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Battery Peak Power Assessment under Various Operational Scenarios: A Comparative Study

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Abstract—The peak power capability of lithium-ion batteries (LIBs), or so-called state of power (SOP), plays a decisive role for electric vehicles to fulfill a specific power-intensive task. Generally, battery SOP can be achieved based on different peak operation modes (POMs), including constant current, constant voltage, constant current and constant voltage or constant power, throughout a prediction window. However, the impact of these POMs on battery peak performance and their interrelationship remain unclear by far. In light of this, we conduct a comparative study to fill this blank. Four key indices, including maximum and minimum instant magnitudes, time-averaged magnitude and falling/rising rate, are adopted to evaluate battery peak performance under each POM. Potential factors, such as load profile, length of the prediction window and battery chemistry, are considered in the comparisons. The results offer valuable insights into the distinct attributes of these POMs and their region-dependent interrelationship.

Index Terms—Batteries, state of power, peak operational mode, comparative study, performance analysis.

NOMENCLATURE

\begin{align*}
X_{\text{avg}} & \quad \text{Average current, voltage or power within a prediction window} \\
\bar{X} & \quad \text{Maximum instant current, voltage or power within a prediction window} \\
\bar{X} & \quad \text{Minimum instant current, voltage or power within a prediction window} \\
\Delta X & \quad \text{Falling (or rising) rate of current, voltage or power within a prediction window} \\
T_s & \quad \text{Sampling time} \\
K & \quad \text{Length of prediction window}
\end{align*}

I. INTRODUCTION

In recent years, growing concerns regarding fossil fuel consumption and severe environmental degradation have spurred rapid advancements in energy storage technology [1], [2]. Among various options, lithium-ion batteries (LIBs) stand out as the leading choice for electric vehicle (EV) applications, prized for their high power density and longevity [3]. However, the rise in reported incidents of battery safety failures and fire accidents has heightened consumer apprehensions [4], [5]. This underscores the importance of advanced battery management systems (BMSs) that not only monitor battery internal states in high precision but also promptly respond to potential risks [6].

Of particular interest among these internal states is the state of power (SOP), which measures the short-term peak power that batteries can deliver to absorb from the EV powertrain and simulates extreme circumstances for power-intensive tasks, such as accelerating an EV to a certain speed in seconds or climbing steep hills [7]. While the definition of SOP is straightforward, it does not specify the way to discharge or charge batteries during a prediction window. Due to the inherent battery characteristic, it is possible to keep only one parameter—either current, voltage or power—constant to maximize the peak power capability [8]. Clearly, this nature induces four commonly used peak operation models (POMs), referred to as constant current (CC), constant voltage (CV), CC-CV, and constant power (CP) [9]. Each mode, with its unique discharge and charge characteristics, leads to diverse peak power performances and SOP estimation outcomes. Compared to other possible POMs, these four POMs are capable of sufficiently addressing most real-world application scenarios while maintaining implementable through on-board BMSs.

CC-POM is usually favored for its ease of implementation and convenience in algorithm development, making it the most extensively researched POM for SOP estimation [10]. Sun et al.
[11] built a first-order resistor-capacitance (1-RC) equivalent circuit model (ECM) to capture battery polarization dynamics and proposed an open-loop prediction method for SOP estimation under the CC-POM. To enhance the model capability in tracing the nonlinear diffusion process, Wang et al. [12] modified a generic 1-RC ECM by incorporating a time-dependent diffusion resistance into a RC network, benefiting SOP estimation performance in a lengthy prediction window. Zhang et al. [13] characterized the fully polarized internal resistance at a quasi-steady state and took it to correct the online identified parameters for state of charge (SOC) and SOP joint-estimation. In [14], [15], a electro-thermal model, combining a dual polarization (DP) model with a thermal model, was proposed for SOC and SOP joint-estimation. Accurate electrical-thermal state estimations contributed to the model robustness against temperature influences. Recently, fractional-order ECMs have gained prominence as an alternative to conventional integer-order ECMs, offering preferable interpretations of battery dynamics across a wide frequency spectrum. In light of this, Guo and Shen [16], [17] proposed a fractional-order ECM with hybrid online and offline parameter identification to enhance the model performance in different timescales, facilitating SOP estimation accuracy under the CC-POM. Their subsequent study [18] further developed a fractional-order multi-model system to accommodate battery dynamics considering complex operating conditions of load, SOC and temperature, and a fractional-order proportional-integral observer was proposed for SOC and SOP joint-estimation. In [19], the phenomenon of distorted polarization dynamics was reported in batteries subjected to extremely high current excitations (>5 C-rate). To address this, a deep neural network was constructed, and a data-model fusion method was introduced for SOP estimation to overcome the limitations of conventional ECMs in reflecting such nonlinear battery behaviors.

Some researchers have also laid their focus on pack-level SOP estimation under the CC-POM. Cell characteristic comparison and “Mean+Difference model” are two effective strategies of picking up the representative cell within a battery pack [20]. In [21], [22], the representative cell was determined by comparing the peak discharge/charge current estimations of all individual cells. Although this approach is straightforward, it demands large memory storages and high computational resources, making it less applicable in practice. In [23], the inherent cell characteristics of open circuit voltage (OCV) and ohmic resistance were extracted to select the representative cell, reducing computational efforts in pack-level SOP estimation. To further skip cell-level modelling and parameterization, a “Mean+Difference model” was leveraged to capture the overall electrical behavior of a battery pack while distinguishing the dissimilar characteristics of individual cells [24], [25]. In this way, the representative cell was chosen by a set of inhomogeneous factors, and battery SOP was calculated based on the peak current estimation of the representative cell and the average cell voltage provided by the “Mean model”.

Moreover, developing a multi-state co-estimation framework that involves SOP with other internal states has emerged as another significant area of research. Hu et al. [26] implemented SOP estimation within a multi-state framework. The results highlighted the inter-coupled correlations of SOP with SOC and state of health (SOH). Following this line of thought, Shu et al. [27] investigated the correlations between OCV and SOC at various aging levels and proposed an improved accumulated ampere-hour (Ah) method to update SOH for accurate SOC and SOP estimation. In [28], a four-layer-network BMS architecture was developed, integrating cloud-side-end interaction and digital twin technology. This architecture enabled SOC, SOH and SOP co-estimation with cell equalization.

In contrast to CC-POM, CV-POM has received far less attention in the literature. Wang et al. [29] explored this area, examining its practical implementation. However, they noted a significant decline in peak power delivery when batteries were discharging under the CV-POM over the high SOC region. To optimize the peak power performance, Pei et al. [30] proposed a CC-CV-POM that forced batteries to discharge or charge under either current constraint or voltage constraint at any instant throughout a prediction window. In [31], a fuzzy logic controller was collaborated with a SOP estimator, aiming to proactively protect batteries from over discharging or charging under the CC-CV-POM. In [32], [33], SOP estimation under the CC-CV-POM was converted into an optimization problem, solved by the algorithm developed based on the model predictive control theory.

