybrid and battery-powered cars and the demand for longer-lasting portable electronic devices have heightened interest in the complicated field of battery modeling. In this research, we will use a form of recursive least square methods to determine the model parameters and analyze battery properties. Few models are as widely used as the electrochemical, black-box, and comparable circuit models. The electrochemical model describes the internal electrochemical process of a battery and how it behaves in relation to the anode and cathode sizes, electrolyte concentration, and other parameters. The model is realistic and easy to understand, however it's not practical for use in online design processes. A large number of factors, some of which are difficult to identify, and complicated electrochemical processes contribute to the high computational complexity of this model's implementation. The nonlinear mapping between a battery's input and output may be approximated using existing samples and black-box models. Many different types of artificial neural networks, support vector machines, recurrent neural networks, deep neural networks, etc., are used to construct black-box models. It takes a lot of training data for this model to show how batteries behave without understanding battery chemistry. This model works well with Li-ion batteries, but it takes a long time to train and uses a lot of computing power.

Furthermore, developing an appropriate training method and choosing hyperparameters need meticulous consideration. The amount and quality of the training data determine how much computing and model accuracy this model requires, however. The mapping learning process is therefore less efficient. Therefore, it is ideal to have a mapping learning algorithm that can handle a lot of training data quickly.

For web-based apps, ECM is the way to go since it meets all of the most important modeling criteria in terms of precision, setup effort, computational complexity, and implementation simplicity. This model explains the battery's dynamic behavior and has a clear structure. The design of control systems may benefit from battery models that are not too complicated. Battery models shouldn't be very computationally expensive since control systems need to work on embedded computers in real-time. Most of these devices use one or two RC-ECMs and are circuit-based. The Rint model, the PNGV model, the combination model, and the RC (resistor-capacitor) network-based model are some of the similar circuit models for Li-ion batteries. The preferred ones are the ones with one or two RC networks.

More model parameters in more complicated ECMs increases the likelihood of over-fitting, which in turn reduces accuracy. This means that the model structure and parameters have a significant impact on ECM accuracy, and that improving model accuracy requires using the right model structure and parameters. Nevertheless, the battery's characteristics change based on temperature, SOC, and C-rate, thus they must be adjusted. The model parameters are identified using the VFFRLS approach described in [7] since they are time-variant. An method called fixed Forgetting Factor Recursive Least Square (FFRLS) is used to compare the developed approach to.

Proposed Battery ECM-Based SOC Estimation

In addition to guaranteeing the vehicle's operational range, SOC estimate helps with energy and power computations. Consequently, it is not an easy process to get an accurate SOC for a moving vehicle. When trying to estimate SOC that is not immediately measurable by any sensor or device, a more complex estimation method is necessary.

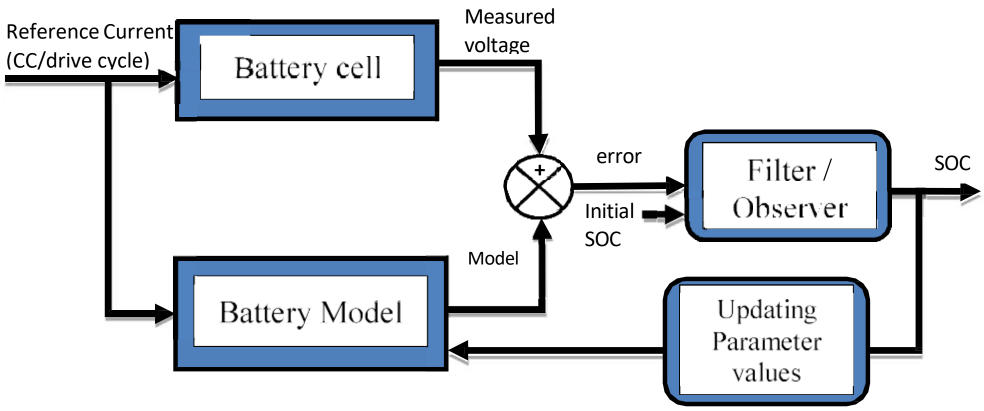

Figure 2 ECM based SOC estimation

A simple, accurate battery model is necessary for the model-based state-of-charge estimation method. SOC is determined by dividing the battery's current by its useable capacity.

$$SOC = \mathrm{SOC}_0 - \int \frac{I_{bat}}{Q_u} dt$$

Here, SOC_0 represents the starting SOC, battery current is represented by I_{bat} and usable capacity is represented by Q_u.

The model-based SOC estimate method's block diagram is shown in Figure 2.
An input current, either continuous or pulsed, is supplied to the battery cell. The current and voltage at the cell's terminals are used to measure sensor noise and process noise. In Figure 2 Filter/Observer might be seen as a controller from a control theory perspective.

Conclusion

This work has presented a novel approach for estimating the optimal state of charge (SOC) for electric car batteries using an Extended Kalman Filter (EKF). The EKF algorithm, known for its recursive nature and ability to handle nonlinearities and uncertainties, offers a robust solution for SOC estimation in electric vehicle (EV) batteries.Through a detailed explanation of the EKF algorithm and its application to battery SOC estimation, we have highlighted its effectiveness in combining measurements from various sensors with a dynamic battery model to accurately estimate the current SOC and predict future SOC values. By iteratively updating SOC estimates based on real-time sensor data, the EKF algorithm enables precise monitoring of battery performance and health.

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