A multi-timescale adaptive dual particle filter for state of charge estimation of lithium-ion batteries considering temperature effect

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Abstract
Accurate estimation of state of charge (SOC) of lithium-ion battery is one of the most crucial issues of battery management system. Temperature has a strong impact on the SOC estimation and the parameters of battery model, such as capacity and open circuit voltage. To improve the accuracy and robustness of battery state estimation, this paper tries to make the following three contributions: (a) A second-order RC battery model is established considering the recovery capacity finding from experimental data for achieving accurate battery dynamic behavior simulation against the dynamic load conditions, especially the current and temperature are both time-varying condition. (b) A multi-timescale adaptive dual particle filter is proposed to identify the battery parameters and estimate the battery SOC with online measured data for satisfying the fast-varying behavior of SOC and slow-varying behavior of battery parameters. The battery parameters are identified with macrotimescale, while the battery state is estimated with microtimescale. (c) The proposed method is validated through a set of experiments, including the time-varying temperature condition, which is overlooked by most previous literatures. The experimental results show that the proposed approach can achieve accurate and robust SOC estimation on a wide range of temperatures.

KEYWORDS
adaptive particle filter, lithium-ion battery, multi-timescale, state of charge, temperature effect

1 | INTRODUCTION

With the concerns for environmental pollution and the depletion of conventional fossil energy, electric vehicles (EVs) have the best development opportunity in recent years. Lithium-ion batteries (LIB) considered as the high-energy system are widely used in EVs for harmfulness to environment and high-energy density.1 The performance of lithium-ion batteries affects the safety, reliability, and efficiency of the EVs. To ensure the batteries work properly, battery management system (BMS) plays a great role in providing the states of battery, such as the state of charge (SOC), which describes the remaining energy of battery.2 Accurate SOC estimation can optimize the energy and battery balance management. However, SOC estimation faces a lot of challenges. On the one hand, SOC cannot be measured directly. On the other hand, the external factors such as the temperature and dynamic load have a huge impact on battery model and SOC estimation.3

On the one hand, many algorithms have been proposed for SOC estimation, for instance Kalman filter (KF).4 These
approaches regard the SOC as a variable of the states to be estimated, and the accumulated error between the prediction voltage and measured voltage is the feedback to update the estimation. The parameters of the battery model can be identified by an offline or online method. The KF is only well-suited for linear system. Therefore, the extended Kalman filter (EKF)\textsuperscript{5,7} and unscented Kalman filter (UKF)\textsuperscript{8-10} were proposed to improve the accuracy of SOC estimation because the battery model was a strong nonlinear system. However, the process noise and measurement noise of those methods were considered as known Gaussian white noise. In fact, the noise may be non-Gaussian distribution under the influence of current and voltage sensors. Particle filter (PF)\textsuperscript{11-14} can be the better choice for SOC estimation. Unlike the KF-based methods, the PF uses a statistical approach which can yield better performance and works particularly well for nonlinear system. In addition, process noise and measurement noise are not limited to satisfy the Gaussian distribution. Wang et al\textsuperscript{11} developed the PF-based observer for SOC estimation combined with electrochemical model. The results showed that PF can obtain accurate SOC estimation under dynamic currents and temperatures, which presented a promising observer prospect for battery state prediction. Later, due to the accurate battery parameters identified by the online method, dual filters were proposed for battery model parameter identification and SOC estimation, and for instance, Guo et al\textsuperscript{15} proposed dual EKF and Liu et al\textsuperscript{16} presented dual PF. The results of experiments and simulation showed that dual particle filter-based method could achieve a high accuracy and robustness for SOC estimation. However, the slow-changing parameters (ohmic resistance and capacity) and fast-changing variables (SOC and voltage) required dual estimator-based algorithms in multi-timescales, namely, microtimescale and macrotimescale.\textsuperscript{17} This had been proven in\textsuperscript{18}, where the accuracy and robustness of the observer were enhanced by dual particle filter with multi-timescales. Besides, the computation was reduced compared with dual particle filter.