While the aforementioned three POMs are intuitively simple, with batteries operating under either constant current or voltage, they result in a time-varying peak power delivery to, or absorption from, the EV powertrain throughout a prediction window. This variability becomes even more pronounced in low or high SOC regions due to rapid changes in battery terminal voltage or peak current. On the contrary, CP operation is more representative of actual battery loadings in EV applications (e.g., EV acceleration, gradient climbing and regenerative braking) than CC or CV operation. Rahman et al. [34] highlighted that CP operations could either maximize vehicle acceleration for a given power rating or minimize the power rating required for a specific level of vehicle acceleration. They further demonstrated that EV powertrains operating at a CP could achieve optimal initial acceleration and gradeability with the minimum necessary power rating [35]. In a pioneering effort, our previous study [36] introduced a model-switching approach for SOP estimation under the CP-POM. This innovative method adopted an unscented Kalman filter based correction strategy to pinpoint the dominant factor limiting the peak power performance of batteries, thus successfully addressing the challenge of formulating battery SOP in an analytic form under the CP-POM.

Despite a plurality of SOP estimation approaches developed in the literature, a majority of them primarily concentrate on SOP estimation in the form of either maximum, minimum or average power within a prediction window, overlooking the characteristics of the entire current, voltage and power evolutions. As a consequence, the interrelationship among these POMs and their subsequent impact on battery peak power performance remain unclear by far. Although a theoretical
analysis of differences in battery peak power performances under the CC, CV, CC-CV, and CP-POMs is straightforward, it is challenging as the peak power expression under the CP-POM cannot be analytically expressed. Therefore, a direct comparison among these POMs is viable only when the model parameters and influencing factors (e.g., battery types and chemistries, length of the prediction window, and load profile) are deterministic. To bridge this gap, we carry out a comprehensive comparison in this study with the following four contributions:

1) We provide a thorough analysis that unveils the unique discharge and charge characteristics of batteries under various POMs. This analysis methodically delineates the boundary conditions subject to different operational constraints, detailing each scenario on a case-by-case basis for all the POMs.

2) We offer a technical overview that clearly elucidates the fundamental principle and algorithm development for SOP estimation under each POM. This includes a particular emphasis on the predictions of the entire current, voltage, and power sequences over a prediction window.

3) With the help of a well-parameterized battery model, we reproduce the battery electrical behaviors under the boundary conditions for each POM and adopt four key indices to evaluate associated peak power performances, including maximum and minimum instant magnitudes, time-averaged magnitude and failing/rising rate. The comparative results reveal the distinct attributes of these POMs and their region-dependent interrelationship.

4) Based on the comparative findings, we offer profound insights into the optimal discharge/charge strategies of batteries to prevent EV underpower in specific application scenarios.

![Fig. 1. Model structure of DP model.](image)

The remainder of this paper is structured below. The battery modelling is introduced in Section 2. The methodologies of SOP estimation under various POMs are summarized in Section 3. Section 4 presents the comparison results and gives relevant discussions. Conclusions are drawn in Section 5.

**II. BATTERY MODELLING**

In this study, we construct a DP model, as shown in Fig. 1, to effectively characterize both fast and relatively slow dynamics of batteries to ensure high-fidelity SOP estimation over extended prediction windows. The discrete-time governing equations of a DP model can be expressed as

\[
\begin{align*}
V_{p1,k} &= V_{p1,k-1} \exp \left( -\frac{T}{\tau_1} \right) + I_{L,k-1} R_1 \left( 1 - \exp \left( -\frac{T}{\tau_1} \right) \right) \\
V_{p2,k} &= V_{p2,k-1} \exp \left( -\frac{T}{\tau_2} \right) + I_{L,k-1} R_2 \left( 1 - \exp \left( -\frac{T}{\tau_2} \right) \right) \\
V_{c,k} &= V_{c,k-1} - V_{p1,k} - V_{p2,k} - I_{L,k} R_0
\end{align*}
\]

where the subscript \( k \) denotes the time step and \( T \) is the sampling time. \( V_{p1} \) and \( V_{p2} \) reflect the polarization dynamics in different timescales. \( \tau_i = R C_i \) \((i=1, 2)\) gives the time constants for two RC networks. \( V_t \) and \( I_L \) stand for the battery terminal voltage and load current (defined as positive for discharge and negative for charge), respectively. \( R_0 \) represents the ohmic resistance. A high-order polynomial is used to capture the nonlinear relationship between OCV and SOC as

\[
V_{oc}^{(SOC)} = \sum_{i=0}^{p} \alpha_i^{(SOC)}
\]

and \( \alpha_i \) \((i=0, 1, \ldots, p)\) are the associated polynomial coefficients.

Then, we re-configure (1) into a generalized state-space model as presented in (3), to facilitate a clear and unified demonstration of SOP estimation methodologies that follows.

\[
\begin{align*}
x_k &= Ax_{k-1} + Bu_{k-1} \\
y_k &= Cx_k + Du_{k}
\end{align*}
\]

where \( x := [V_{p1}, V_{p2}, V_{oc}]^T \), \( y := V_t \), \( u := I_k \) and

\[
A = diag \left[ \exp \left( -\frac{T}{\tau_1} \right), \exp \left( -\frac{T}{\tau_2} \right), 1 \right]
\]

\[
B = \begin{bmatrix}
R_1 \left( 1 - \exp \left( -\frac{T}{\tau_1} \right) \right) \\
R_2 \left( 1 - \exp \left( -\frac{T}{\tau_2} \right) \right) \\
-\eta T \frac{V_{oc}^{(SOC)}}{3600 C_n}
\end{bmatrix}
\]

\[
C = \begin{bmatrix}
-1 & -1 & 1
\end{bmatrix}
\]

\[
D = -R_0
\]

where \( C_n \) denotes the nominal capacity of a battery and \( \eta \) denotes the Coulombic efficiency. \( V_{oc}^{(SOC)} \) represents the first-order derivative of the OCV-SOC polynomial.

**III. METHODOLOGY**

In this section, we consider a SOP prediction window extending from time \( k+1 \) to \( k+K \) (indicating a window length of \( K \) time steps) and incorporate standard operational constraints on current and voltage to delineate the boundary conditions for each POM. A generalized model representation, given in (3), is leveraged to facilitate the algorithm derivations.
Fig. 2. Battery discharge behaviors under the CC-POM dominated by: (a) current constraint; and (b) voltage constraint.

