Novel Polarization Voltage Model: Accurate Voltage and State of Power Prediction

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\textbf{ABSTRACT} Accurate prediction of battery voltage and state of power (SOP) is a challenge for a battery management system to achieve charge/discharge safety protection and power distribution. An accurate, simple and implementable battery model is key to realizing battery simulation and state estimation/prediction. To establish a battery model that can easily realize battery voltage and SOP prediction, this paper proposes a novel polarization voltage (NPV) model based on current and time by simplifying the equation describing the polarization characteristics in the electrochemical model. The NPV model is implementable for high-precision prediction of battery voltage and SOP at \( t \)-second \((t > 0)\) under any constant current \((I \neq 0)\). Based on the relationship between model parameters and state of charge (SOC), the SOP prediction model with different SOC is successfully realized. The prediction results show that the battery is charged from SOC = 0 to cut-off voltage with 3C, and the high-precision prediction of polarization voltage and terminal voltage can be obtained by using the NPV model. The average errors of the polarization voltage and voltage terminal are only 1.4\% and 0.4\%, respectively. For the 3C discharge process, the maximum prediction error of terminal voltage is \(-4.7\%\), and the error at the end of discharge is only \(-1.1\%\), with an average error of 0.6\%. The average error of SOP at \( t \)-second = 10s predicted by the NPV model is only 0.78\%. More importantly, the NPV model parameters are obtained from just small-batch data, and it is timesaving for practical testing with simple structures. Therefore, the NPV model is suitable for battery simulation, state prediction, fast charging security and energy management with broad application prospects.

\textbf{INDEX TERMS} Novel polarization voltage model, voltage prediction, state of power, lithium ion battery, electric vehicle.

\textbf{NOMENCLATURE}

\textbf{ABBREVIATIONS}

| SOP | state of power |
|-----|----------------|
| NPV | novel polarization voltage |
| SOC | state of charge |
| EVs | electric vehicles |
| V2G | vehicle-to-grid |
| BMS | battery management system |
| RC | resistor-capacitance |
| OCV | open-circuit voltage |
| OPV | original polarization voltage |
| CHA | charge |
| DCH | discharge |

\textbf{SYMBOLS}

- \( I_{\text{max}} \) \quad \text{maximum current}
- \( U_{\text{max}}/U_{\text{min}} \) \quad U_{\text{max}} \text{ is upper cut-off voltage and } U_{\text{min}} \text{ is lower cut-off voltage}
- \( t/t_{\text{cha}} \) \quad \text{the operating time of the constant current}
- \( U_L \) \quad \text{terminal voltage}
- \( U_{\text{ocv}} \) \quad OCV
- \( U_{\text{op}} \) \quad \text{polarization voltage}
- \( \tau \) \quad \text{the polarization time of RC network}
- \( \eta \) \quad \text{polarization overpotential}
- \( t_{\text{cha}} \) \quad \text{Li}^+ \text{ transference number}
- \( R \) \quad \text{ideal gas constant}
- \( T \) \quad \text{Kelvin temperature}
- \( F \) \quad \text{Faraday constant}
- \( C_L(L, t) \) \quad \text{Li}^+ \text{ concentrations at the positive electrode of the battery}
$C_e(0, t)$ Li$^+$ concentrations at the negative electrode of the battery
$I$ C-rate
$R_{\text{c}}$ resistance
$U_{\text{op}}(t, \text{I})$ the NPV model

**I. INTRODUCTION**

Batteries are crucial elements of electric vehicles (EVs) [1]–[6]. Since batteries can both absorb and release energy, EVs can achieve the function of vehicle-to-grid (V2G), which can cut peaks, fill valleys and provide power to users [7]–[10]. To ensure the safety of the battery system during charge/discharge, it is necessary to accurately predict the battery system voltage, to prompt the battery management system (BMS) via taking protective strategies in advance, as well as safeguarding the battery system under safe operating conditions. The state of power (SOP) of a battery system reflects the maximum available power to be output or input in a short period [11]. Moreover, SOP is the primary reference index for EVs to realize the functions of accelerating, feedback braking and peak cutting and valley filling, which are crucial for battery energy management [12]–[15]. Battery models can simulate the characteristics of the battery and have become an effective means by which simulate and analyze battery performance [16]–[21]. Therefore, it is a challenge for battery safety protection and energy management to establish a battery model that can accurately predict battery voltage and SOP.