On the other hand, to improve the estimation accuracy, some literatures have investigated the impact of temperature on batteries. A thermal model coupled with electrochemical model was proposed to study the battery inner temperature.\textsuperscript{19,20} Liu et al\textsuperscript{21} proposed a high-fidelity battery model that was synthesized from electrical, thermal, and aging models. Ref.22 developed a battery model coupling both the electric and thermal characteristics to optimize the battery charging patterns. Multi-dimensional thermal models were also investigated to study the internal behavior of batteries under different temperature conditions.\textsuperscript{23} But compared with the internal thermal behavior of cells, the impact of temperature on estimating SOC, which is more important for optimizing the charging and discharging strategies, ensuring the safety, prolonging the working time of the lithium-ion battery, is not clearly described. For example, the parameters of the battery, for instance, open circuit voltage (OCV) and capacity, are easily affected by temperature variations. To address these problems, Xing et al\textsuperscript{24} proposed a SOC-OCV-temperature model to study the temperature impact on OCV. A correction coefficient was used to improve the model. However, the internal resistance was considered as a constant value. Liu et al\textsuperscript{16} developed a temperature-compensated battery model. The relationship between OCV and temperature was described as a linear function. However, the effect of temperature on capacity was not addressed. Yang et al\textsuperscript{25} studied the impact of temperature on capacity, parameters, and OCV. Nevertheless, the model was simple and the relationship between OCV and temperature was still not clearly described. For example, the OCV in the estimator was simply obtained by 2D linear interpretation, and the relational expression between OCV and temperature was not specified. Although accurate estimation results have been offered with those models considering temperature effect, some issues need to be addressed before implementation of the approaches in BMS application. Firstly, the dynamic load where elements such as temperature and current synchronously vary was overlooked by most of these approaches. Their experimental conditions were usually dynamic current load with constant temperature\textsuperscript{26} or no load with temperature variations.\textsuperscript{27} Secondly, most of these methods used the same timescale for parameter identification and state estimation, despite the fact that the battery system states incline to change fast over time while parameters are prone to vary slowly over time. Furthermore, this will result in heavy computation burden of BMS. Thus, approach with multi-timescales, where microtimescale is used to estimate the states and the macro-timescale is used to identify the parameters, will reduce the computational burden of BMS. Therefore, the approach with adaptive algorithm still need to be investigated for improving the accuracy of battery for SOC estimation.

The aim of this paper is to develop an integrated method for SOC estimation that considers the temperature impact while retaining the accuracy under dynamic conditions where temperature and current synchronously vary. Firstly, a second-order RC model is presented to improve the robustness of the battery model against the effect of temperature on parameter fluctuation. Secondly, a dual particle filter estimator with multi-scale is employed for identifying the battery model parameters and estimating the battery state due to its robustness and accuracy for SOC estimation. Finally, the method with a second battery model over a wide temperature range is established. The proposed algorithm is validated under the abovementioned dynamic conditions. The rest of this paper is organized as follows. Section 2 describes battery model, test platform, and test procedures for validation. Section 3 studies the effect of temperature on OCV and capacity of the battery and builds the relationship between OCV, capacity, and temperature. On the basis, a second-order RC battery model is
proposed considering the recovery capacity and OCV-SOC curve dependence on temperature. Section 4 develops the dual particle filter with multi-timescales to estimate SOC. An adaptive method is employed to calculate the demand of the noise variance for improving the estimation accuracy. The results and discussion of the proposed method under different dynamic load conditions are described in Section 5, followed by the conclusion in Section 6.

2 | BATTERY MODEL AND EXPERIMENTS

2.1 | A second-order RC battery model

Due to the complication of electrochemical models and electrochemical impedance models, the equivalent circuit models (ECMs) have been widely applied in SOC estimation for its ease of implementation. The ECMs normally include an internal resistance, a series of polarization resistors and capacitances (RC), and an open circuit voltage (OCV), such as Rint model, Thevenin model, and nth-order RC model. The accuracy of the model is close with the number of RC. It is proved that a model with one or two RC network(s) seems to be a well choice and adequately satisfies the requirements of battery state estimation. Therefore, a second-order RC network equivalent circuit model is presented in this paper.

The schematic of the model is displayed in Figure 1. The model consists of an internal resistance $R_0$, a second RC networks $R_1C_1, R_2C_2$ (where $R_1, R_2$ and $C_1, C_2$ are the polarization resistors and capacitances, respectively), and a power source $U_{oc}$. The dynamic behaviors of the battery model are depicted by Equation (1).

$$
\begin{align*}
U_i &= U_{oc} + R_0I + U_1 + U_2 \\
U_1 &= \exp\left(-\Delta t / \tau_1\right)U_i + R_1(1 - \exp\left(-\Delta t / \tau_1\right))I \\
U_2 &= \exp\left(-\Delta t / \tau_2\right)U_2 + R_2(1 - \exp\left(-\Delta t / \tau_2\right))I
\end{align*}
$$

where $\tau_i (i = 1, 2)$ is the time constant, which equals to $\tau_i = R_iC_i$, and $\Delta t$ denotes the sampling time. $I$ is the current load (positive denotes charge process, while negative denotes discharge process). $U_i (i = 1, 2)$ is the polarization voltage of RC networks. $U_i$ is the terminal voltage of the battery.

2.2 | Test platform

In order to investigate the dynamic characterization of battery, a test platform is constructed to obtain experimental data, such as current, voltage, temperature, and OCV. Figure 2 presents the schematic of the test platform. It includes three parts: a host computer, a battery tester, and thermal chamber. The host computer is used to control all experiments, and to store and analyze experimental data. The battery tester can generate different charging and discharging voltage and current to simulate working conditions. The large thermal chamber can work at a wide range temperature conditions for fulfilling the cells and battery pack experiments. The three parts communicate with each other by CAN bus or TCP/IP.

The lithium cobalt nickel manganese oxide (NMC) batteries are tested based on the test platform. The main product specifications of the cells are presented in Table 1. The cells are repeatedly tested at a wide range temperature conditions: 0°C, 10°C, 20°C, 30°C, 40°C, and 50°C, and rest in the thermal chamber for 2 hours before running experiment for reaching the test temperature condition.