A. Constant-current Peak Operational Mode

CC-POM attains the peak power performance of batteries by maximizing a constant discharge/charge current over the prediction window, namely \( u_{k+1} = u_{k+2} = \ldots = u_{K} \). Fig. 2 illustrates the typical evolutions of current, voltage and power when batteries are discharging under the CC-POM. In the high SOC region, current serves as the dominant factor limiting the peak power performance of batteries, where the peak discharge current is held at the current constraint, and the terminal voltage continues to decline throughout the window, yet it does not reach the lower cut-off threshold. With battery SOC decreases, the terminal voltage at the end of the window will touch the lower cut-off threshold at a moment, and thereafter the peak discharge current starts to drop, indicating a shift of the dominant limitation factor from current to voltage [37]. For the case that batteries are charging under the CC-POM, the peak charge current also keeps constant, while the evolutions of voltage and power demonstrate the opposite trends to the discharge case in Fig. 2, and their magnitudes continue to grow throughout the window. Hence, the boundary condition of CC-POM occurs either throughout the prediction window (i.e., from time \( k+1 \) to \( k+K \)) or at the end of the window (i.e., time \( k+K \)). For the former case, the peak discharge/charge current equals to associated current constraint from time \( k+1 \) to \( k+K \). For the latter case, the terminal voltage reaches the cut-off threshold only at time \( k+K \). The electrical behaviors of batteries at time \( k+K \) can be simulated by (4) through iterating the state space model in (3).

Algorithm 1: Pseudocode for discharge/charge SOP estimation under the CC-POM.

\[
\begin{align*}
\text{for } j = 1: K & \text{ do} \\
\text{if } j = 1 & \text{ then} \\
\quad x_{k+j} & \leftarrow A x_{k+j-1} + Bu_{k} \\
\text{else} & \\
\quad x_{k+j} & \leftarrow A x_{k+j-1} + Bu_{\text{max/min}, k+j-1} \\
\text{end if} & \\
\quad y_{k+j} & \leftarrow C x_{k+j} + Du_{\text{max/min}, k+j} \\
\quad u_{\text{max}, k+j} & \leftarrow u_{\text{max}, k+j} \times y_{k+j} \\
\text{end for} & \\
\end{align*}
\]

where \( u_{k} = I_{L,k} \) denotes the load current in real-time (i.e., time \( k \)) and \( u_{j} \) denotes the peak discharge/charge current within the prediction window. Under the boundary condition, we formulate the voltage-constraint peak discharge/charge current as

\[
\begin{align*}
\left\{ \begin{array}{l}
\psi_{\text{dis}, v}^{\text{MC}} = \frac{y_{\text{max}}}{C} - CA^{K} x_{k} - CA^{K-1} Bu_{k} \\
\psi_{\text{chg}, v}^{\text{MC}} = \frac{y_{\text{max}}}{C} - CA^{K} x_{k} - CA^{K-1} Bu_{k}
\end{array} \right. \\
\forall j = 1, \ldots, K
\end{align*}
\]

The dominant limitation factor and the multi-constraint peak discharge/charge current can be determined by comparing the peak discharge/charge current under the current and voltage constraint and picking up a conservative one, as expressed in (6).

\[
\begin{align*}
\left\{ \begin{array}{l}
\psi_{\text{dis}, i}^{\text{MC}} = \min \left( \psi_{\text{dis}, i}^{\text{MC}}, \psi_{\text{chg}, i}^{\text{MC}} \right) \\
\psi_{\text{chg}, i}^{\text{MC}} = \max \left( \psi_{\text{dis}, i}^{\text{MC}}, \psi_{\text{chg}, i}^{\text{MC}} \right)
\end{array} \right. \\
\forall j = 1, \ldots, K
\end{align*}
\]

where \( \psi_{\text{dis}, i}^{\text{MC}}, \psi_{\text{chg}, i}^{\text{MC}} \) denote the peak discharge/charge current under the multi-constraints, current constraint, and voltage constraint, respectively.

Having the multi-constraint peak discharge/charge current, we re-iterate the state space model in (3) to predict the voltage and power sequences under the CC-POM. The entire process of SOP estimation and power sequence prediction under the CC-POM is presented in Algorithm 1.

B. Constant-voltage Peak Operational Mode

CV-POM attains the peak power performance of batteries by maximizing a variable discharge/charge current under a constant terminal voltage over the prediction window, namely \( y_{k+1} = y_{k+2} = \ldots = y_{k+K} \). Fig. 3 illustrates the typical evolutions of current, voltage and power when batteries are discharging under the CV-POM. In the high SOC region, current serves as the dominant factor limiting the peak power performance of batteries, where the peak discharge current always reaches the
current constraint at the outset of the window, and thereafter it continues to decline in order to maintain a constant terminal voltage concerning the growing polarization overpotential inside batteries. This constant terminal voltage will gradually move down with the decline of SOC. There will be a moment when the battery terminal voltage reaches the lower cut-off threshold. In the following, the peak discharge current at the outset of the window will no longer be constrained by the current but shifting to the voltage. For the case that batteries are charging under the CV-POM, the terminal voltage also keeps constant, while the evolutions of current and power demonstrate the same trends to the discharge case in Fig. 3, and their magnitudes continue to decline throughout the window.

Hence, the boundary condition of CV-POM occurs either at the outset of the window (i.e., time $k+1$) or throughout the prediction window (i.e., from time $k+1$ to $k+K$). For the former case, the peak discharge/charge current equals to associated current constraint at time $k+1$. For the latter case, the terminal voltage is maintained at the cut-off threshold from time $k+1$ to $k+K$. To determine the dominant factor limiting the battery peak power performance, it requires to check the instant peak discharge/charge current at time $k+1$ in (7).

If $\frac{y_{\text{max/min},k+1}}{D} \geq \frac{y_{\text{max},k+1}}{D}$, it indicates that the terminal voltage will not exceed the cut-off threshold if batteries are operating under the current constraint at time $k+1$, which allows $u_{\text{max/min},k+1} = u_{\text{max},k+1}$; otherwise, we have to set $u_{\text{max/min},k+1} = u_{\text{max},k+1}$ to avoid beaching the voltage constraint.

In order to avoid incorrect calculation of the multi-constraint peak discharge/charge current at $k+1$, we derive the constant terminal voltage throughout the window by

$$y_{k+1} = CAx_{k+1} + CBu_k + DU_{\text{max/min},k+1}$$

This enables a step-wise prediction of the current and power sequences under the CV-POM for the remaining prediction window in (9).

$$x_{k+1} = Ax_{k+1} + Bu_{\text{max/min},k+1}$$

$$u_{\text{max/min},k+1} = \frac{y_{\text{max}/\text{min},k+1} - CAx_{k+1}}{D}$$

$$p_{\text{max/min},k+1} = u_{\text{max/min},k+1} \times y_{k+1}$$

where $p_{\text{max/min},k+1} \ (j=1,\ldots,K)$ denotes the battery peak power sequence. The entire process of SOP estimation and power sequence prediction under the CV-POM is presented in Algorithm 2.

Algorithm 2: Pseudocode for discharge/charge SOP estimation under the CV-POM.