Empirical model is a kind of battery model describing the voltage characteristics based on the relationship between voltage, current and state of charge (SOC). The conventional empirical models are the Shepherd Model, Universal Model, Nernst Model and “Combined” Model. [22]. These four models can describe the voltage characteristics to a certain extent, but they cannot accurately describe the polarization characteristics of the battery. For example, the Universal Model is established according to the current and SOC, and its output voltage is constant, which cannot reflect the polarization characteristics of the battery. The “combined” model has all the advantages of the above three models and describes the characteristics of the voltage to a certain extent. However, it cannot reflect the dynamic characteristics of the voltage, which limits its use. These models cannot fully reflect the characteristics of the voltage, so they cannot be used for high-precision SOP prediction. SOP prediction based on the empirical model is mainly based on the definition of SOP, that is, the power when the battery reaches the cut-off voltage in a certain period (such as 1s, 10s, etc.) under a constant current $I_{\text{max}}$, i.e., $\text{SOP} = U_{\text{max}/\text{min}} \times I_{\text{max}}$ [23]–[25]. The SOP obtained based on the above method is the simplest, but it needs continuous attempts to obtain accurate SOP, which is still inefficient, time-consuming, and is only suitable for use in the laboratory and not conducive to application in real-world vehicles.

The $N$-order resistor-capacitance (RC) equivalent circuit model describes the polarization processes with RC networks, which overcomes the shortcoming of the empirical model that cannot describe the polarization characteristics, and commonly used in battery simulation, analysis and state estimation, such as SOC and SOP [26]–[32]. To obtain accurate simulation and state prediction results, the order should be increased [33], and model parameters should be updated in real time according to SOC and temperature. The higher the order, the more complex the model, so as to be not conducive to practical application.

Electrochemical models use a series of partial differential equations to describe the real electrochemical reaction processes inside the battery, which can describe the dynamic behavior of the battery and is very suitable for high-precision voltage simulation and state estimation [5], [34]–[39]. The most commonly used electrochemical mechanism models are the Pseudo-two-Dimensional model and the single particle model [40]–[44]. These kinds of model have high precision but require heavy computation, and they need special computing software to realize high-precision voltage simulation and state estimation, which is difficult to be integrated in a BMS.

The battery is regarded as a “black box” based on a data-driven method [45]–[48]. The most significant advantage of this method is that it does not need to consider the actual electrochemical reaction of the battery. Taking the influencing factors as input and the target characteristic quantity (such as SOC and SOP) as output, it can learn and train test data through data analysis and machine learning to realize the output of the target characteristic quantity [49]–[56]. This method breaks through the traditional modeling method with a good application prospect. However, this method needs to learn lots of historical data of different working conditions and different temperatures to obtain good prediction results, which limits its actual application.

To realize the accurate prediction of battery voltage and SOP, a novel polarization voltage model is proposed. This paper makes several original contributions and improvements to the current research as follows:

1. A novel polarization voltage (NPV) model based on current and time is established by simplifying the equations describing the polarization characteristics in the electrochemical battery model. The NPV model is simple and implementable, and the parameters can be identified by using just small-batch data, and it is timesaving for practical testing with simple structures.

2. High-precision prediction of battery voltage and SOP can be realized. The proposed model can accurately predict battery voltage and SOP at $t$-second ($t > 0$) with high-precision under any constant current ($I \neq 0$). Based on the relationship between model parameters and SOC, the power prediction model under different SOC is successfully obtained.

The rest of the paper is organized as follows: Section II describes the experimental method to provide data support for the establishment of the polarization voltage model, and tests SOP at $t$-second = 10s. Section III describes the shortcomings
II. EXPERIMENTS

Five LiFePO₄ batteries numbered 1-5 with 3.2V/56Ah were selected, and the parameters of these batteries are shown in Table 1. The battery test system was Digatron BTS 600, and the thermostat was Taichy MHX-408NKM, the configuration of the test system is depicted in Fig. 1. To explore the relationship between voltage and current, 3C current was used to charge the battery for 40s, the sampling time was 0.1s, and the test temperature was 25°C. The test curve is depicted in Fig. 2.

