

# FPGA BASED BATTERY SOC ESTIMATION USING DEKF ALGORITHM

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**Abstract:** Nowadays, the amount of portable electronics products like mobile telephones and laptop computers has grown explosively. These developments have a resulted in massive demand for secondary battery. The useful of lithium-ion batteries included no memory effect, high operation voltage, and high energy density. Therefore, it's the foremost popular secondary battery for consumer electronics. The SoC and the capacity of a lithium-ion battery are estimated using the dual EKF with the proposed method. In this report, a FPGA (Field Programmable Gate Array)-based SOC estimation algorithm is developed. The System-In-the-Loop (SIL) simulation provides a platform to develop a full FPGA-based Algorithm, using SOC

**Keywords:** Energy storage; Lithium-ion battery; Battery management system BMS; battery design; state of charge SoC.

## I INTRODUCTION

Lithium battery has been widely utilized in the energy storage field thanks to its high energy density, long cycle life, high voltage, and outstanding security [1]. Generally, in order to make sure the efficiency and reliability of the energy storage system, battery packs are monitored by the battery management system &#40;BMS&#41;. And therefore the state estimation of the battery is that the essential function of the BMS. The accurate online state estimation can contribute to watch the battery's state of charge (SOC) and state of health (SOH) clearly in order that here as on able charge-discharge are often performed to stay its high-efficiency working conditions and long life [2]. SOC and SOH represent the battery's energy and lifelong, respectively. They are the core aspects of the battery BMS. the normal method assumes that the SOC is determined by the integral of the present input and Output from the battery over time. This is an open-loop-based approach, the result to which is usually accompanied by poor estimation accuracy and therefore the Accumulation of sensor errors [3]. Moreover,

within the past, the battery's capacity variation were to not be taken under consideration during the lifetime; the estimation method had great shortage. In fact, it comes with irreversible chemical reactions and physical changes within the working process of the battery, which make SOC and SOH tightly including one another. Improper battery state estimation method can cause premature usage and deterioration of the battery [5]. As the impedance and capacity of the battery change with time, the utmost power and energy which will be delivered by the battery are going to be reduced. This technical problem are often solved by simultaneously estimating the SOC and therefore the SOH of the battery. The contribution of this paper is to determine a replacement equivalent circuit model supported the lithium battery external characteristic, and therefore the battery parameters are identified by considering the influence of capacity fade, voltage rebound, and internal capacitance-resistance performance. The connection between the ohmic internal resistance and real capacity is obtained by degradation test. Then, the twin extended Kalman

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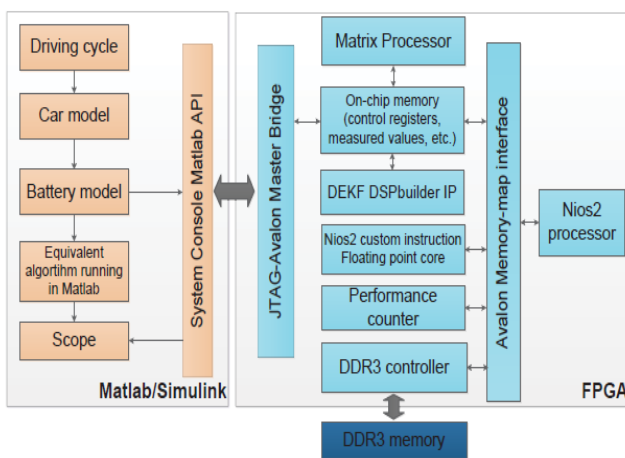
filter(DEKF) is employed to perform real-time prediction of the lithium battery state.

**II LITERATURE SERVEY**

The Literature Survey was carried out where different types of methods were assessed and their advantages and disadvantages were found out. The overall consensus which can be derived from the literature survey is that numerous models as well as algorithms have been developed in order to effectively predict two of the most important parameters i.e. how to measure SOC accurately by using dekf Algorithm.

More advanced techniques include Kalman Filter, Fuzzy Logic, Neural Networks, etc. Among different solutions, Kalman Filter is considered to be one of the most popular methods. It is designed to strip unwanted noise out of a stream of data. It operates by predicting the new state and its uncertainty. For nonlinear systems SOC estimation using Kalman filter will reduces the state matrix dimensions and may improve the estimation robustness

**III WORKING**



**Fig.1 Working diagram of battery model**

Battery Model. The battery performance is closely associated with its internal parameters. And the change rule of characteristic parameters are often analyzed by establishing the reasonable equivalent model [12]. so as to realize the real-time state analysis, not only the working characteristics, including voltage rebound effect, hysteresis, and electromotive force-SOC (EMF-SOC), got to be taken into consideration within the model but also the complex electrochemistry mechanism should be avoided the maximum amount as possible. Therefore, mainly that specialize in the

analysis of external characteristics, a replacement circuit containing a controlled source is established because the equivalent circuit model of the lithium battery.