\% Initialization \%
Input: A, B, C, D, K, $x_0$ and $u_0$
Output: $u_{\text{max/min},k+1}$ and $y_{\text{max/min},k+1}$, $j=1,\ldots,K$
\% Determine constant discharge voltage \%
1: $x_{k+1} \leftarrow Ax_k + Bu_k$
2: $u_{\text{max/min},k+1} \leftarrow \frac{y_{\text{max/min},k+1} - CAx_{k+1}}{D}$
3: if $u_{\text{max/min},k+1} = u_{\text{max},k+1}$ then
4: $y_{k+1} \leftarrow CAx_k + CBu_k + DU_{\text{max/min},k+1}, j=1,\ldots,K$
else
7: $y_{k+1} \leftarrow y_{\text{min/max}}, j=1,\ldots,K$
8: end if
\% Peak power sequence prediction \%
9: $p_{\text{max/min},k+1} \leftarrow u_{\text{max/min},k+1} \times y_{k+1}$
10: for $j = 2; K$ do
11: $x_{k+1} \leftarrow Ax_{k+1} + Bu_{\text{max/min},k+1}$
12: $u_{\text{max/min},k+1} \leftarrow \frac{y_{k+1} - CAx_{k+1}}{D}$
13: $p_{\text{max/min},k+1} \leftarrow u_{\text{max/min},k+1} \times y_{k+1}$
14: end for

C. Constant current-Constant voltage Peak Operational Mode

CC-CV-POM combines the attributes of both CC-POM and CV-POM, which attains the battery peak power performance by implementing the two POMs in the high and low SOC regions, with a transitional CC-CV phase in-between. As can be seen, besides a transitional CC-CV phase in Fig. 4 (b), the electrical behaviors of batteries in Fig. 4 (a) and (c) are completely the same as the CC-POM and CV-POM, respectively. Therefore, pinpointing the mode shift of this transitional CC-CV phase becomes the key for SOP estimation under the CC-CV-POM. This can be achieved by comparing the magnitudes of $u_{\text{max/min},k+1}$ in (5), $u_{\text{max}/\text{min},k+1}$ in (7) and $u_{\text{max},k+1}$, which falls within the following three cases [32].

1. Case 1: $u_{\text{max/min},k+1} \geq u_{\text{max}/\text{min},k+1}$. It indicates a complete CC-POM without a mode shift, and the entire process of SOP estimation and power sequence prediction can be referred to Algorithm 1.
Case 2: \( \left| u_{\text{dischg,stat}}^{\max/min,k+1} \right| \geq \left| u_{\text{dischg}}^{\max/min} \right| \). It indicates a complete CV-POM without a mode shift, and the entire process of SOP estimation and power sequence prediction can be referred to Algorithm 2.

Case 3: \( \left| u_{\text{dischg,stat}}^{\max/min,k+1} \right| < \left| u_{\text{dischg}}^{\max/min} \right| < \left| u_{\text{dischg,stat}}^{\max/min} \right| \). It indicates the occurrence of a transitional CC-CV phase and a mode shift within a prediction window. The mode-shifting moment, denoted as \( K_{\epsilon} \), marks the instance when the terminal voltage reaches the cut-off threshold for batteries operating under the current constraint from the outset of the prediction window. The entire process of SOP estimation and power sequence prediction under the CV-POM is presented in Algorithm 3.

Fig. 4. Battery discharge behaviors under the CC-CV-POM dominated by: (a) current constraint; (b) hybrid current and voltage constraint; and (c) voltage constraint.

Algorithm 3: Pseudocode for discharge/charge SOP estimation under the CV-POM.

\[
\text{\% Initialization } \%
\]
\[
\text{Input: } A, B, C, D, K, x, \text{ and } u,
\]
\[
\text{Output: } u_{\text{dischg,MC}}^{\max/min,k+1}, y_{k+1}, \text{ and } P_{\text{dischg}}^{\max/min,j}, j=1,...,K
\]
1: Calculate \( u_{\text{dischg,stat}}^{max/min,k+1} \), \( j=1,\ldots,K \) via (5);
2: \text{ if } \( \left| u_{\text{dischg,stat}}^{max/min,k+1} \right| \geq \left| u_{\text{dischg}}^{max/min} \right| \) then
\[
\text{\% Complete CC POM } \%
\]
3: \( u_{\text{dischg,MC}}^{max/min,k+1} \leftarrow u_{\text{dischg,stat}}, j=1,\ldots,K \);
4: Implement Algorithm 1;
5: Return \( u_{\text{dischg,MC}}^{max/min,k+1}, y_{k+1}, \text{ and } P_{\text{dischg}}^{max/min,j}, j=1,...,K \);
6: else
\[
\text{\% Start iteration under the CC-POM } \%
\]
7: for \( j=1:K \) do
8: \( u_{\text{dischg,MC}}^{max/min,k+1} \leftarrow u_{\text{dischg,stat}} \);
9: if \( j=1 \) then
10: \( x_{k+1} \leftarrow Ax_{k+1} + Bu_k \);
11: else
12: \( x_{k+1} \leftarrow Ax_{k+1} + Bu_{\text{dischg,MC}}^{max/min,k+1} \);
13: end if
14: \( y_{k+1} \leftarrow Cx_{k+1} + Du_{\text{dischg,MC}}^{max/min,k+1} \);
15: if \( y_{k+1} \leq y_{min} \) or \( y_{k+1} \geq y_{max} \) then
\[
\text{\% Detect a mode shift to CV-POM } \%
\]
16: \( y_{k+1} \leftarrow y_{\text{min/max}} \);
17: \( u_{\text{dischg,MC}}^{max/min,k+1} \leftarrow y_{k+1} - CAx_{k+1} \);
18: \text{ end if}
19: \( P_{\text{dischg}}^{max/min,k+1} \leftarrow u_{\text{dischg,MC}}^{max/min,k+1} \times y_{k+1} \);
20: end for
21: end if

D. Constant-power Peak Operational Mode

Unlike the aforementioned three POMs, CP-POM straightforwardly maximizes the discharge/charge power as the product of peak current and terminal voltage and maintains it throughout the prediction window. This can be intuitively converted into an optimization problem with an objective function expressed as

\[
\begin{align*}
\max P_{k+j} &= \max \left\{ u_{k+j} y_{k+j} \right\} \\
\text{s.t.} & \quad P_{k+j} = P_{k+j} y_{k+j} \\
& \quad u_{\min} \leq u_{k+j} \leq u_{\max} \\
& \quad y_{\min} \leq y_{k+j} \leq y_{\max} \\
& \quad \forall \ j = 1,\ldots,K
\end{align*}
\]

