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# A framework for state-of-charge and remaining discharge time prediction using unscented particle filter

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## HIGHLIGHTS

- A framework for state-of-charge and remaining discharge time prediction is proposed.
- The unscented particle filter is employed to improve the observation accuracy.
- The recursive method is presented to predict the probable future current.

## ARTICLE INFO

*Keywords:*
State observation
Battery modeling
System identification
Bayes estimation
Load behavior prediction

## ABSTRACT

As a typical complex system, the lithium-ion battery system is characterized by strong coupling and nonlinearity, which brings great challenges to its modeling, state estimation, and control. The modeling and state estimation especially the state-of-charge and remaining discharge time are key issues for the battery management system. This paper details a framework for observation of the battery state-of-charge and remaining discharge time by using the unscented particle filter. First, an equivalent circuit model considering hysteresis is presented and verified at different temperatures. Then the framework for observation of the battery state-of-charge and remaining discharge time is proposed using the unscented particle filter in order to improve the observation accuracy. The recursive method is employed to predict the probable future current considering the historical data. In addition, the prediction results of the probable future current with different forgetting factors are compared and analyzed in order to select the optimal parameter for the remaining discharge time prediction. Finally, experiments under different dynamic driving cycles at different temperatures are carried out to verify the proposed method. The performance of the unscented particle filter and the extended Kalman filter are compared and analyzed. The experimental results indicate that the proposed unscented particle filter method has high accuracy and fast convergence under dynamic driving cycles.

## 1. Introduction

### 1.1. Motivation and challenges

In the past decades, the rapid development of battery electric vehicles has driven the progress of battery and energy storage technology [1]. Due to the large-scale and unitized use of single cells, the power battery system has brought new problems to safety and has become a technical bottleneck for the promotion and application of the electric vehicles. As a typical complex system, the lithium-ion battery system is characterized by strong coupling and nonlinearity, which brings great challenges to its control and management [2]. Therefore the battery management system is significant to ensure the safe and efficient operation of the battery system [3]. The power battery is a complex nonlinear time-varying system that contains plenty of time-varying states such as the state-of-charge (SOC) [4], state-of-energy (SOE) [5], state-of-power (SOP) [6], and slowly changing parameters of the cell model. The accurate observation of the battery state especially the SOC is the key issue of the battery management system which is also the basis of the balancing strategies [7] and premise to both energy and power calculations. For the hybrid energy storage systems in hybrid electric vehicle or fuel cell vehicle applications, those parameters are usually key constraints in energy management strategies [8].

The battery SOC is defined as the ratio between the remaining capacity and the total available capacity. Distinguish from the fuel gauge, the SOC is not a directly measurable value. Because there is no sensor available to measure the SOC, the SOC needs to be estimated by using the measured voltage, current, and temperature. Although the battery

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**Nomenclature**

*Acronyms & abbreviations*

| | |
|---|---|
| SOC | state-of-charge |
| SOE | state-of-energy |
| SOP | state-of-power |
| RDT | remaining discharge time |
| OCV | open-circuit voltage |
| EKF | extended Kalman filter |
| UKF | unscented Kalman filter |
| PF | particle filter |
| NN | neural network |
| SVM | support vector machine |
| DWT | discrete wavelet transform |
| UPF | unscented particle filter |
| MRDT | minimum remaining discharge time |
| MRCT | minimum remaining charge time |
| ECM | equivalent circuit model |
| UDDS | urban dynamometer driving schedule |
| FUDS | federal urban driving schedule |
| RMSE | root-mean-square error |
| RLS | recursive least-squares |
| TCP/IP | transmission control protocol / Internet protocol |