2.3 | Test procedures

The test procedures are shown in Figure 3, which include three types of tests (capacity test, OCV test, and dynamic test). To study the temperature effect on battery model, the procedures are performed in a wide temperature range from 0°C to 50°C interval of 10°C. The reason for choosing this temperature range is that the power batteries of EVs are

![FIGURE 1](image1.png)

**FIGURE 1** The schematic of the battery model

![FIGURE 2](image2.png)

**FIGURE 2** The schematic of the battery test platform
usually not allowed to work when the temperature is below zero degree or above 50°C. To investigate the characteristics of the battery, capacity test for calibrating the maximum available capacity of the battery, OCV test for obtaining the OCV-SOC function curve, and dynamic test for validating the proposed algorithm are executed at each temperature condition.

The maximum available capacity of a fully charged battery is related with the working conditions, which is different from the nominal capacity. To study the maximum available capacity, the capacity test is designed as follows: charge a battery through constant current-constant voltage (CC-CV) approach at room temperature\textsuperscript{33,34} and then soak the fully charged cell at the test temperature for about 2 hours to ensure a uniform temperature throughout the battery. Discharge the battery using a constant current of 1.2 A at the test temperature. The maximum available capacity is averaged over five tests.

The OCV as a function of SOC and temperature is very vital for SOC estimation. It can be obtained the true value from the terminal voltage by resting the battery for a period time after charging and discharging. The battery is charged through CC-CV approach. For obtaining the OCV at different SOC levels, the battery is discharged at the current of 2.4 A for 6 minutes, and rest for 2 hours to reach the stable state before the next test is executed.

The dynamic test is tested with two kinds of current profiles: the federal urban driving schedule profile (FUDS) and the dynamic stress test profile (DST). DST designed by US Advanced Battery Consortium (USABC) is a simplified variable power discharge cycle with the same average characteristics, and it uses a 360 seconds sequence of power steps with only 7 discrete power levels. The profile of DST is shown in Figure 4A. FUDS also designed by USABC is an automobile industry standard vehicle time-velocity profile for city driving. A completed FUDS current profile of 1372 seconds is shown in Figure 4B. The positive current represents charging process, while the negative denotes discharging.

### 3 | TEMPERATURE EFFECT ON BATTERY MODEL

#### 3.1 | Temperature effect on capacity

To investigate the capacity change caused by temperature, the fully charged cell is discharged to cutoff voltage with a constant current load under a certain temperature. And then, the cell is charged to cutoff voltage using constant current and constant voltage charging mode. It is noted that, compared with the nominal capacity (nominal capacity is tested at room temperature of 25°C), the results show that when the temperature is above 30°C, the maximum available capacity at a certain temperature increases, and when the temperature is below 30°C, the maximum available capacity decreases. It can be concluded that the cells are not completely discharged when the terminal voltage of the battery reaches the cutoff voltage at the temperature below 30°C.

Thus, further tests are performed to study this phenomenon at the temperature below 30°C. The cells discharged to cutoff voltage rest for 2 hours at thermal chamber with 30°C for reaching steady condition and then are discharged to cutoff voltage again. The results are presented in Figure 5. The lines with marks are the first experimental results, while the lines without marks are the second experimental results. It can be seen that the maximum available capacity of the test cells with the temperature below 30°C increase, when the test temperatures return to 30°C, which makes them maximum available capacity equal to the discharge capacity at 30°C. This is called recovery capacity. Recovery capacity refers to the capacity that the battery, which discharges to cutoff voltage at low temperature, can release energy again after shelving for a specified time at high temperature.

It can be seen that the maximum available capacity is variational if the working temperature changes. Therefore, the recovery capacity should be taken into account when the working condition is time-varying temperature, for instance, a cell firstly working at a temperature of 10°C, and later, the cell working at a temperature of 40°C.

### 3.2 | Temperature effect on OCV

To describe the relationship of OCV-SOC-temperature, the fully charged cells are discharged 10% of nominal capacity by the hybrid pulse, and they will reach the steady condition after resting 2 hours. Afterward, they are repeatedly discharged by a 10% of the nominal capacity and rest 2 hours until the capacity reaches 10% of the nominal capacity. The procedures are employed to obtain the OCV data from 0°C to 50°C. The dynamic response surface of the OCV-SOC at different temperature is presented in Figure 6. It is clear that the higher temperature is, the larger the voltage is. However, the difference of the deviation under different SOC is very small.

In this paper, we use a linear formula to simulate the relationship between temperature and OCV for alleviating the complexity of the battery model. The relationship curve based on the analysis of experimental data is described as follows:

| TABLE 1 The main product specifications of test batteries |
|--------------------------------------------------------|
| Nominal voltage (V) | 3.6 |
| Nominal capacity (Ah) | 2.4 |
| Charge cutoff voltage (V) | 4.2 |
| Discharge cutoff voltage (V) | 2.75 |
where $U_{oc}(SOC, T)$ is the OCV function of SOC and temperature at the temperature $T_0$ ($T_0 = 20^\circ C$). $rel_{i=1,2}(SOC, T)$ is the temperature correction coefficient, which is identified by the nonlinear least square method using the lsqcurvefit function of Matlab. The results of $rel_{i=1,2}$ are presented in Table 2.