The interplay between peak current and terminal voltage at time \( k+j \) is described as

\[
\begin{align*}
P_{k+j} &= u_{k+j} y_{k+j} \\
&= u_{k+j} (CAx_{k+j} + Du_{k+j}) \\
&= u_{k+j} (CAx_{k+j} + CBu_{k+j} + Du_{k+j})
\end{align*}
\]

The problem of current prediction at time \( k+j \) boils down to a quadratic equation as

\[
a u_{k+j}^2 + bu_{k+j} + c = 0
\]

and the coefficients are

\[
\begin{align*}
a &= D \\
b &= CAx_{k+j} + CBu_{k+j} \\
c &= -P_{k+j}
\end{align*}
\]

Solving the quadratic equation in (12) yields the peak current prediction at time \( k+j \). Then, it allows us to work out the associated terminal voltage prediction by

\[
y_{k+j} = \frac{P_{k+j}}{u_{k+j}}
\]

Algorithm 4: Pseudocode for discharge SOP estimation under the CP-POM.

\[
\text{\% Initialization } \%
\]
\[
\text{Input: } A, B, C, D, K, x, u, p_{0}, \text{ and } \text{Iter}_{\text{max}}
\]
\[
\text{Output: } u_{\text{dischg,MC}}^{max/min,j}, y_{k+j}, \text{ and } P_{\text{dischg}}^{max/min,j}, j=1,...,K
\]
\[
\text{\% Start iteration with an initial guess } P_{0} \%
\]
1: \( P_{0}^{\text{iter}1} \leftarrow P_{0}, j=1,...,K \);
2: \( \text{Limit} \leftarrow 1 \);
3: for \( \text{Iter}=1: \text{Iter}_{\text{max}} \) do
4: for \( j=1:K \) do
Calculate $u_{\text{iter}}^{\text{MC}}$ by solving (12):

6: \[ y_{k+j}^{\text{iter}} \leftarrow P_{k+j}^{\text{iter}} u_{k+j}^{\text{iter}}. \]

7: \[ x_{k+j}^{\text{iter}} \leftarrow A x_{k+j-1}^{\text{iter}} + B u_{k+j-1}^{\text{iter}}. \]

end for

8: switch (Limit)

9: Case 1:

\% Voltage constraint \%

10: \[ Y_{\text{ref}} < Y_{\text{min}} \]

11: \[ \varepsilon \leftarrow Y_{\text{ref}} - y_{k+j}^{\text{iter}} \]

Case 2:

\% Current constraint \%

12: \[ Y_{\text{ref}} < u_{\text{max}}^{\text{iter}} \]

13: \[ \varepsilon \leftarrow Y_{\text{ref}} - u_{k+j}^{\text{iter}} \]

end switch

14: if \[ |u_{k+j}^{\text{iter}}| > |u_{\text{max}}^{\text{iter}}| \] then

Mode \leftarrow 2;

else if \[ |\varepsilon| \leq \varepsilon_{\text{th}}\% \times Y_{\text{ref}} \] then

Break;

end if

21: Calculate Kalman gain $G$ through UKF;

22: \[ P_{k+j}^{\text{iter+1}} \leftarrow P_{k+j}^{\text{iter}} + G \times \varepsilon; \]

24: end for

25: Return \[ u_{\text{iter}}^{\text{MC}} \leftarrow u_{k+j}^{\text{iter}}; \]

\[ y_{k+j}^{\text{iter}} \leftarrow y_{k+j}^{\text{iter}}; \]

\[ P_{\text{iter}}^{\text{MC}} \leftarrow P_{\text{iter}}^{\text{MC}}, j=1,...,K; \]

end if

Algorithm 5: Pseudocode for charge SOP estimation under the CP-POM.

\% Initialization \%

Input: A, B, C, D, K, $x_1$, $u_0$, $P_0$, $\varepsilon_{\text{th}}\%$ and Iter$_{\text{max}}$

Output: $u_{\text{iter,MC}}^{\text{MC}}$, $y_{k+j}$ and $P_{\text{iter}}^{\text{MC}}, j=1,...,K$

\% Start iteration with an initial guess $P_0$ \%

1: $P_{k+j}^{\text{iter}} \leftarrow P_0, j=1,...,K; \]

2: for Iter$_{\text{iter}}$=1: Iter$_{\text{max}}$ do

3: for $j=1:K$ do

4: Calculate $u_{k+j}^{\text{iter}}$ by solving (12);

5: \[ y_{k+j}^{\text{iter}} \leftarrow P_{k+j}^{\text{iter}} u_{k+j}^{\text{iter}}; \]

6: \[ x_{k+j}^{\text{iter}} \leftarrow A x_{k+j-1}^{\text{iter}} + B u_{k+j-1}^{\text{iter}}; \]

7: end for

8: $Y_{\text{ref}} \leftarrow Y_{\text{max}}$

9: \[ \varepsilon \leftarrow Y_{\text{ref}} - y_{k+j}^{\text{iter}} \]

10: if \[ |u_{k+j}^{\text{iter}}| > |u_{\text{min}}^{\text{iter}}| \] then

11: \[ u_{\text{iter}}^{\text{MC}} \leftarrow u_{\text{iter}}^{\text{MC}}; \]

12: \[ y_{k+j}^{\text{iter}} \leftarrow CA x_{k+j} + C B u_{k+j} + D u_{\text{iter}}^{\text{MC}}; \]

13: \[ P_{k+j}^{\text{iter}} \leftarrow u_{\text{iter}}^{\text{MC}} \times y_{k+j}, j=1,...,K; \]

14: Repeat Step 3-6 given $P_{\text{iter}}^{\text{MC}}, j=1,...,K; \]

15: Break;

16: else if \[ |\varepsilon| \leq \varepsilon_{\text{th}}\% \times Y_{\text{ref}} \] then

Fig. 5. Battery discharge behaviors under the CP-POM dominated by: (a) current constraint; and (b) voltage constraint.

Fig. 6. Battery charge behaviors under the CP-POM dominated by: (a) current constraint; and (b) voltage constraint.