*Notation*

| | |
|---|---|
| $z$ | battery SOC |
| $v_{rc}$ | overall voltage of the resistor-capacitor pairs |
| $\Delta t$ | sampling time interval |
| $I$ | current |
| $v_h$ | battery hysteresis voltage |
| $\eta$ | Coulombic efficiency |
| $\gamma$ | positive constant |
| $Q$ | battery capacity |
| $\mathrm{OCV}_{chg}$ | OCV for charging |
| $\mathrm{OCV}_{dchg}$ | OCV for discharging |
| $v_{d,j}$ | voltage of the $j$th resistor-capacitor pair |
| $\theta$ | parameter vector |
| $\varphi$ | data input vector |
| $P$ | error covariance matrix |
| $\kappa$ | scale factor for RLS |
| $K$ | gain matrix |
| $R_0$ | Ohmic resistance |
| $R_{d,j}$ | diffusion resistor of the $j$th resistor-capacitor pair |
| $C_{d,j}$ | diffusion capacitor of the $j$th resistor-capacitor pair |
| $\tilde{i}$ | future current considering historical driving profile |
| $w$ | process noise |
| $\delta$ | measurement noise |
| $Qs$ | process noise covariance |
| $R$ | measurement noise covariance |
| $X^{(i)}$ | state variable of the $i$th particle |
| $Y^{(i)}$ | measurement of the $i$th particle |
| $W$ | weight of the particle |
| $L$ | dimension of the augmented state |
| $\sigma$ | scaling parameter of UPF |
| $q^{(i)}$ | likelihood associated with the $i$th particle |
| $\bar{q}^{(i)}$ | the normalized likelihood associated with the $i$th particle |
| $\lambda$ | forgetting factor |
| $\tilde{i}_{dchg}$ | maximum probable future discharge current |
| $\tilde{i}_{chg}$ | maximum probable future charge current |

SOC can indicate the residual capacity of the battery, it cannot directly tell the driver how long the battery will last, because the dynamics of the operating conditions are not included in the definition of SOC. Therefore a more intuitive indicator is required to directly reflect the time of endurance of the vehicle. For the advanced prediction of the endurance time of electric vehicles, a framework for observation of both SOC and remaining discharge time (RDT) is presented in this paper.

### *1.2. Literature review*

There are numerous approaches for the battery SOC estimation and the most commonly used SOC observation methods can be divided into four types: voltage-based table lookup methods, current-based coulomb counting methods, model-based observers and data-driven approaches. As the open-circuit voltage (OCV) is not equal to the terminal voltage, approximating SOC via table lookup method using the terminal voltage is truly accurate only when the battery is resting [9]. This is because the hysteresis, the diffusion and polarization voltages, and the ohmic losses are not considered in this method. Therefore this method is only suitable for the specific resting condition in laboratory testing. For engineering realization, a conventional approach is the current-based coulomb counting method. The advantage of this open-loop approach is convenient and easy to implement [10]. However, this approach has three main drawbacks. First, the initial value determines the accuracy of the estimation. Second, the estimation accuracy is easily affected by the sensor noise, thus the reliability and accuracy are highly requested for sensors. Third, parameters and capacity degradation due to battery aging are ignored.

To overcome the above drawbacks, the close-loop model-based observers are presented for battery state estimation. One of the most representative studies is the extended Kalman filter (EKF) based SOC estimation presented by Gregory Plett in 2004 [11], which details the mathematical background, system modeling, model identification and solution for the state estimation of Li-ion batteries. To obtain better convergent and robust results, He et al. [12] and Sun et al. [13] developed the frameworks for SOC estimation by using adaptive EKF and unscented Kalman filter (UKF), respectively. Hu et al. [14] proposed an adaptive Luenberger observer for the SOC estimation of lithium-ion batteries. The observer gain can be adaptively adjusted using a stochastic gradient approach. The results show that the proposed method can accurately estimate SOC without a heavy computational load. Wang et al. [15] and Tulsyan et al. [16] employed the particle filter (PF) for SOC estimation. Unlike the EKF and UKF methods, the PF method uses a statistical approach which can yield better performance and works well for nonlinear system. Ye et al. [17] proposed an improved adaptive PF for SOC estimation which can eliminate the estimation error due to battery degradation and initial SOC errors. Wei et al. [18] presented a recursive total least squares-based observer to enhance the online model identification and SOC estimation. Xiong et al. [19] proposed the H infinity filter for OCV and SOC estimation which can result in accurate SOC estimation with a maximum error of 1%. Wang et al. [20] and Tang et al. [21] explored and proposed the multi-model switching estimation algorithms which can online select the most suitable model for SOC estimation. Lin et al. [22] studied the electrochemical mechanism models including the average-electrode model and the single-particle model. The EKF method has been employed for SOC estimation with the electrochemical mechanism models. Sturm et al. [23] proposed a battery state estimation method using a physicochemical model. The state-estimation results showed that the proposed method has good robustness against changing boundary conditions and pulsed current signals. Mu et al. [24] presented a SOC estimation framework for the lithium-ion batteries by using the fractional-order impedance model, and the estimation error of the