3.3 | Battery model considering temperature effect

On the finding of experiments, this section presents the battery model considering temperature effect to simulate the dynamic behaviors of lithium-ion battery considering temperature effect in detail.

To estimate SOC, the definition of SOC should be described, and the relationship between SOC and the parameters of battery model, such as current, capacity, and OCV, should be figured out. Generally, the SOC stands for the remaining capacity of a cell or battery package, which is defined as the ratio of the residual capacity to the nominal capacity:

$$SOC_t = SOC_{t_0} + \int_{t_0}^{t} \frac{n_i}{C_n} dt$$

where $SOC_t$ presents the SOC at the sampling time $t$, and $C_n$ denotes the nominal capacity. $\eta$ is the coulomb efficiency (for discharge $\eta = 0.99$).

Considering the temperature effect on battery capacity, we use the maximum available capacity ($C_T$) to replace the nominal capacity $C_n$, which considers the change of maximum available capacity at a certain temperature operation and the recovery capacity at time-varying temperature condition. Combining Equation (3), the state equation of SOC estimation can be written as follows:

$$SOC_t = SOC_{t_0} + \int_{t_0}^{t} \frac{n_i}{C_T} dt$$

FIGURE 3 | The schematic of the battery test procedures

FIGURE 4 Dynamic test profiles; (A) DST test current profile, (B) FUDS test current profile
According to the model-based SOC estimation, OCV is the known knowledge, which is a function of SOC. $U_{oc}$ can be expressed as follows using an electrochemical model:

$$U_{oc} = K_0 + K_1z + K_2z^2 + K_3 + K_4/z + K_5\ln(z) + K_6\ln(1 - z)$$

where $U_{oc}$ presents the OCV, $z$ is the abbreviation of SOC, and $K_i$ ($i = 0, 1, \ldots, 6$) are the coefficients.

According to the temperature-based OCV, we conduct the measurement equation of SOC estimation Equation (6). At this point, both temperature and current are input variables, and the output variable is the terminal voltage of the cells.

$$U_i(T, SOC) = U_{oc}(SOC, T_0) + T \times rel_1(SOC) + rel_2(SOC) + I \times R_0 + U_1 + U_2$$

where $T$ is the practical working temperature. $U_{oc}(SOC, T_0)$ is the base value at temperature 20°C for deriving $U_{oc}(SOC, T)$. $T_0$ is the fixed temperature 20°C.

In addition, the temperature also has a significant effect on the other battery parameters like battery terminal voltage and internal resistance. However, those battery parameters will be identified online in real-time in this work. The effect of temperature on those parameters can be addressed by online identification method.4,5

4 | MULTI-TIMESCALE DUAL ADAPTIVE PARTICLE FILTER

4.1 | Multi-timescale adaptive dual particle filter

Usually, the battery model is a strong nonlinear model and time-varying system. The SOC and parameters of the battery change at different timescales, microtimescale and macrotimescale. The former concerns the fast time-varying specific of the SOC, while the latter concerns the slowly time-varying specific of the parameters. To acquire the microtimescale and macrotimescale specifics of the battery states, a multi-timescale algorithm using the discrete-time state-space equation is constructed, where the parameters and the SOC are estimated on macrotimescale and microtimescale, respectively. The discrete-time dynamic system, including state $x$ and the parameters of the battery $\theta$, is shown as the Equation (7):

$$\begin{align*}
\theta_{t+1} &= \theta_t + \delta_t \\
x_{l,k+1} &= f(x_{l,k}, \theta_t, u_{l,k}) + \omega_k \\
y_{l,k+1} &= h(x_{l,k}, \theta_t, u_{l,k}) + \nu_k
\end{align*}$$

where $x_{l,k+1}$ presents the state vector, while $y_{l,k+1}$ represents the measurement vector. $\theta_t$ is the battery parameter vector. $k (k = K, 2K, 3K, \ldots)$ and $l (l = L, 2L, 3L, \ldots)$ are the microtimescale for the state vector and macrotimescale for parameters vector, respectively. $K$ is the system sample time, which is equal to 1 second. Note that the value of $L$ representing level of timescale separation should be appropriate for ensuring the system stability and estimation accuracy. $u_{l,k}$ is the system input, $\omega_k$, $\nu_k$, and $\delta_t$ represent the process noise with covariance $Q_\omega$, measurement noise with covariance $R$, and parameter process noise with covariance $Q_\theta$, respectively.