Based on the chain-like relationship described in (11)-(14), the electrical behaviors of batteries can be forecasted ahead and iterated step-by-step till the end of a prediction window. It is obvious that a given CP corresponds to two unique sequences of peak current and terminal voltage within the window. However, the boundary condition occurs differently for battery discharging and charging under the CP-POM, as illustrated in Fig. 5 and Fig. 6, respectively. As can be seen, the peak current and terminal voltage grow and decline monotonically for the discharge case, but they show the opposite trends for the charge case. This necessitates a separate consideration in algorithm development. In our previous work, we have proposed a model-switching approach for discharge and charge SOP estimation under the CP-POM, and the main processes are presented in Algorithm 4 and Algorithm 5, respectively. Interested readers could refer to [36] for more details. TABLE 1 summarizes the boundary conditions for SOP estimation under various POMs.
17: Break;
18: end if
19: Calculate Kalman gain $G$ through UKF;
20: $p_{k+j}^{\text{iter}} \leftarrow p_{k+j}^{\text{iter}} + G \cdot \varepsilon$;
21: end for
22: Return $u_{\text{MC}, k+j}^{\text{iter}} \leftarrow u_{k+j}^{\text{iter}}$;
\[
y_{k+j} \leftarrow y_{k+j}^{\text{iter}};
p_{k+j}^{\text{iter}} \leftarrow p_{k+j}^{\text{iter}}, j=1,...,K;
\]

### TABLE 1
A SUMMARY OF BOUNDARY CONDITIONS FOR SOP ESTIMATION UNDER VARIOUS POMS

<table>
<thead>
<tr>
<th>POM</th>
<th>Boundary condition</th>
<th>$u$</th>
<th>$y$</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC-CCOM</td>
<td>Current constraint</td>
<td>$k+1 - k+K$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Voltage constraint</td>
<td>-</td>
<td>$k+K$</td>
</tr>
<tr>
<td>CV-POM</td>
<td>Current constraint</td>
<td>$k+1$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Voltage constraint</td>
<td>-</td>
<td>$k+1 - k+K$</td>
</tr>
<tr>
<td>CC-CV-POM</td>
<td>Current constraint</td>
<td>$k+1 - k+K$</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Hybrid constraint</td>
<td>$k+1 - k+K_c$</td>
<td>$k+K_c - k+K$</td>
</tr>
<tr>
<td>CP-POM</td>
<td>Current constraint</td>
<td>$k+K$ (dis)/$k+1$ (chg)</td>
<td>-</td>
</tr>
<tr>
<td></td>
<td>Voltage constraint</td>
<td>-</td>
<td>$k+K$</td>
</tr>
</tbody>
</table>

### IV. RESULTS AND DISCUSSIONS

#### A. Battery Experiments

In this study, we investigate the peak power performances of two commercial LIBs with different chemistries (i.e., NMC and LFP). The detailed battery specifications and design limits are listed in TABLE II. All experiments are carried out on a test bench for battery capacity calibration and model construction. Fig. 7 shows the experimental setup, which includes a host computer that interfaces with a battery tester (i.e., Arbin BT2000). The computer manages the testing program and collects data via TCP/IP ports. For each test, the battery is placed in a thermal chamber, of which temperature is monitored with a thermocouple attached on its surface. The following test procedures are conducted on both two batteries:

![Battery test bench](image)

**Fig. 7.** Battery test bench.

(1) Static capacity test is performed by discharging the battery at 0.2 C-rate after it is fully charged.

(2) OCV test is performed by discharging the battery from 100% to 0% SOC at an interval of 5% SOC. The battery will be relaxed for 1 hour between two intervals.

(3) Hybrid-pulse tests are performed at each 5% SOC from 90% to 10% SOC, as shown in Fig. 8 (a) and (b). A hybrid-pulse sequence (Fig. 8 (c)) comprises several 30-s discharge/charge pulses at ±0.2, ±0.5, ±1 and ±1.5 C-rates to characterize battery dynamics under different current excitations, and each of them is followed by a 40-s relaxation.

(4) Dynamic load tests are carried out by discharging the battery from 90% SOC to 10% SOC under dynamic load profiles. In this study, we choose an urban dynamometer driving schedule (UDDS) profile (see Fig. 9 (a)) for the NMC battery and a hybrid federal urban driving schedule-US06 driving schedule (FUDS-US06) profile (see Fig. 9 (b)) for the LFP battery, considering potential profile influence on battery peak power performance.

<table>
<thead>
<tr>
<th>Type</th>
<th>NCR18650B</th>
<th>ANR28650M1B</th>
</tr>
</thead>
<tbody>
<tr>
<td>Battery chemistry</td>
<td>NMC</td>
<td>LFP</td>
</tr>
<tr>
<td>Nominal capacity (Ah)</td>
<td>3.2</td>
<td>2.5</td>
</tr>
<tr>
<td>Current range (A)</td>
<td>-4.8/10</td>
<td>-5.5/11</td>
</tr>
<tr>
<td>Voltage range (V)</td>
<td>3/4.2</td>
<td>2.5/3.6</td>
</tr>
<tr>
<td>SOC range (%)</td>
<td>10/90</td>
<td>10/90</td>
</tr>
</tbody>
</table>

The experimental data from the hybrid-pulse tests are used to parameterize the DP models for NMC and LFP batteries by minimizing the sum of the squared errors between the measured voltage and the predicted voltage from the DP model. A hybrid particle swarm optimization-genetic algorithm method, enabling both fast convergence speed and desirable searching...
capability, is adopted to obtain the optimal model parameters. The details of this optimization method can be referred to [9]. Fig. 8 (d) and (e) exemplify the voltage fitting results at 60% SOC and the root-mean-square errors (RMSEs) of the DP model for NMC battery over the whole SOC range, respectively. We further examine the well-parameterized DP models for NMC and LFP batteries under dynamic load profiles, and the open-loop prediction results are presented in Fig. 9. It can be seen that the DP models prove to be accurate in describing battery behaviors under dynamic conditions, laying the foundation for subsequent battery peak power assessments in high reliability.

B. Key Indices

In this study, we are interested in the evolutions of battery current, voltage and power within a prediction window. We particularly focus on the maximum and minimum instant magnitudes, time-averaged magnitude, and falling/rising rate of these parameters. The reasons are:

- The maximum and minimum instant magnitudes correspond to the best and worst performances of battery current, voltage or power over the prediction window. They are also highly critical for battery safety as they characterize the boundary conditions of each POM.

- The time-averaged magnitudes of current and power can directly unveil the Ah-throughput and energy-throughput over the window, indicating the discharge/charge capability of each POM. The time-averaged magnitude of voltage reveals the voltage level that batteries could provide or receive over the prediction window, building the linkage between time-averaged magnitudes of current and power.

- The falling/rising rate defines the variation rate from the best (or worst) to the worst (or best) performance, reflecting the discharge/charge stability of each POM.

Based on these attributes, we take them as four key indices to quantitively evaluate battery peak power performances and make fair comparisons among different POMs. These four key indices are defined as

\[
\begin{align*}
\bar{X} &= \max \{ |X_1|, \ldots, |X_K| \} \\
\hat{X} &= \min \{ |X_1|, \ldots, |X_K| \} \\
X_{\text{avg}} &= \frac{1}{K} \sum_{j=1}^{K} X_j \\
\Delta X &= \frac{\bar{X} - X}{X_{\text{avg}}} 
\end{align*}
\]

where \( X \) represents either current, voltage or power within a prediction window. \( \bar{X} \) and \( \hat{X} \) denote the maximum and minimum instant magnitude of \( X \), respectively. \( X_{\text{avg}} \) gives the time-averaged magnitude of \( X \) while \( \Delta X \) indicates the falling/rising rate of \( X \) over the window.