The SOP test is based on its definition, that is, the power of the battery when it reaches the cut-off voltage under the constant maximum current. The four batteries numbered 2-5 were tested at 5°C, 15°C, 25°C and 45°C respectively. The minimum test current was 0.5C and the maximum current was 300 A, about 5.36C¹ (this is due to the limitation of the maximum output current of the equipment). The test current interval should be extended, such as 0.5C, 1C, 1.5C, 2C, 3C, etc.

III. SHORTCOMING OF THEVENIN MODEL

A. DEFINITION OF POLARIZATION VOLTAGE

According to the battery model, the terminal voltage is composed of equilibrium potential, ohmic polarization, concentration polarization and electrochemical polarization. The equilibrium potential is a constant, which is approximate to open-circuit voltage (OCV) and can be obtained after one-hour rest. The polarization voltage can be defined as:

$$U_{op} = U_L - U_{ocv}$$  \hspace{1cm} (1)

where $U_L$ is terminal voltage, $U_{ocv}$ is OCV, and it is specified that charging is positive. It is noted that $U_{ocv}$ in (1) is a constant value. Once OCV is determined, it remains constant throughout the whole process.

B. LIMITATIONS OF THE THEVENIN MODEL

The first 10s, 20s and 40s of pulse data are selected, the parameters of the Thevenin model are identified by the least squares algorithm, and the polarization voltages of 11s-40s are predicted.

Different amounts of necessary data are used to identify the Thevenin model, and the prediction effects of the identified Thevenin model are quite different, as depicted in Fig. 3. From the identification results, the first 10s of necessary data are selected to identify the Thevenin model, and the prediction error² of the Thevenin model is the largest, with a maximum error of 24.1%. However, with the increase of the selected necessary data, the accuracy of the identified

¹C is C-rate, which is the ratio of the charge/discharge current to the rated capacity of a battery.

²The error refers to the relative error of the polarization voltage rather than the relative error of the terminal voltage, and the following error is the same as here.
Thevenin model is higher. Therefore, the accuracy of the Thevenin model identified by the first 40s of necessary data is the best, and the prediction error at 40s is 5.6%. According to the simulation results of the Thevenin model (Fig. 3 (a)), after 3τ (τ = R_p C_p), the polarization voltage calculated by the Thevenin model enters the steady state, and it cannot continue to reflect the polarization voltage characteristics, so the prediction error increases with time. In other words, the fewer necessary data selected to identify the parameters of the Thevenin model, the less suitable the identified parameters are to describe the characteristics of the battery. However, the polarization voltage calculated by these parameters will enter the steady state sooner and cannot fully reflect the polarization characteristics of the battery.

IV. MODELING METHOD FOR POLARIZATION VOLTAGE MODEL

According to the analysis in Section III, the Thevenin model cannot accurately simulate and predict the polarization voltage, and the accuracy of SOP calculated by the Thevenin model cannot be guaranteed. In order to achieve high-precision voltage and SOP prediction, the polarization voltage needs to be re-defined.

A. ORIGINAL POLARIZATION VOLTAGE MODEL

1) MODEL STRUCTURE

Based on the electrochemical theory of the battery, the polarization overpotential is logarithmic to the Li⁺ concentration under the constant current [38]:

$$\eta = (1 - t_+) \frac{2RT}{F} \ln \left( \frac{C_e(L, t)}{C_e(0, t)} \right)$$

(2)

where $t_+$ is Li⁺ transference number, $R$ is ideal gas constant (8.314 J mol⁻¹ K⁻¹), $T$ is Kelvin temperature (K), $F$ is Faraday constant (C mol⁻¹); $C_e(L, t)$ and $C_e(0, t)$ are Li⁺ concentrations at the positive and negative electrodes of the battery, respectively.

