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Hybrid unscented particle filter based state-of-charge determination for lead-acid batteries

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ABSTRACT

Accurate prediction of cell SOC (state of charge) is important for the safety and functional capabilities of the battery energy storage application system. This paper presents a hybrid UPF (unscented particle filter) based SOC determination combined model for batteries. To simulate the entire dynamic electrical characteristics of batteries, a novel combined state space model, which takes current as a control input and let SOC and two constructed parameters as state variables, is advanced to represent cell behavior. Besides that, an improved UPF method is used to evaluate cell SOC. Taking lead-acid batteries for example, we apply the established model for test. Results show that the evolved combined state space cell model simulates battery dynamics robustly with high accuracy and the prediction value based on the improved UPF method converges to the real SOC very quickly within the error of±2%.

1. Introduction

As being robust, tolerant to abuse and having high surge-to-weight ratio with low cost, lead-acid batteries are widely used in numerous fields, which range from the relatively small portable equipments to the extremely large systems in loading level, such as telecommunication facilities, motor vehicles, emergency lighting alarm and power generations plants, etc. Real-time estimation of cell SOC, i.e., available capacity, is vital to the safety and functional capabilities of the overall system. Failure of a battery might lead to reduced performance, operational damage and even disastrous result.

Different estimation methods have been evaluated in many literatures. Some of them are related with voltage measurement, like fixed cut-off voltage when discharging, open circuit voltage, voltage under load, etc. Besides that, chemistry-dependent methods, impedance analysis [1,2], electrochemical modeling [3], and circuit models [2,4,5] are also common selection. These methods depend on the special concrete models and are hard to extract model parameters. ANN (artificial neural network) based methods[6–9] are widely utilized for capacity evaluation, which don't require knowledge of cell internal structure but rely greatly on the net training data, so do Fuzzy-logic-based models [9,10]. Techniques using EKF (extended kalman filter) [11–13] linearize the cell model equations and implement a Kalman filter to update the SOC. The linearization to formulate the EKF results in the low convergence rate and reduces the prediction accuracy. UKF techniques [14] approximate nonlinear cell model with Gaussian probability distribution, which behave better but still converge a little slow. Particle filters adopt Monte Carlo sampling methods which are able to represent any probability density function, and approach the Bayesian optimal estimate with sufficient samples. Well designed particle filter methods can be made more accurate than the EKF and UKF ones. [15–19] presents a particle filter based method for SOC determination. To accurately estimate the SOC of a battery with the UPF (unscented particle filter) method, a very precise battery state-space model must be available [15]. adopts an electrochemical model for cell, which is usually difficult to build an accurate one because of the complexity of the electrochemical reaction process [16]. constructs a combined exponential equation to represent the relation among cell capacity, internal impedance, aging rate and cycle number [17]. employs SOC as the only state variable to describe the dynamics of the cell [18]. takes into account the hysteresis effect of charging/discharging current to cell performance besides SOC [19]. takes the drift current as the state variable besides cell SOC and employs more parameters like running mileage into model states. Besides the current, temperature, cycle number, storage time, available and nominal capacity, cell, a dynamic nonlinear system, behaves differently under the influence of nonlinear open-circuit voltage, transient response, hysteresis effect and so on. Moreover, those data like running mileage or life cycle can't be accessed directly at most time. So a more comprehensive

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and workable model, considering the entire dynamic electrical characteristics, is required to established to simulate cell behavior. When employing UPF method to solve the cell state-space model, traditional methods [16–19] usually start to predict cell SOC with some random initial particles, which results in more time or greater number of particles to access the real value. So an improved UPF method is required to shorten the convergence time with fewer particles when evaluating available capacity.

This paper advances a hybrid UPF (unscented particle filter) based model to describe cell dynamics and estimate its SOC with high confidence. It is organized as follows. Firstly, we discuss a simple discrete state space cell model, which uses SOC as the only state variable and current as a control input. Secondly, an equivalent electrical battery model is introduced to simulate cell dynamics. Thirdly, a combined state space model is established to evaluate battery behavior, such as available capacity, open-circuit voltage, hysteresis effect and transient response, etc. Finally, we apply an improved UPF based method for SOC prediction of lead-acid batteries at different discharging and charging current. Results of lab tests on LEOCH DJ300 (2V/300Ah) lead-acid batteries with pulse discharging current, compared with model prediction of different methods, are presented.