C. Comparison Results and Analysis

As the effectiveness of the algorithms introduced in Section III has been thoroughly examined in the literature while the accuracy of the DP models has been experimentally validated across the whole SOC range, we reasonably consider the SOP estimation results under the CC, CV, CC-CV, and CP-POMs as reliable reference values to ensure the fair and robust comparison and analysis.

Fig. 9. Model prediction results under dynamic load profiles of: (a) UDDS; and (b) hybrid FUDS-US06.
Fig. 10. Peak discharge power of NMC battery under UDDS profile over the prediction windows of: (a) 10 s; and (b) 30 s.
Fig. 11. Peak charge power of NMC battery under UDDS profile over the prediction windows of: (a) 10 s; and (b) 30 s.
Fig. 12. Peak discharge power of LFP battery under FUDS-US06 profile over the prediction windows of: (a) 10 s; and (b) 30 s.
Fig. 13. Peak charge power of LFP battery under FUDS-US06 profile over the prediction windows of: (a) 10 s; and (b) 30 s.

Fig. 10-Fig. 13 demonstrate the peak power performances of the NMC battery and LFP battery under the UDDS profile and FUDS-US06 profile, respectively. The prediction windows of interest are selected as 10 s and 30 s to explore the potential impact of window length on the comparison results. As can be seen from the simulation results, current, voltage and power
under the four POMs appear highly consistent interrelationship on the two batteries. Particularly, this interrelationship also remains unchanged across different load profiles and prediction windows, yet it exhibits clear dependency on regions governed by different operational constraints. The detailed analysis is presented in the following.

In the region governed by current, the CC-POM and CC-CV-POM induce completely the same battery behaviors over the prediction window (see Fig. 14 (a) and Fig. 15 (a)) and yield the highest $\tilde{u}$, $\tilde{y}$ and $u_{avg}$ with lowest $\Delta u$ among all the four POMs. This is because the battery continues to operate under the current constraint throughout the window. Under such a persistent peak discharge/charge current, the CC-POM and CC-CV-POM result in the lowest $y$, $y$ and $y_{avg}$ when discharging but the highest $\tilde{y}$, $\tilde{y}$ and $y_{avg}$ when charging. Interestingly, we find that for both discharge and charge cases $\bar{P}$ and $P_{avg}$ for both discharge and charge cases, even though it has higher $\bar{P}$. Obviously, the CV-POM presents the worst $\bar{u}$ and $u_{avg}$ among the four POMs as the peak discharge/charge current reaches the threshold just at the outset of a window. This significantly limits its current and power performances over the remaining window, resulting in the lowest $\bar{P}$ and $P_{avg}$ but highest $\Delta P$.

In the region governed by voltage, the CV-POM and CC-CV-POM induce completely the same battery behaviors over the prediction window (see Fig. 14 (c) and Fig. 15 (c)) and yield the highest $\tilde{u}$ and $u_{avg}$ among all the four POMs. This is achieved by forcing the battery to discharge/charge under the lower/upper cut-off voltage, resulting in the lowest/highest $\tilde{y}$, $\tilde{y}$ and $y_{avg}$. From the results, this CV operation delivers the greatest $P$ and $P_{avg}$, indicating its superior discharge/charge capability at relatively low SOCs. Comparatively, the CC-POM and CP-POM provide $\tilde{u}$ and $u_{avg}$ far below the ones offered by the CV-POM, leading to compromised $\bar{P}$ and $P_{avg}$ for both discharge and charge cases. It is worth noting that the CC-POM outperforms the CP-POM in $P_{avg}$ when discharging but this relationship is reversed when charging.

The area between the regions governed by current and voltage features a transitional zone, where the CC-CV-POM

![Fig. 14. A comparison of battery discharge behaviors over the prediction window under: (a) current constraint; (b) hybrid current and voltage constraint; and (c) voltage constraint.](image-url)
gradually transforms from CC-POM to CV-POM and the battery is limited under the hybrid current and voltage constraint. In this transitional zone, the peak discharge/charge current of the CC-POM will drop below the current constraint, and the constant discharge/charge voltage of the CV-POM has not reached the lower/upper cut-off threshold (see Fig. 14 (b) and Fig. 15 (b)). Apparently, the CC-CV-POM induces highest \( u_{\text{avg}} \) and \( y_{\text{avg}} \) among all the four POMs, giving rise to the highest \( P_{\text{avg}} \) and \( P_{\text{max}} \). As a difference, the CC-CV-POM yields the lowest \( u_{\text{avg}} \) and \( y_{\text{avg}} \) when discharging but the highest \( u_{\text{avg}} \) and \( y_{\text{avg}} \) when charging. In the meantime, the interrelationship among the remaining three POMs evolves dynamically in this transitional zone. Under the CV-POM, \( u_{\text{avg}} \) and \( P_{\text{avg}} \) will ascend from the lowest to the highest ranking, while under the CC-POM, \( u_{\text{avg}} \) and \( P_{\text{avg}} \) will descend from the highest to the lowest or second-lowest ranking, differing from those for discharging or charging.

Based on the comparison results, we have summarized the interrelationships among these POMs in TABLE III-TABLE V, focusing on their current, voltage and power characteristics. From these comparisons, a strong correlation emerges between \( P_{\text{avg}} \) and \( u_{\text{avg}} \), as highlighted in red in TABLE III and TABLE V. This suggests that higher Ah-throughput over a prediction window leads to increased energy delivery or absorption. However, such a correlation is not evident between \( P_{\text{avg}} \) and \( y_{\text{avg}} \), indicating a weak dependency of energy throughput on terminal voltage. Additionally, these rankings offer a clear understanding of each POM with their distinct attributes.

- The CC-POM excels in current and power performance in the region governed by current, topping the rankings in time-averaged current (i.e., \( u_{\text{avg}} \)) and power (i.e., \( P_{\text{avg}} \)) as well as maximum instant current (i.e., \( u_{\text{max}} \)) and power (i.e., \( P_{\text{max}} \)). However, when the dominant operational constraint turns to voltage, there is a swift decline in peak discharge/charge current. This reduction impairs the peak power capability over a prediction window, affecting the rankings of the aforementioned indices. Notably, the CC-POM maintains the highest minimum instant current (i.e., \( u_{\text{min}} \)) across all the regions.
- The CV-POM yields subpar current and power performances in the region governed by current, but it ascends to the highest rankings in time-averaged current (i.e., \( u_{\text{avg}} \)) and power (i.e., \( P_{\text{avg}} \)) when the dominant operational constraint turns to voltage. Nevertheless, despite the CV-POM holds the highest minimum instant voltage (i.e., \( y_{\text{min}} \)) across all the regions, it tops the rankings in falling/rising rate of current (i.e., \( u_{\text{max}} \)) and power (i.e., \( P_{\text{max}} \)), indicating the worst discharge/charge stability among the four POMs.
- The CC-CV-POM combines the attributes of both CC-POM and CV-POM and proves to have the optimal discharge/charge capability across all the regions as it achieves the highest rankings in time-averaged current.
(i.e., \( u_{\text{avg}} \)) and power (i.e., \( P_{\text{avg}} \)) as well as maximum instant current (i.e., \( \bar{u} \)) and power (i.e., \( \bar{P} \)). This superior performance is realized by consistently discharging or charging the battery under the operational constraint of either current or voltage throughout the prediction window, thereby maximizing the utilization of the remaining capacity. On the other hand, such an aggressive strategy causes a high ranking in \( \Delta P \), reflecting a poor discharge/charge stability of the CC-CV-PO.