With the above discrete-time dynamic system, the battery states and parameters can be estimated online in multi-timescale. According to the system, a multi-timescale dual particle filter algorithm is used to identify the parameters of the battery in the macrotimescale for reducing the computation and predict the battery states in microtimescale for the fast time-varying specific.37
The PF is a high-efficient filter for tracking the states, even under the nonlinear system. The core idea of PF is the Bayesian learning technique with Monte Carlo method. The PF uses random particles that are obtained from a priori distribution and updated by a measured vector to approximate posterior probability density function. The algorithm can achieve a high performance for using a statistical method. The detail process of the proposed method is presented in Table 3.

### TABLE 2
The results of the correction coefficient

| SOC (%) | 100 | 90  | 80  | 70  | 60  |
|---------|-----|-----|-----|-----|-----|
| Rel₁ (10⁻²) | 0.26 | 0.35 | 0.42 | 0.52 | 0.78 |
| Rel₂ (10⁻³) | -3.30 | -5.65 | -7.14 | -9.82 | -16.32 |

| SOC (%) | 50  | 40  | 30  | 20  | 10  |
|---------|-----|-----|-----|-----|-----|
| Rel₁ (10⁻²) | 0.39 | 0.37 | 0.41 | 0.25 | -0.08 |
| Rel₂ (10⁻³) | -6.94 | -6.88 | -8.32 | 10.19 | 10.19 |

### TABLE 3
Algorithm of the multi-timescale adaptive dual particle filter

**Step 1:** Initialization:
Initialize the values of the system states and parameters: \( \hat{\theta}_0 = x_0 + \omega_0 \)

: \( \tilde{\theta}_0 = \theta_0 + \delta_0 \)

Loop: for \( k = 1,2,... \)

**Step 2:** State estimation with microtimescale: Generate random particles:

\[
\hat{x}_{i,k}^{(j)} = x_{i,k-1} + \sqrt{Q_{i,k-1}} \epsilon_{i,k}^{(j)} \quad (j = 1,2,...,N_i)
\]

Where, \( \epsilon_{i,k}^{(j)} \) is a random number belonging to Gaussian white noise.

Sample weights:

\[
q_i = \frac{1}{N_i} \exp\left(-\frac{(y_{i,k} - \hat{y}_{i,k}^{(j)})^2}{2\sigma_i^2}\right)
\]

Normalize the weights: \( \tilde{q}_i = q_i / \left( \sum_{j=1}^{N_i} q_j \right) \)

Obtain the resampling values \( \hat{x}_{i,k}^{(j)} \) through: \( N_{re} = 1 / \sum_{i=1}^{N_i} (\tilde{q}_i)^2 \)

Estimate the state vector: \( \hat{x}_{i,k} = \frac{1}{N_i} \sum_{j=1}^{N_i} \hat{x}_{i,k}^{(j)} \)

Adaptive noise variance of the battery states:

\[
\sigma_{\theta,k} = \begin{cases} 
\min (e_{\theta,k} \sigma_{\theta,max}) & e_{\theta,k} > \sigma_{\theta,k-1} \\
\max (a \sigma_{\theta,k-1}, \sigma_{\theta,min}) & e_{\theta,k} \leq \sigma_{\theta,k-1}
\end{cases}
\]

Where, \( e_{\theta,k} = \frac{1}{L} \sum_{i=1}^{L} |\hat{\theta}_{i,k} - \hat{\theta}_{i,k-1}| \)

**Step 3:** Parameter estimation with macrotimescale (if \( L = 0 \), where \( L \) is the step length):

For \( l = 1 + L \)

Generate random particles of parameter:

\( \hat{\theta}_{l,k} = \hat{\theta}_{l-1} + \sqrt{Q_{\theta,k}} \epsilon_{\theta,k}^{(j)} \quad (j = 1,2,...,N_{\theta}) \)

Where, \( \epsilon_{\theta,k}^{(j)} \) is a random number belonging to \( (0-1) \).

Sample weights:

\[
q_{\theta} = \frac{1}{N_{\theta}} \exp\left(-\frac{(y_{\theta,k} - \hat{y}_{\theta,k}^{(j)})^2}{2\sigma_{\theta}^2}\right)
\]

Normalize the weights: \( \tilde{q}_{\theta} = q_{\theta} / \left( \sum_{j=1}^{N_{\theta}} q_j \right) \)

Obtain the resampling values \( \hat{\theta}_{l,k}^{(j)} \) through: \( N_{re} = 1 / \sum_{j=1}^{N_{\theta}} (\tilde{q}_j)^2 \)

Estimate the state vector: \( \hat{\theta}_{l,k} = \frac{1}{N_{\theta}} \sum_{j=1}^{N_{\theta}} \hat{\theta}_{l,k}^{(j)} \)

Adaptive noise variance of the battery parameters:

\[
\sigma_{\theta,k} = \begin{cases} 
\min (e_{\theta,k} \sigma_{\theta,max}) & e_{\theta,k} > \sigma_{\theta,k-1} \\
\max (a \sigma_{\theta,k-1}, \sigma_{\theta,min}) & e_{\theta,k} \leq \sigma_{\theta,k-1}
\end{cases}
\]

Where, \( e_{\theta,k} = \frac{1}{L} \sum_{i=1}^{L} |\hat{\theta}_{i,k} - \hat{\theta}_{i,k-1}| \)

From the adaptive method, the large noise variance will be used to realize the convergence quickly when the desire value of noise variance is large. Meanwhile, the small value of noise variance will be applied to improve the estimated accuracy. The performance of the adaptive technique had been proven in, which showed accurate and robust estimation.