The Li⁺ concentration is directly proportional to the current and time, so the polarization overpotential is also logarithmic to the current and time, and in the case of constant current, this relationship is simplified to $\alpha \ln(t)$. The components of a lithium ion battery, such as the separator, electrolyte, and collector, hinder the transmission of lithium ions and the flow of electrons, showing resistance characteristics. Therefore, the polarization voltage will be affected by the resistance $R_\Omega$ and increase with the increase of the current. Under the operating of the current, the polarization direction of the battery will be changed, that is, under the charging current, the polarization will shift to the positive direction, while under the discharge current, the polarization will shift to the negative direction. In general, assuming that the internal temperature of the battery remains constant, (2) can be simplified as a function of time under the constant current combined with the ohmic voltage drop (i.e., $R_\Omega I$) and the polarization direction of OCV (i.e., $\beta$). The original polarization voltage (OPV) model can be expressed as:

$$U_{op} = \alpha \ln(t) + R_\Omega I + \beta$$

(3)

where $I$ is C-rate, $I \neq 0$; $t$ is the operating time of the constant current, $t > 0$, $R_\Omega$ is resistance; $\alpha$ and $\beta$ are constants.

2) VERIFICATION OF THE OPV MODEL

To verify the prediction ability of the OPV model, the first 2s, 3s, 5s and 10s data of 0.5C-3C current and voltage are selected as the necessary data to identify the coefficients and the OPV model is used to predict the polarization voltage of 10s-40s.

The impact of the amount of necessary data and C-rate on prediction error is shown in Fig. 4. As depicted in Fig. 4 (a), the prediction error increases with the increase of prediction time. The prediction error of the OPV model identified by the first 3s of necessary data is −5.4% at 11s, the prediction error increases with the increase of prediction time, and the prediction error at 40s is as high as −12.6%. The prediction error of
The OPV model identified by the first 5s of necessary data is $-10.5\%$ at 40s, while the prediction error of the OPV model identified by the first 10s of necessary data is only $-7.2\%$ at 40s. The above analysis shows that the OPV model requires sufficient necessary data to achieve a satisfactory prediction effect. In general, the more necessary data selected, the more the OPV model can reflect the characteristics of the real polarization voltage, and the better the prediction result will be.

The prediction results of polarization voltages with different C-rates using the OPV model identified by the first 3s of necessary data are shown in Fig. 4 (b). The OPV model has the best prediction effect for the polarization voltage under 1C, and the error at 40s is only $-4.3\%$. However, with the increase of C-rate, the errors of 1.5C and 2C at 40s are as high as 12.4% and $-15.2\%$, respectively. In other words, the prediction error increases with the increase of C-rate. Even so, the prediction accuracy of the OPV model is higher than that of the Thevenin model. From Fig. 4 (a), when the necessary data of 10s is selected, the overall error is kept within 10%, and the prediction error within the latter 14s is kept within 5%. Overall, the amount of necessary data, prediction time and C-rate all affect the prediction results.

In general, if the prediction error is within 5%, the necessary data of 10s should be selected, and the prediction time can only reach the last 14s, which is far from meeting the actual prediction application. The ideal result should be to select a small amount of data to obtain the best and the most prolonged prediction results. Therefore, the OPV model needs to be further analyzed and optimized.

**B. NOVEL POLARIZATION VOLTAGE MODEL**

1) **MODELING METHOD**

According to (2), $t_+\frac{1}{t_+}$ is Li$^+$ transfer number, so $t_+$ should also be related to time, not a constant. As shown in Fig. 5, $\alpha$ decreases with the increase of time, and it is logarithmic to time. Therefore, the relationship between $\alpha$ and time can be described by (4):

$$f(t) = \alpha' \ln(t) + \beta'$$

where $f(t) = \alpha$, $\alpha'$ and $\beta'$ are the coefficients to be determined.

$\alpha$ in (3) is re-optimized by (4) to obtain a novel polarization voltage (NPV) model:

$$U_{\text{op}} = \alpha \ln^2(t) + \beta \ln(t) + R_\Omega I + \gamma$$

where $I$ is C-rate, $I \neq 0$; $t$ is the operating time of the constant current, $t > 0$, $R_\Omega$ is resistance, $\alpha$, $\beta$, $\gamma$ are the coefficients.

2) **VERIFICATION OF THE NPV MODEL**

Recalculating the data in Section IV.A.2, using the NPV model formed in (5), the prediction results have been improved fundamentally, as depicted in Fig. 6 (a). The prediction errors of the NPV model are all less than 5% within 40s (Fig. 6 (a)) and the errors are smaller with the increase of the C-rate (the prediction errors with 2C and 3C are within 2%,
as depicted in Fig. 6 (b)). Although more necessary data are selected, the smaller the final prediction error will be, the first 3s necessary data can also keep the prediction error within 5% (Fig. 6 (a)). In a word, the optimization for coefficients $\alpha$ is very productive and successful, and it is certain that only first 3s necessary data are needed to obtain a prediction error of no more than 5% in 40s.