The model is predicated on Thevenin's theorem and consists of the same voltage source and equivalent impedance .related with the SOC, SOH, and dealing conditions of the battery. Therefore ,the equivalent voltage source EB consists of voltage EMF and hysteresis voltage Vh. because th voltage-controlled voltage source (VCVS), EMF is controlled by voltage VSOC. And Ccap is that the capacity of the battery, which is said with the SOH. and therefore the current flowing through C cap is adequate to the working current IB. Therefore, the worth of VSOC are often wont to represent the battery SOC:

$C_{cap} - C_{remain} C_{cap}$ , (1) where t is that the working time and C remain is that the remaining capacity. Hysteresis voltage This also a voltage-controlled voltage source (VCVS), which is controlled by voltage VLh. the present flowing through inductance Lh is  $\beta IB$ . Hysteresis voltage is influenced by previous working current, in which the characteristic are often described by a circuit containing the inductance. the worth of Vh is decided by charging and discharging conditions: therefore, the equivalent voltage source is

$$VSOC + Vh = VLh.$$

Open Circuit Voltage Method. there's approximately a linear relationship between the SOC of the lead-acid accumulator and its circuit voltage(OCV) given by

$$VOC(t) = a_1 \times SOC(t) + a_0, e$$

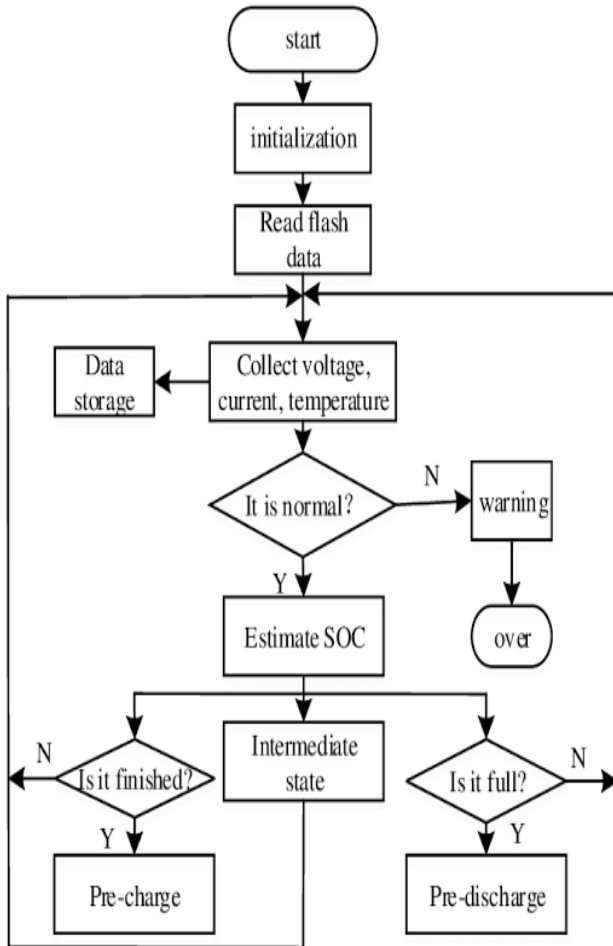
the SOC of A battery is defined because the ratio of its current capacity(Q(t)) to the nominal capacity(Qn). The nominal capacity is given by the manufacturer and represents the utmost amount of charge which will be stored within the battery. The SOC are often defined as follows:

$$SOC(t) = \frac{Q(t)}{Qn}$$

Where SOC(t) is that the SOC of the battery at t, a 0 is that the battery terminal voltage when SOC = 0%, and a1 is obtained from knowing the worth of a0 and VOC(t) at SOC = 100%. By , the estimation of the SOC is like the estimation of its OCV. The OCV method supported the OCV of batteries is proportional to the SOC whether are disconnected from the hundreds for a

period longer than two hours. However, such a long disconnection time could also be too long to be implemented for battery. Unlike the lead-acid accumulator, the Li-ion battery doesn't have a linear relationship between the OCV and SOC. A typical relationship of Li-ion battery between SOC and OCV is

**IV.FLOW CHART:**



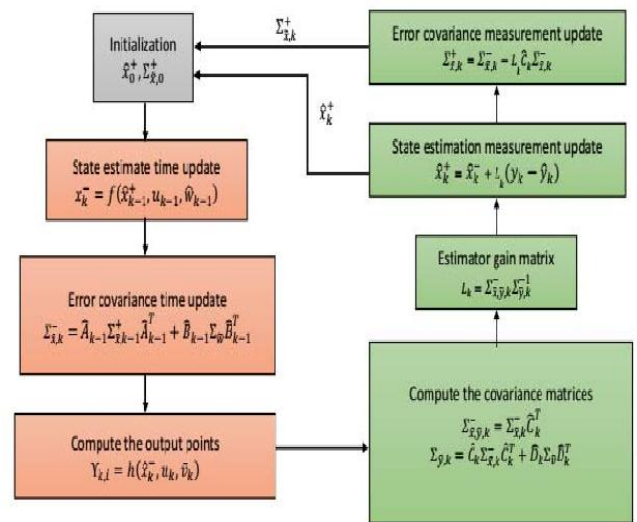
**Fig.2 Flow Chart**

The method used are explained as follows:

SoC represents the available battery capacity that can be withdrawn from the battery and is used to prevent its over-discharge or over-charge as well as to operate the battery in such a manner that aging effects are reduced. SoC estimation has drawn the attention of many researchers, and many different methods have been proposed [18]. To make a classification of the methods is not an easy task because most approaches point to the combination of two or more methods and the inclusion of different heuristic or deterministic mathematical tools. This review will show that it is common to find a mix of both open circuit voltage (OCV) and coulomb

counting (CC) methods. It is common for these combinations to involve a variety of improvements in the initial and online SoC estimation since methods applied separately can suffer from some inaccuracies. For example, [8] combined the algorithm OCV method fullcharge detector/dynamic load observer, and, as the key function, the CC method with robust extended Kalman filter algorithm (REKF). The combinations make it harder to sort out each approach into a specific method classification. However, based on the classification made in [4], and from the published literature on this topic in the last five years, this review proposes two categories (direct and indirect methods), and several subcategories that summarize trends in SoC estimation. Figure 3 displays a summary of these categories with their main drawbacks.

**V.DEKFALGORITHM:**



**Fig.3DEKFmethod**

the EKF has attracted increasing attention and become one among the foremost commonly used methods to estimate the battery SoC even when the initial SoC is unknown [97]. KF is that the optimum state estimator for linear systems. If the system is nonlinear, a linearization process are often used at whenever step to approximate the system with a linear time varying (LTV) system. This LTV system is then utilized within the KF, leading to an EKF on the important system . employing a nonlinear model like that presented in Equations (3) and (4), and taking under consideration an equivalent considerations for  $w_k$  and  $v_k$ , at whenever step,  $f(x_k, u_k)$  and  $g(x_k, u_k)$  are linearized by a first-order Taylor-series expansion. Assuming that

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$f(x_k, u_k)$  and  $g(x_k, u_k)$  are differentiable in the least operating points  $(x_k, u_k)$ :  $f(x_k, u_k) \approx f(\hat{x}_k, u_k) + \frac{\partial f(x_k, u_k)}{\partial x_k}$

$x_k = \hat{x}_k (x_k - \hat{x}_k)$ ;  $g(x_k, u_k) \approx g(\hat{x}_k, u_k) + \frac{\partial g(x_k, u_k)}{\partial x_k}$

Combining these two equations with Equations (3) and (4), the linearized equations that describe the important system state as a function of itself (known inputs  $u_k$  and  $\hat{x}_k$ , and therefore the unmeasurable noise inputs  $w_k$  and  $v_k$ ), we have:  $x_{k+1} \approx \hat{A}_k x_k + f(\hat{x}_k, u_k) - \hat{A}_k \hat{x}_k + w_k$ ;  $y_k \approx \hat{C}_k x_k + g(\hat{x}_k, u_k) - \hat{C}_k \hat{x}_k + v_k$ , where  $\hat{A}_k = \frac{\partial f(x_k, u_k)}{\partial x_k}$

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The linearization process made in EKF uses the first- or second-order terms of the Taylor series expansion to approximate a nonlinear model, which degrades the SOC estimation accuracy. To beat this, rather than local linearization, the unscented Kalman filter (UKF) captures the distribution characteristics of a system consistent with a series of sigma points [98]. The UKF supported unscented transform not only doesn't require the calculation of a Jacobian matrix but features a higher order of accuracy within the noise statistics estimation than the EKF, like the mean and error but features a higher order of accuracy within the noise statistics estimation than the EKF, like the mean and error covariance of the state vector of the battery system [97]. Figure 9 shows the UKF algorithm. The sigma points and weighted coefficients calculations, also because the covariance matrix of the error factors included within the Kalman gain.

**VI.RESULTS**

Open-Circuit State. When the initial charge is 92%, the SOC estimation is performed within the open-circuit state. The measuring voltage nearly remains constant thanks to the zero working current, as showing. When initial error is 0, the SOC estimated by both methods is

on the brink of 92% with a touch fluctuate, as how. Because the present is zero, CC-Soc and REAL-SOC have an equivalent value at this point, and the two curves are basically coincident. And when 2% initial error exists, the SOC estimated by the DEKF method can converge to real value, but the estimation still contains initial error by using the CC method

**VII.CONCLUSION**

(1) DEKF principle using in battery state estimation is analyzed based on the relation of SOC and SOH. A simulation model is established to analyze the estimation ability with the influence of different initial errors.

(2) The SOC estimation experiments are performed by, respectively, using the traditional CC method and DEKF method in three different working conditions. By comparison with the estimation results of the CC method, the results of DEKF are still earthe real values, even if the errors of sensors exist. When 10% initial errors are introduced, the DEKF can correct the errors, and the estimation can fast convert get real values. The average errors are less than 3% in all kinds of working conditions, which verifies the feasibility of the algorithm.

**VIII.APPLICATION**

- o Electric Vehicle
- o Pc/Communication
- o Grid Power Infrastructure.
- o Consumer Electronics.
- o Active contribution step towards Digital India

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