From Table 2, step 1 initials the starting values of the system and parameters. Step 2 refreshes the states of model, which includes input particles, normalize the weights, resampling, and state estimation. Step 3 updates the parameter value of the battery model. Step 2 and Step 3 are online updates of the model states and parameters.

As we know, PF method depends on the noise variance and the number of the samples to track the target. Therefore, improper noise variance will affect the estimation accuracy and convergence speed. A small noise variance may make the samples unable to contain the real values resulting in the loss of the target and decreasing the convergence speed. A large noise variance may lead to a large number of invalid samples and decrease the accuracy of SOC estimation. In this paper, an adaptive noise variance is constituted to improve performance of the multi-timescale particle filter. The adaptive method is depicted as follows:

\[
\sigma_{\theta,k} = \begin{cases} 
\min (e_{\theta,k} \sigma_{\theta,max}) & e_{\theta,k} > \sigma_{\theta,k-1} \\
\max (a \sigma_{\theta,k-1}, \sigma_{\theta,min}) & e_{\theta,k} \leq \sigma_{\theta,k-1}
\end{cases}
\]

where \( i = x, \theta \) denotes the states and parameters. \( \sigma_{\theta,max} \) and \( \sigma_{\theta,min} \) are the maximum and minimum noise variance, respectively. \( \alpha \) is the attenuation factor for controlling the rate of reduction of noise variances. \( e_{\theta,k} \) is the desire value of the noise variance. Equation (9) shows the calculated expression of the desire value. \( \lambda \) is the length of smooth window. The process is also presented in Table 3.
For each sampling time, fresh states and parameters of the battery model will be estimated based on the previous states and parameters.

4.2 Application to battery system

To build the dynamic battery system with dual scales, for state estimation, we use SOC and polarization voltage \( U_1 \), \( U_2 \) to denote the state vector of battery states, for parameters identification, the internal resistance, polarization resistors, and capacitances are selected as the state vector of battery parameters. The terminal voltage \( U \) denotes the measurement vector. Based on the proposed battery model, we get the discrete-time equations:

\[
\begin{align*}
\theta_{k+1} &= \theta_k + \delta_k \\
x_{l,k+1} &= f(x_{l,k}, \theta_k, u_{l,k}) + w_k \\
y_{l,k+1} &= h(x_{l,k}, \theta_k, u_{l,k}) + v_k
\end{align*}
\]

\[
\begin{align*}
\theta_{k+1} &= \theta_k + \delta_k \\
\begin{bmatrix}
\text{SOC}_k \\
U_{1,k} \\
U_{2,k}
\end{bmatrix}
= & \begin{bmatrix} 1 & 0 & 0 & 0 \\
\exp(-\Delta_t/\tau_1) & 0 & 0 & \exp(-\Delta_t/\tau_2) \\
0 & 0 & 0 & 0
\end{bmatrix}
\begin{bmatrix}
\text{SOC}_{k-1} \\
U_{1,k-1} \\
U_{2,k-1}
\end{bmatrix}
+ \begin{bmatrix}
1/C_f \\
R_1(1-\exp(-\Delta_t/\tau_1))I_{k-1} + \omega_{1,k-1} \\
R_2(1-\exp(-\Delta_t/\tau_2))I_{k-1} + \omega_{2,k-1} + \omega_{3,k-1}
\end{bmatrix}
\end{align*}
\]

\[
U_{l,k} = U_{oc,l,k} + T \times \text{rel}_{1,l} + \text{rel}_{2,l} + I_k \times R_{0,l} + U_{1,k} + U_{2,k} + v_k
\]

where

\[
\begin{align*}
\theta_k &= [R_0 \ R_1 \ R_2 \ C_1 \ C_2] \\
x_k &= [\text{SOC}_k \ U_1 \ U_2] \\
y_{k,l} &= U_{l,k,l} \\
u_{k,l} &= I_{k,l}
\end{align*}
\]

Equation (10) denotes the proposed battery model equations for estimating SOC considering the effect of temperature on the OCV and capacity. The parameters of the proposed model can be identified online, and the results of SOC estimation can be more accurate based on the model.

4.3 Implementation of the proposed algorithm

With the proposed algorithm, the system states and parameters of the battery can be predicted in microtimescale and macrotimescale separately. In online estimation procedure, the measured data of battery, including the current, voltage, and temperature are transferred to the proposed estimator for estimating the system states and parameters.

4.3.1 Real-time data measurement

During the dynamic cycle tests, the temperature, terminal voltage, and current of the cells are obtained from the corresponding sensors. The measured data are transmitted to the computer by the TCP/IP and CAN bus. The proposed method is executed with the Matlab software.