2. Discrete state space cell model with one state and one input

Cells, nonlinear dynamic systems, can be represented by a discrete state-space form. Using cell remaining capacity $SOC(k)$ as the only system state and instantaneous current $i^{\pm}(k)$ as an input, we may describe system dynamics with the following state space model [6,11],

$$SOC(k) = SOC(k-1) - \frac{\eta(i^{\pm}(k), T(k))\Delta t}{C_{\text{Capacity}}} i^{\pm}(k),\ k = 1, 2, \ldots \tag{1}$$

$$V(k) = \left[K_0, K_1, K_2, K_3, K_4\right][1, SOC(k), 1/SOC(k), \ln(SOC(k), \ln(1-SOC(k)))]^T - i^{\pm}(k)R^{\pm} \tag{2}$$

where $\eta(i^{\pm}(k), T(k))$ is cell coulombic efficiency which differs with charging/discharging current $i^{\pm}(k)$ and cell temperature $T(k)$ at the *kth* sample time. Δt is the sampling period and C_{Capacity} is the nominal capacity of cell. The vector $V(k)$ is the cell terminal voltage, $K_i (i = 1, 2, 3, 4)$ is the constant chosen to make the model fit the data well, and $R^{\pm}$ is the cell internal resistance which differs for different charge/discharge state and SOC level. It acts as a positive resistance R^{-} when discharging with current i^{-} and a negative resistance R^{+} when charging with current i^{+}.

Assume that open circuit voltage.

$$V_{oc}(SOC(k)) = \left[K_0, K_1, K_2, K_3, K_4\right][1, SOC(k), 1/SOC(k), \ln(SOC(k), \ln(1-SOC(k)))]^T \tag{3}$$

Cell output Equation (3), turned to be a linear model, can be written as.

$$V(k) = V_{oc}(SOC(k)) - i^{\pm}R^{\pm} \tag{4}$$

Drawn as an equivalent circuit, this output equation is depicted in Fig. 1. Then we may find that the output function, which just makes a limited constant $R^{\pm}$ represent the cell internal resistance, doesn't reflect the cell internal resistance enough. It doesn't characterize the transient response and hysteresis effect of cell which will contribute to the difference between the predicted cell voltage and the real one.

3. An equivalent electrical battery model

As shown in Fig. 2 [5], advances an electrical model to describe the dynamic characteristics of a battery. Self-discharge resistor (*R*self_Discharge) characterizes the self-discharge energy loss. Full-capacity capacitor C (Capacity) represents the available capacity stored in the battery. A current-controlled current source is used to model the cell behavior among SOC, runtime and initial capacity. On the other hand, a voltage-controlled voltage source is employed to bridge SOC to open-circuit voltage. The shaded RC parallel network, consisting of *R*transient_S, *C*transient_S, *R*transient_L and *C*transient_L, is used to characterize the hysteresis effect and transient response of cell.

The electrical battery model captures almost the entire dynamic electrical characteristics: nonlinear open-circuit voltage, current, temperature, cycle number, storage time, transient response, hysteresis effect, available and nominal capacity, etc.

Describing the electrical battery model with state space functions, we may get the state function.

$$\begin{bmatrix} \dot{V}_{soc}^{g} \\ \dot{V}_2 \\ \dot{V}_2 \end{bmatrix} = \begin{bmatrix} 0, 0, 0 \\ 0, \dfrac{-1}{R_{\text{Transient\_S}} C_{\text{Transient\_S}}}, 0 \\ 0, 0, \dfrac{-1}{R_{\text{Transient\_L}} C_{\text{Transient\_L}}} \end{bmatrix} \begin{bmatrix} V_{soc} \\ V_1 \\ V_2 \end{bmatrix} + \left[\frac{-1}{C_{\text{Capacity}}}; \frac{1}{C_{\text{Transient\_S}}}; \frac{1}{C_{\text{Transient\_L}}}\right] i \tag{5}$$

and the output function

$$V = \left[1, -1, -1\right][V_{SOC}, V_1, V_2]^T - iR_{series} \tag{6}$$

Discretized at a small sampling period Δt and combined with SOC description (1), the equations can be written as follows.

$$\begin{bmatrix} SOC(k) \\ V_{soc}(k) \\ V_1(k) \\ V_2(k) \end{bmatrix} = \begin{bmatrix} 1, 0, 0, 0 \\ 0, 1, 0, 0 \\ 0, 0, 1 - \dfrac{\Delta t}{R_{\text{Transient\_S}} C_{\text{Transient\_S}}}, 0 \\ 0, 0, 0, 1 - \dfrac{\Delta t}{R_{\text{Transient\_L}} C_{\text{Transient\_L}}} \end{bmatrix} \begin{bmatrix} SOC(k-1) \\ V_{soc}(k-1) \\ V_1(k-1) \\ V_2(k-1) \end{bmatrix} + \left[\frac{-1}{C_{\text{Capacity}}}; \frac{-\eta(i^{\pm}(k), T(k))}{C_{\text{Capacity}}}; \frac{1}{C_{\text{Transient\_S}}}; \frac{1}{C_{\text{Transient\_L}}}\right] \Delta t i^{\pm}(k)$$

$$V\left(k\right) = \left[0, 1, -1, -1\right][SOC(k), V_{soc}(k), V_1(k), V_2(k)]^T - i^{\pm}\left(k\right) R_{series} \tag{7}$$