3) PHYSICAL SIGNIFICANCE OF THE NOVEL VOLTAGE AND NPV MODELS

Combined with NPV and OCV, a novel voltage model can be obtained (Fig. 7).

$$U_L = U_{ocv} + U_{op}(I, t)$$  \hspace{1cm} (6)

where $U_L$ is terminal voltage, $U_{ocv}$ is OCV, and it is constant, $U_{op}(I, t)$ is the NPV model, $I$ is C-rate, and it is positive with charging.

According to Section IV.A.1, the physical significance of the novel voltage and NPV models can be summarized as:

$\alpha \ln^2(t) + \beta \ln(t)$ : This is a simplification of (2). The polarization voltage is affected by current and time, which is logarithmic to time with constant current. This part corresponds to the RC network in the Thevenin model, and the unit of $\alpha$ and $\beta$ is V.

$R_{\Omega}$: The polarization voltage is affected by resistance and is proportional to the current. Where $R_{\Omega}$ describes the ohmic resistance of the battery, so $R_{\Omega}$ describes the ohmic voltage drop, this part is the same as the description of the ohmic voltage drop in the Thevenin model. In particular, $R_{\Omega}$ is not exactly equivalent to ohmic resistance, because $I$ is C-rate, so the unit of $R_{\Omega}$ is V/C-rate.

$\gamma$: In this model, OCV is regarded as constant and does not change with the current. In fact, under the operating of current, OCV will deviate from the initial state, and its polarity will also change. Under the positive current, the polarity of OCV will shift to the charging state, otherwise, the polarity of OCV will shift to the discharging state. The different characteristic of OCV in the charge state or discharge state is called “hysteresis eye” [57], [58]. Therefore, $\gamma$ is the correction of OCV polarity, and its unit is V. The Thevenin model does not consider the OCV polarity, so it does not have this part.

$U_{ocv}$: This part represents the OCV. However, it is different from conventional OCV because it is specified in this paper that OCV is constant. Once the value of OCV is determined, OCV will remain unchanged, which is a major advantage of the novel voltage model.

V. APPLICATION OF THE NPV MODEL: VOLTAGE AND SOP PREDICTION

The NPV model can directly predict the polarization voltage at $t$-second. It should be noted that (1) is used to calculate the real polarization voltage, and the OCV should remain constant through the whole calculation process. Since OCV remains constant, the sum of OCV and the predicted polarization voltage is the predicted value of the terminal voltage.

According to the definition of SOP, combined with the NPV model, a novel SOP prediction model at $t$-second is:

$$SOP = C_n \frac{U_{\max}/\min - U_{ocv} - [\alpha \ln^2(t) + \beta \ln(t) + \gamma]}{R_{\Omega}}$$  \hspace{1cm} (7)

where $C_n$ is the value of the rated capacity, $U_{\max/\min}$ is the cut-off voltage of the battery, and $t$ is $t$-second ($t > 0$), which is the prediction time.

To verify the prediction accuracy of SOP by the NPV model, the selected current should be smaller than the current corresponding to the actual SOP. For example, the maximum charging current corresponding to the maximum charging power at SOC = 0.2 in the ambient temperature of 25° is 5.3C. Therefore, in the selection of data, the pulse current of 0.5C, 1C, 1.5C, 2C, and 3C can be selected. For each
Although the prediction error of 20s is more than points in the charge/discharge states are shown in Table 2. The prediction results of the NPV model at different SOC data for parameter identification of the NPV model. current, only the first 3s of data is selected as the necessary data for parameter identification of the NPV model.

**VI. RESULTS AND DISCUSSION**

**A. VOLTAGE PREDICTION RESULTS**

The prediction results of the NPV model at different SOC points in the charge/discharge states are shown in Table 2. Although the prediction error of 20s is more than $-5.79\%$ at SOC $= 0.8$ in the discharge state, it has been reduced to $-5.16\%$ at 40s. Moreover, the absolute errors of the predicted values at other SOC points in charge/discharge states are within 3.4%. Therefore, the NPV model can accurately predict the polarization voltage at different SOC points in the charge/discharge states.

