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Improved simulated annealing algorithm based state of charge determination for $LiFePO_4$ batteries in electric vehicles

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Abstract. The accurate online estimation of available capacity remained in electric vehicles is challenging owing to extensive computational requirement, measurement noise and convergence issues. Added with the search limitation from state space equations and first order low pass filter, this paper presents an improved simulated annealing algorithm based method to evaluate the cell state, where a combined state space model is employed to simulate battery dynamics. The method is verified by the experiment data collected from battery test system. Results illustrate that the proposed improved simulated annealing algorithm based method estimates the cell remained capacity with great performance and is little influenced by initialization, current disturbance and measurement noise.

Key words. Improved simulated annealing algorithm, combined state space model, state of charge, lifepo$_4$ batteries.

1. Introduction

Being low cost, safety, longevity and environmental compatibility, $LiFePO_4$ batteries are used extensively in electric vehicles (EVs) and hybrid electric vehicles (HEVs). To ensure the safety and functional capabilities of HVs and HEVs, it is a vital issue for the battery management systems to realize the precise online estimation of available capacity [1]. Failure cases may result in reduced performance, operational damage and even disastrous outcome.

The state of charge (SOC) of $LiFePO_4$ battery is usually estimated by a method based on the characteristics of the battery because it is incapable of being measured

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directly. Many different methods have been developed for that. Electrochemical model is usually impractical to be used for online estimator because of its great quantity of computation [2]. Electrical circuit models (ECMs) are widely utilized for battery state determination owing to their relatively simple mathematical structure. Kalman filter is a most common selection for accessing cell SOC. It operates recursively on streams of noisy input data to produce a statistically optimal estimate of the underlying system state. Reference [3] employs two different battery parameter identification methods and presents an enhanced closed loop extendKalman filter (EKF) estimator to realize an accurate SOC estimation. Reference [4] adopts EKF to update the parameters of battery pack by real-time measured data and unscented Kalman filter (UKF) to estimate the SOC of battery pack. Nevertheless, the EKF [5] and UKF [4, 6] based methods are influenced greatly by the specified original value especially in a nonlinear system. If a given initial state is far away from the real one, the prediction accuracy will decline and the convergence will even be lost in some cases.

Particle filter (PF) based methods use random particles satisfied with specified distribution to represent the possible SOC, and get a set of particles with associated importance weights to represent the posterior probability density. [7] advances an unscented PF based degradation model to predict the remaining useful life of cell. [8] proposes an improved adaptive PF based online adaptive estimator to evaluate SOC, which is capable of eliminating the estimation error from the battery degradation and initial state errors. Being short of effective search mechanism, normal PF based methods do not guarantee achieving a global optimal value after a great quantity of computation.

To settle the existing issues on battery SOC estimation, this paper puts forward an improved simulated annealing (SA) based method, which occupies the advantage of global optimization, to predict the cell SOC. It is organized as follows. This paper first employs a combined state space model to simulate battery dynamics. Then an improved simulated annealing based method is used to determine the available capacity of $LiFePO_4$ batteries at different discharging pulse current. Finally results of lab tests on 18650 size cells with pulse discharging current, contrasted with traditional prediction method, are presented.

2. Battery Modeling

Since SOC is incapable of being detected directly, an accurate cell model about SOC must be set up first for $LiFePO_4$ batteries.

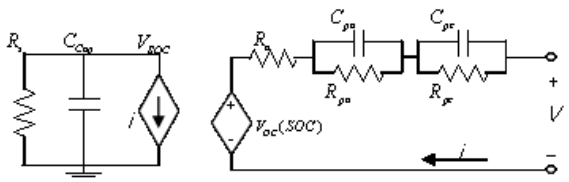

Fig. 1. Electrical circuit model of LiFePo4 batteries

2.1. Electrical circuit model

An effective ECM may simulate the dynamic behavior of cell and provides an insight into its internal mechanism. A two-order electrical circuit model with two controlled sources is displayed in Figure.1. The controlled current source is regulated by the battery flowing current (i) and used to model the cell behavior among SOC, runtime and open circuit voltage. It adopts self-discharge resistor (Rs)to characterize the self-discharge energy loss and full-capacity capacitor (C_{Cap}) to represent the available capacity stored in the battery. The controlled voltage source incorporates three parts: open-circuit controlled voltage (V_{oc}), ohmic resistance R_o and the shaded RC parallel network which incorporates electrochemical polarization resistance (R_{pa}),electrochemical polarization capacitance(C_{pa}), concentration polarization resistance (R_{pc}) and concentration polarization capacitance(C_{pc}). The model characterizes the transient response and polarization effect of cell. Nevertheless, it does not describe the nonlinear relation among open-circuit voltage, SOC, and charging or discharging curren.