4.3.2 Online parameter identification

On the basis of the presented battery model, the iteration process of the model parameter identification can be built using the proposed algorithm with macrotimescale. For the first iteration of macrotimescale, the parameters of the model such as OCV, internal resistance, polarization capacitance, and polarization resistance are firstly identified based on the initial battery parameters and states. For the next iteration, the parameters are identified based on the identification results of the previous step and the updated battery states on the step III.

4.3.3 Adaptive particle filter-based SOC estimator

With the battery parameters identified online, the proposed algorithm with microtimescale is executed to achieve accurate SOC estimation for overcoming the disturbance of the battery working condition. Firstly, the battery states are estimated with the process of traditional particle filter. And then, the demand of the system noise variance will be updated for the next iteration. When the battery parameters such as current and terminal voltage change, the system noise variance will be simultaneously updated to attenuate the parameter errors between the previous and next step and track the actual states of the battery. When the states are stable, the system noise variances are close to the maximum values for pursuing high accuracy.

In this paper, the microtimescale is selected as \( K = 1 \) second. The macrotimescale is selected as \( L = 60 \) seconds.\(^{37}\) The initial battery parameters are obtained from offline identification based on the experimental data.\(^{40}\) The noise covariance and initial states of the estimator are shown in Table 4. The flow chart of multi-timescale dual adaptive particle filter (MDAPF) for online battery state estimation is shown as Figure 7.

5 RESULTS AND DISCUSSIONS

Estimation ability, robustness, and computation are key factors in SOC estimation. These factors are very vulnerable to external interference such as the dynamic current and time-varying temperature. This paper proposes an adaptive dual
particle filter based on the proposed model for SOC estimation, considering the recovery capacity and the multi-scales. To assess the performance of the proposed algorithm, the NMC cells of type IFP18650 are tested in the SOC range of 100%~10% under dynamic conditions. Furthermore, the condition with dynamic current and time-varying temperature which is overlooked by most researches is employed to validate the capability of the proposed method. The numerical indicator mean absolute error (MAE) and root mean square error (RMSE) evaluate the ability of the proposed algorithm.

| Battery state/parameter | Maximum value of noise variance | Minimum value of noise variance |
|-------------------------|---------------------------------|-------------------------------|
| SOC                     | 0.05                            | 0.0001                        |
| $U_1/U_2$               | 0.02                            | 0.0001                        |
| $R_1/R_2$               | 0.005                           | 0.0001                        |
| $C_1/C_2$               | 100                             | 1                             |
| $R_0$                   | 0.005                           | 0.0001                        |

**TABLE 4** Initialization of noise variances

**Figure 7** Flow chart of the adaptive MDAPF estimator
FIGURE 8  The estimation results of voltage and SOC at different temperatures. A, Test at 10°C, B, Test at 30°C, C, Test at 50°C
5.1 Validation at constant temperature

Literatures in\textsuperscript{38,40} have investigated the performance of the adaptive particle filter for state of charge. The results showed that the adaptive particle filter can provide higher accuracy and robustness compared with EKF and UKF methods. Hence, this paper mainly discusses the effect of temperature on SOC estimation.

The validation of the proposed method is executed with FUDS cycle at different temperature conditions. In this work, three typical temperature cases (10°C, 30°C, and 50°C) are selected for analysis. The battery model without considering the temperature influence (CM) is used to assess the performance of the battery model considering the temperature effect (TM). Figure 8 shows the results of estimated voltage and SOC compared with the reference values at three temperatures conditions (10°C, 30°C, and 50°C, respectively). The numerical indicators of MAEs and RMSEs are represented in Figure 9.

Figure 8A depicts the test results at 10°C. It can be seen that the TM model-based estimated voltage tracks the measured value well leading to accurate SOC estimation, as shown in Figure 8A-1 and A-2. The maximum estimation SOC error is less than 1.4%. From Figure 9, it is obvious that the MAE is less than 0.93%, and the RMSE is less than 0.98%. Although the first half of estimation SOC of CM model-based can be accurate, the estimation SOC errors are getting larger at the latter part with maximum SOC error 2.7%, as shown in Figure 8A-4. The MAE and RMSE are 1.0% and 1.39%, respectively. The main reason is that the TM-based method can adapt to the change of temperature. For instance, it uses the OCV ~ SOC dynamic response surface instead of the conventional OCV-SOC, which is often established at room temperature, to estimate SOC. The influence of temperature on battery parameters enlarges at low temperature case, which decreases the estimation accuracy. It can be concluded that the TM battery model can compensate the influence of temperature on battery. The results at 30°C shown in the Figure 8B are similar with that at 10°C.

Slightly more accurate results of the SOC estimation at 50°C can be seen from Figure 8C compared with the results at 30°C. The MAE and RMSE are 0.45% and 0.5%, respectively. It can be seen that the fluctuation of SOC error at 50°C is smaller than that at 10°C. This can be explained by the increase complication in the internal battery as the temperature tends to decrease, and for instance, the lower the temperature is, the less active the battery is. This also can illustrate that the slightly more accuracy of estimated SOC at 50°C than that at 10°C. From the above results, the temperature has a significant effect on the battery parameters and SOC estimation. Due to the proposed method, the accuracy estimation can be achieved at different temperature conditions.