The battery is charged with constant current at 0.5C, 1C and 1.5C, and each pulse is charged for 3s. The voltage and current are selected as the necessary data for parameter identification of the NPV model, and polarization voltages of 2C and 2.5C in 2 minutes are predicted. The accuracy of the NPV model prediction results for 2 minutes polarization voltage is the same as that of 40s polarization voltage prediction (Section IV.B.3). The final prediction error is within 2%, and the overall errors are kept within 5%, as depicted in Fig. 8 (a), and the overall prediction errors of the Thevenin model remained within 19% (Fig. 8 (a)) regardless of whether the model parameters are identified by 10s with 1C or 2 minutes with 1.5C. The polarization voltage is always decreasing because it reached the maximum value of steady state after $3\tau$ so that the error is reduced to within 3% at 2 minutes. However, with the increase of time, the error increases and exceeds 10%. Therefore, no matter how the parameters of the Thevenin model are selected and how long is taken to predict the polarization voltage, the result is not ideal, that is, the Thevenin model is not suitable for voltage prediction, but only suitable for dynamic analysis.

By charging the battery directly from the SOC $= 0$ to the cut-off voltage with 3C, the NPV model is identified by discontinuous pulses, and the polarization voltage and terminal voltage are predicted by the NPV model. For the prediction error of the polarization voltage, except that the prediction errors at 6s-55s are about 20%, the overall errors are within 5%, and the error of the terminal polarization voltage is 2.5%, as depicted in Fig. 8 (b). Moreover, the average error of the polarization voltage is only 1.4%. As the OCV remained during the whole process, it is easy to calculate the prediction error of terminal voltage. The average error of the terminal voltage is only 0.4%.

**TABLE 2. Prediction results at different SOC points in the charge (CHA)/discharge (DCH) states.**

| Time/s | Relative Error% | State | SOC |
|--------|-----------------|-------|-----|
|        | 20              | 30    | 40  |
| 2C     | -3.36           | -0.90 | -2.20|
| C-rate | -5.79           | -5.35 | -5.16|
| 3C     | -2.28           | -2.79 | -2.88|
|        | -0.64           | -1.33 | -1.95|

At SOC $= 0$, the battery is charged with 0.5C-2C, each pulse lasted for 5s without any rest, and then the battery is charged to the cut-off voltage with 3C. Only the first 3s data of each pulse are selected to identify the model parameters of the NPV model, and the 3C process charging is predicted. For the prediction errors of the polarization voltage, the overall errors are within 10% except that the prediction errors at 13s-51s are about 30%, as depicted in Fig. 8 (b). For the prediction errors of the terminal voltage, the overall errors are within 3.3%, and the average error is only $-1.6\%$. No matter if the first 3s data of continuous pulse or discontinuous pulse are used as the necessary data, the NPV model can well predict the polarization voltage and terminal voltage of the battery with high accuracy. This is very effective for the prediction of charging current, charging time and provides support for battery safety protection.

The predicted results of the terminal voltage by (6) in the discharge state are shown in Fig. 9. For the 2-minute discharge process, the maximum prediction error of 2.5C and 3C at different SOC points is only $-3.6\%$, and the error is close to 0 at the end of discharge, as depicted in Fig. 9 (a). For the 3C discharge process, as depicted in Fig. 9 (b), the maximum prediction error of the novel voltage model identified by discontinuous pulses is $-4.7\%$, and the error at the end of discharge is only $-1.1\%$. The maximum prediction error and the error at the end of discharge of the novel voltage model identified by continuous pulses are $-2.3\%$. In general, the NPV and novel voltage models can achieve high-precision prediction of the polarization and terminal voltages.

**B. SOP PREDICTION RESULTS**

The prediction results of the SOP are shown in Fig. 10. In the charge state, as depicted in Fig. 10 (a), the prediction errors of SOP exceed 10% when SOC $= 0.9$ at different temperatures. Although the maximum error is 7.9% in the interval of SOC $= [0.7, 0.8]$ at 15° and 45°, the errors of other temperatures and SOC points are less than 5%, and the average error of all predicted values is only 2.4%. In the discharge state, as depicted in Fig. 10 (b), the maximum error is only $-6.4\%$, with an average error of about 3%. In summary, the SOP
The SOP prediction model proposed in Section VI can be used to realize high-precision SOP prediction. To realize the SOP prediction in any working condition, it is necessary to carry out multiple pulse test for different SOC, and the test process is time consuming. The polarization voltage is different under different SOC, and the corresponding model parameters are also different. If the relationship between model parameters and SOC can be built, the SOP prediction in any working condition can be realized.