2.2. Combined state space model for $LiFePO_4$ batteries

Based on the electrical circuit model, experience equations and coulomb counting method [9], this paper achieves the cell state $x(k)$ at kth sample time with a discrete combined state space model [10],

$$E = E_0 \left(1 - \alpha \left(1/2 - \xi\right)\right) , \tag{1}$$

where $Cap$is the cell nominal capacity, $V$is the terminal voltage and $K_i(i = 0, 1, 2, 3, 4)$ is the coefficient,Δt is the specified small sampling period, $\eta$is the cell coulombic efficiency differing with current i (assumed positive for discharge, negative for charge) and cell temperature T.

The model for $LiFePO_4$ batteries has the advantage of reflecting the effect of SOC, internal resistance and the polarization effect resulted from RC network. Moreover, it is simple for understand and realization, and provides an insight into the internal mechanism of battery.

2.3. Model parameters identification

Given training data set, parameters $(K_0, K_1, K_2, K_3, K_4, R_o)$ in experience model (1) are calculated with recursive least square (RLS) regression algorithm. The appropriate time constant of polarization($\tau_{pa} = R_{pa}C_{pa}, \tau_{pc} = R_{pc}C_{pc}$)needs to be given in advance based on the battery characteristics. Then Simulated Annealing satisfied with the loss function (2) is used to access the optimal values of the left parameters, such as R_o, R_{pa}, C_{pa}, R_{pc}, C_{pc}.

$$h(\xi) = h_0 \left[1 - (1 - \beta_1)\left(\xi + 1/2\right)\right] \cdot \left[1 - (1 - \beta_2)\left(\eta + 1/2\right)\right] , \tag{2}$$

where$V(k)^*$ is the measured cell terminal voltage at the kth sample time.

3. Improved simulated annealing algorithm based SOC estimation method

The established combined state space model for $LiFePO_4$ batteries (1) is a time-varying nonlinear equation. The coming approach aims at accessing the optimal value satisfying with (2) using those measured value, such as $i(k)$, $T(k)$ and $V\ (k)^*$.

3.1. Improved simulated annealing algorithm

Simulated annealing (SA) is a metaheuristic technique for approximating the global optimum of a given function in a large search space. It is an analogy with thermodynamics, which incorporates a temperature parameter into the minimization procedure. SA algorithm is capable of avoiding becoming trapped in local minima, which explores parameter space at high temperatures and restricts exploration at lower temperatures[11].

When the SA algorithm works, it is common to start with a random solution and let the annealing process improve on that. If starting with a solution that has been heuristically built, the algorithm has greater possibility to get the optimal solution with less time. This paper adopts an improved SA algorithm to evaluate SOC, which starts with an initial temperature (T) and keep decreasing the temperature with a decay parameter.

The fitness function at a state $x(t)$ is defined as

$$\rho = \rho_0 \left[1 - (1-\beta)\left(\xi + 1/2\right)^2\right], \tag{3}$$

where $V(x(t))$is the evaluated terminal voltage for a neighbor state $x(t)??a$ is the specified distance between $V(x(t))$ and $V(k)^*$ when fitness $Fit(x(t))$ is 0.5.

At the tth iteration step, the improved algorithm always accepts the neighbour state ($x(t)$) with greater fitness ($Fit(x(t))$ and accepts the one with less fitness providing that the following equation is satisfied,

$$e^{(-(Fit(x(t))-Fit(x(t-1)))/T)} \geq rand \tag{4}$$

where$rand$ is a random value located in [0,1].

If the tolerance mechanism (5) is achieved, the improved SA algorithm outputs the optimal state.

$$|s_1 - s_2| < tol, \tag{5}$$

wheretol is the specified tolerance, s_1 and $s_2$are the two accessed states with best fitness. When (5) is satisfied, it means there exists little change in the best states for a certain period.

With the global search ability of improved SA, it helps to find an optimal value closed to the real one based on the established $LiFePO_4$ battery model (1).

3.2. Improved SA based SOC evaluation method

Due to lack of knowledge about real cell state, typical SA based methods try to find an optimal SOC satisfied with the loss function (2) in a region [0,1], which costs a large number of calculation resulting from the cooling process and the big search range. To solve this problem further, this paper advances an improved SA based SOC determination method.

At the initial steps without adequate state information, the improved method employs SA to access SOC in a range [0,1] as the traditional one. When the specified maximum iteration $k_s$is arrived, it turns to evaluate cell states in an abbreviated range for reducing computation amount. The range is defined as

$$\begin{cases} SOC(k) \in [0,1], \ k \leq k_s \\ SOC(k) \in [SOC_0 - r, \ SOC_0 + r], \ k > k_s \end{cases} \tag{6}$$

wherek_s is a natural number, r is a small positive plus and SOC_0 is accessed by the state space equations in (1),

$$SOC_0{=}SOC(k-1) + \frac{-\eta(i(k-1), T(k-1))\Delta t}{Cap} i(k-1) \tag{7}$$

Working under the limited search region (6), the traditional SA based method costs less computation amount to access the optimal prediction of cell SOC. However, it will bring big error when there exists large current disturbance and measurement noise, and the error between two neighboring predicted available capacity is beyond the allowed maximum difference. In this situation, this paper employs firstorder low pass filter (8) to remove noise.

$$SOC(k) = \alpha * SOC(k) + (1-\alpha) * SOC(k-1), \ \alpha = 1/(t_f * f) \tag{8}$$

wheret_f is filter time and f is sample frequency.