5.2 Validation at time-varying temperature

Based on the above analysis, we expect that the proposed method can still provide accuracy and robustness estimation at time-varying temperature condition. To further investigate the performance of the proposed approach, the DST cycle with time-varying temperature is executed, where the temperature starts at 0°C and goes up 10°C per hour. The value of the time-varying temperature is recorded by the thermal chamber, which is shown in Figure 10. The estimation results, including estimated voltage and SOC, are presented in Figure 11. It can be seen that the temperature has significant
effect on the battery voltage and parameters. Although the high dynamic of the temperature, the estimated voltage still accurately tracks the measured one. As a result, the maximum error estimation SOC is about 3.12%, while the MAE is 2.65% and the RMSE is 2.69%. As expected, these errors are slightly larger than that at constant temperature tests due to the higher dynamic temperature. The precise tracking of the estimated voltage and SOC at time-varying temperature condition further proves the capability of the temperature compensation battery model and the adaptive multi-timescale dual particle filter.

5.3 | The effect of multi-timescale on SOC estimation

In this section, the influence of the multi-timescale and single-timescale on SOC estimation is discussed. The
computational time is also investigated to assess the proposed multi-timescale adaptive dual particle filter (MDAPF) compared with single-timescale adaptive dual particle filter (SDAPF), respectively. For the former, the multi-timescales are selected with macrotimescale ($L = 60$ seconds) and microtimescale ($K = 1$ second). For the latter, the sampling time of single-timescale is set as 1 second. The voltage and SOC estimation results are shown in Figure 12.

As can be seen from Figure 12, the fluctuation of the SOC estimation results with single-timescale is relatively larger than that with multi-timescale. The reason is that, with single-timescale, the parameter update frequency is high, and the fact is that the battery parameters are prone to slowly vary over time, which makes the larger fluctuation of terminal voltage. It is worth noted that the SOC estimation results of SDAPF are more accurate than that of MDAPF at the end of experiment due to increasing complexity at the low SOC range. This leads us to think the theoretical selection of multi-timescale needs to be investigated for the best parameter update frequency.

For MDAPF method, we use three cases to study the effect of multi-timescale on computational time: MDAPF-1 with macrotimescale ($L = 30$ second) and microtimescale ($K = 1$ second), MDAPF-2 with macrotimescale ($L = 60$ seconds) and microtimescale ($K = 1$ second), and MDAPF-3 with macrotimescale ($L = 120$ seconds) and microtimescale ($K = 1$ second). For SDAPF method, the single-timescale is selected as 1 second. The test is executed on a laptop with 8.0 G RAM and 2.90 GHz CPU. The simulation is run for sampling data 120 times. The computational time of the two methods is presented in Figure 13. From Figure 13, SDAPF method for SOC estimation takes 0.507 second. The MDAPF-based three cases for SOC estimation take 0.478, 0.461, and 0.443 second, which save 5.72%, 9.07%, and 12.62% compared with the SDAPF method.

It is clear that the proposed multi-timescales filter not only reduces the computational time, but also increases the robustness. Through the analysis of the experimental verification, the proposed approach has demonstrated its performance, which is proven by the adaptive estimation algorithm, especially under the conditions with temperature and current both time-varying. These conditions are more dynamic than those studied in previous works. This can make the proposed method appropriate for dynamic conditions with time-varying temperature. Furthermore, due to the simple battery model and accurate estimation algorithm, the proposed approach can be implemented in the actual BMS.

6 | CONCLUSIONS

The change of the working condition can influence SOC estimation significantly. This paper proposes a model-based algorithm to investigate the effect of dynamic load on SOC estimation of lithium-ion battery, especially time-varying temperature condition. Firstly, based on experiments, a second-order RC battery model has been proposed to describe the dynamic behaviors of the battery considering the recovery capacity and OCV-SOC curve dependence on temperature. Secondly, an adaptive multi-timescale dual particle filter is presented to identify the battery parameters and estimate SOC. The multi-timescale on SOC estimation is investigated compared with the single-timescale. The proposed algorithm cannot only accurately track the battery states, but also reduce the computation. Lastly, the performance of the proposed approach proven by a set of experiments can accurately estimate the battery voltage and SOC, even under dynamic condition with current and temperature both time-varying. Under such working condition, the estimation error is less than 3.2%, and the MAE and RMSE are 2.65% and 2.69%, respectively. The proposed approach cannot only precisely estimate the parameters and SOC under dynamic load conditions, but also can be used in the BMS due to its simplicity and appropriate computation.

There are still some parts needed to be improved. One is that the battery health state should be considered. A full model depicting the battery degradation process and reducing the algorithm sensitivity to the battery aging behaviors or environment noises are the main challenges for SOH (state of health) estimation. Another is that the theoretical fundamental for multi-timescale selection has been overlooked. We should theoretically investigate how to determine the macro-timescale value for ensuring the stability and accuracy of the approach.

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