At different temperatures, \( \alpha, \gamma \) and \( R_\Omega \) of the SOP model in the charge/discharge states have good correspondence with SOC, and they increase/decrease regularly along with the increase of SOC, as depicted in Fig. 11 (a). However, \( \beta \) in the charge/discharge states varies irregularly near a specific value at different temperatures, so their corresponding relationship with SOC is weak. Therefore, the relationship between parameters \( \alpha, \gamma, R_\Omega \) and SOC can be described by (8).

\[
f(SOC) = k_1 \ln(SOC) + k_2 \ln(1 - SOC) + \frac{k_3}{SOC} + k_4 \tag{8}
\]

where \( k_1 \rightarrow k_4 \) are constants.

Note that (8) refers to the form describing the relationship between voltage and SOC in Ref [22]. This is because there is a correspondence between the model parameters and SOC in this paper, and there is also a correspondence between SOC and OCV, so there is an indirect correspondence between the model parameters and OCV. Therefore, (8) is selected to describe the corresponding relationship between model parameters and SOC.

It is noted that when SOC = 0.9 in the charge state, the predicted SOPs of the model have significant errors compared with the real SOPs. Therefore, when (8) is used to solve the parameters, the parameters of this point need to be removed to avoid affecting the accuracy of the parameters. Since parameter \( \beta \) varies around a specific value with the increase of SOC,
the parameter values of all SOC can be summed and averaged as the new $\beta$.

The relationship between model parameters and SOC in (8) is used to recalculate $\alpha$, $\beta$, $\gamma$, $R_g$, and the model in Section VI is used to predict SOP. According to the prediction results, as depicted in Fig. 11 (b), the prediction accuracy is much improved, especially at SOC $= 0.9$, the prediction error is only 7.8%, while the overall prediction errors are around 3%, and the average error is 0.78%. Therefore, using (8) to describe the relationship between model parameters and SOC is very successful.

**C. DISCUSSION ON THE APPLICABILITY OF THE NPV MODEL**

According to the relationship between the polarization overpotential and Li$^+$ concentration, with the premise that the current direction remains unchanged, the polarization overpotential is related to the operating of current. Based on this relationship, the NPV model is obtained. Therefore, the NPV model is only applicable to the case of unidirectional current and cannot be applied to the case of current direction change, which is the limitation of this model. Since the parameters of the NPV model need to be identified by the data of continuous 3s current and voltage, specific test pulses are required, which also limits the range of use of the model. Although the polarization voltage model has certain limitations, in the case of fast charging, the charging current is very large, and the current direction does not change. Therefore, the polarization voltage model can be used to predict the battery voltage (as proved in Section VI.A). The BMS can use appropriate safety protection strategies according to the predicted voltage to avoid battery overcharge. SOP refers to the power at $t$-second ($t > 0$) reaches the cut-off voltage with a constant current. Therefore, the NPV model can also be used to predict SOP (as proved in Section VI.B), and a BMS can achieve the best energy management based on the predicted SOP.
VII. CONCLUSIONS AND OUTLOOK

The universally used Thevenin model is more suitable for dynamic simulation/synthesis of batteries rather than prediction, such as voltage and power. By simplifying the equations describing the polarization characteristics in the electrochemical battery model, this paper proposes the NPV model based on current and time. This model is simple and implementable to the high-precision prediction the voltage and SOP at t-second (t > 0) under any constant current (I ≠ 0). More importantly, only small-batch data is needed to identify the model parameters. Therefore, it is timesaving for practical testing with simple structures, which is suitable for battery simulation and state estimation/prediction, as well as for fast charging control and energy management.

The applicability and prediction accuracy of the NPV model under different state of health (SOH) need to be future verified. The correlation coefficient between model parameters and SOH needs to be deeply explored so as to realize online accurate voltage and power prediction over the whole life of the battery and provide more technique support for energy scheduling and fast charging of electric vehicles.

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