4. Results and discussion

To verify the advanced supervised SA based method for SOC estimation, experiments with 3.2V/60AH $LiFePO_4$ batteries at different charging and discharging process were performed.

This paper adopts a combined state space model [9] to describe the dynamic characteristics of $LiFePO_4$ battery. Based on the established cell model, the performance of normal SA based method is shown in Fig.2. It shows that the estimated SOC converges to the measured one quickly, but the predicted value is a fluctuated one with prediction error over 10% in many cases. This situation originates in measurement noise and not using the information in the state equation of (1).

Since that, this paper advances an improved SA based method to realize the SOC determination. Based on normal SA algorithm, it employs the search limitation (6) to accelerate search speed and firstorder low pass filter (8) to remove noise.

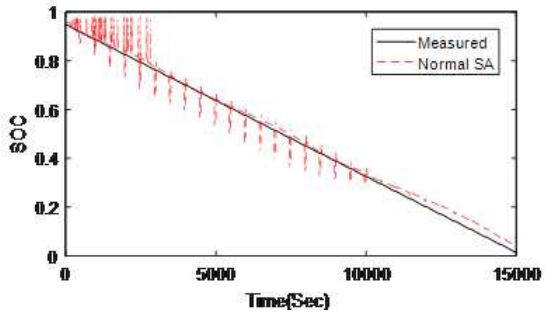

Fig. 2. SOC determination performance using normal SA based method

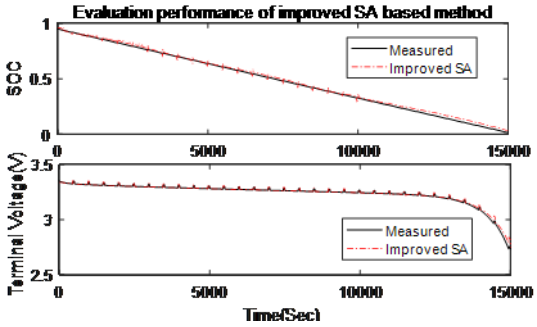

Fig. 3. Performance of improved SA based method

Fig.3 presents the evaluation performance of the improved SA based method, which signifies that the evaluated SOC and terminal voltage converges to the measured ones quickly. This case stems from two cases. One is the accurate established $LiFePO_4$ model, and the other is the effective global search ability of improved SA. When the available capacity of cell is 0.95, the search performance of the improved SA based method is depicted in Fig.4, which demonstrates that the improved SA helps to find optimal kids quickly with small iteration number even given a random original value.

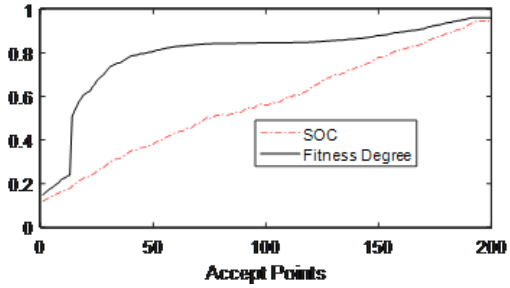

Fig. 4. The search performance of improved SA based method

Table 1. The prediction performance comparison of cell SOC using different methods

Methods	Mean	Variance	Max
Improved SA	1.62e-02	1.27e-04	3.92e-02
Normal SA	2.27e-02	6.65e-04	0.20

Table 1 presents the statistic list of the absolute SOC prediction error between the normal SA based method and the improved one in pulse discharge process. It demonstrates that the mean absolute SOC estimation error of the improved SA based method is less than 2% and its prediction variance as little as 1.27e-04, which is approximately one fifth of that of normal SA based method. With the use of the improved method, the maximum prediction error reaches a value under 4%, which declines more than one order of magnitude compared to the normal method. Furthermore, the improved SA based method is little influenced by the unknown initial state.

5. Conclusion

This paper proposes an improved SA based method to evaluate the available capacity of $LiFePO_4$ batteries. Here a combined state space model is adopted to simulate cell dynamics, such as available capacity, transient response and polarization effect. Normal SA based method may access cell SOC fast resulting from its effective global search mechanism, but it brings undesired fluctuant prediction with error beyond 10% in some cases and requires a great amount of computation. Added with the search limitation from state space equations and first order low pass filter, this paper advances an improved SA based method to access cell SOC. Finally Results of lab tests on 18650 size cells, contrasted with traditional method, are presented. Results show that the proposed improved SA based method is capable of evaluating cell SOC with great performance despite the errors from initialization, current disturbance and measurement noise.

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