- Among the four POMs, the CP-PO exhibits relatively compromised performances in time-averaged current (i.e., \( u_{\text{avg}} \)) and power (i.e., \( P_{\text{avg}} \)) across all regions. Whereas it stands out with the lowest falling/rising rate of power (i.e., \( \Delta P \)) and highest minimum instant power (i.e., \( P \)), indicating the capability to supply persistent and stable power. In addition, unlike the other three POMs, the CP-PO only reaches the boundary condition at either outset or end of a prediction window. Although this attribute limits the current and voltage performances within a prediction window, it contributes to the reduced risk of exceeding the design limit when batteries are discharging/charging at the peak power, thereby enhancing the operational safety.

### TABLE III

**The Ranking of Battery Power Performance Under Various POMs**

<table>
<thead>
<tr>
<th>Discharge</th>
<th>( \bar{P} ) (W)</th>
<th>( P ) (W)</th>
<th>( P_{\text{avg}} ) (W)</th>
<th>( \Delta P ) (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC-PO</td>
<td>=1 =3 3 =2 → 2/4</td>
<td>1 → 3 =2</td>
<td>3 3 3</td>
<td></td>
</tr>
<tr>
<td>CV-PO</td>
<td>=1 =1 =1 4 → =2/3</td>
<td>4 → =1 1 1 =1</td>
<td>1 1 =1</td>
<td></td>
</tr>
<tr>
<td>CC-CV-PO</td>
<td>=1 =1 =1 =2 → =2/3</td>
<td>1 1 =1 1 =1 2</td>
<td>1 1 =1</td>
<td></td>
</tr>
<tr>
<td>CP-PO</td>
<td>4 4 4 1 1 1 =3 →</td>
<td>4 4 4 4 4 4 4 4</td>
<td>4 4 4 4</td>
<td></td>
</tr>
</tbody>
</table>

*Note: c1, c2 and c3 indicate the cases of battery peak power performance under the current constraint, hybrid current & voltage constraint, and voltage constraint, respectively.

The notation ‘=’ indicates that two POMs have the same rank;

The notation ‘\( x \rightarrow y \)’ indicates that the rank of a POM is either a or b.

The notation ‘\( x \rightarrow y \)’ indicates that the evolution of rank for a POM.

### TABLE IV

**The Ranking of Battery Terminal Voltage Performance Under Various POMs**

<table>
<thead>
<tr>
<th>Discharge</th>
<th>( y )</th>
<th>( y_{\text{avg}} )</th>
<th>( \Delta y )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC-PO</td>
<td>=2 =2 3 =3 =1 =3</td>
<td>→ 2 =2 2 2</td>
<td>2 2 2 2 2 2</td>
</tr>
<tr>
<td>CV-PO</td>
<td>=2 =3 =3 =1 1 =1 =1</td>
<td>→ =3 4 4 4 3</td>
<td></td>
</tr>
<tr>
<td>CC-CV-PO</td>
<td>=2 =3 =3 =3 =3</td>
<td>=1 =3 4 =3 =2</td>
<td>3 3 3 3 3 3</td>
</tr>
<tr>
<td>CP-PO</td>
<td>1 1 1 2 =2/3 =1 2</td>
<td>→ 1 1 1 1 1 1</td>
<td></td>
</tr>
</tbody>
</table>

### TABLE V

**The Ranking of Battery Peak Current Performance Under Various POMs**

<table>
<thead>
<tr>
<th>Discharge</th>
<th>( \bar{u} )</th>
<th>( u )</th>
<th>( u_{\text{avg}} )</th>
<th>( \Delta u )</th>
</tr>
</thead>
<tbody>
<tr>
<td>CC-PO</td>
<td>=1 =3 1 =1 1 =2</td>
<td>→ 3 =2 3 4</td>
<td>4 4 4 4 4 4</td>
<td></td>
</tr>
<tr>
<td>CV-PO</td>
<td>=1 =1 =1 4 → =2/3</td>
<td>4 → =1 1 1 =1</td>
<td>1 1 =1 =1 =1</td>
<td></td>
</tr>
<tr>
<td>CC-CV-PO</td>
<td>=1 =1 =1 =1 =1 =1</td>
<td>→ =2/3 =1 1 =1 1 =3</td>
<td>1 1 =1 =1</td>
<td></td>
</tr>
<tr>
<td>CP-PO</td>
<td>3 3 3 2/4 3</td>
<td>→ 4 2 2 2 2 2</td>
<td>2 2 2 2 2 2</td>
<td></td>
</tr>
</tbody>
</table>
V. CONCLUSION

This paper conducts a comparative analysis of battery peak power performances under various peak operational modes (POMs). For this analysis, four key indices are utilized: maximum and minimum instant magnitudes, time-averaged magnitude, and falling/rising rate. The comparison results demonstrate distinct attributes of these POMs, which yield diverse peak power performances in the regions governed by different operational constraints and lead to region-dependent interrelationship among these POMs. Such findings are highly consistent after changing potential factors, such as load profile, length of the prediction window and battery chemistry. In addition, our analysis reveals that no single POM can be deemed universally optimal for all conceivable application scenarios. The suitability of each POM varies significantly depending on specific circumstances. For instance, the CC-CV-POM, combining the advantages of CC and CV-POMs in different regions, emerges as the preferred strategy for EV regenerative braking as it could maximize the recovery of vehicle kinetic energy during decelerations. Conversely, the CP-POM may offer advantages for EV acceleration and gradient climbing, where the task completion primarily relies on the minimum achievable power, especially encountering the following three scenarios: (1) maximize the vehicle acceleration at a specific power rating; (2) optimize the power rating needed for desired vehicle acceleration performance; (3) optimize the gradeability at the lowest power rating. In this regard, it is advisable for on-board BMSs to achieve strong adaptability in driving strategy formulation, considering the optimal POM tailored to specific requirements for each case. Moreover, temperature and battery aging are two critical factors that could potentially impact the peak power performance of batteries. We maintain that our comparative findings regarding the interrelationship among battery SOPs under the four POMs should hold within the same modelling framework, albeit with potential variations in the magnitudes of these SOPs at different temperatures and aging states.

REFERENCES


