

Polarization-Induced SOC Mis-estimation in a Manned Electric Aircraft Battery: Cell Characterization, First-Flight Evaluation, and 2RC- EKF Correction

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Abstract: This study investigates voltage-based state-of-charge (SOC) mis-estimation and dynamic polarization in the KLA-100X, Korea's first manned electric-propulsion aircraft, using first-flight telemetry and bench tests of identical LG INR21700M50LT cells. Constant-current discharge tests at 25 °C and 1.01C, 2.02C, and 3.03C identified effective ohmic resistances of 22.18, 19.04, and 18.03 mΩ and polarization-relaxation time constants of 62.0–73.9 s. During cruise, the voltage-based SOC differed from the reference coulomb-counting SOC by an average of 21.4 percentage points (pp), with a maximum error of 26.4 pp. After time-aligning the equilibrium OCV decrease caused by SOC depletion, the 32.1 V cruise voltage drop was decomposed into an ohmic component of 21.5 V (67.0%) and a dynamic polarization component of 10.6 V (33.0%), equivalent to about 5.7 pp SOC. The flight-identified relaxation time constant was 47.7 s, approximately 35% shorter than the 25 °C bench-interpolated value of 73.3 s. Incorporating this value into a 2RC-EKF reduced the cruise SOC error from 21.4 to 4.4 pp and the overall SOC RMSE from 12.5 to 3.8 pp. Compared with a 1RC-EKF, the 2RC-EKF reduced pack-voltage prediction RMSE by 28.6% during the propulsion-load period.

Keywords: Manned electric aircraft; Battery management system; State of charge; Polarization; Second-order RC equivalent circuit model; Extended Kalman filter; Flight test

1. Introduction

Since the European Union Aviation Safety Agency (EASA) granted the world's first type certificate for a fully electric aircraft to the Pipistrel Velis Electro in June 2020 [1], the development of light electric aircraft has accelerated worldwide. In parallel, operational and safety performance standards for rechargeable lithium battery systems, such as RTCA DO-311A [2], have been established. Unlike conventional aircraft powered by internal-combustion engines, electric aircraft rely primarily on batteries as their propulsion energy source. Because the remaining energy cannot be measured directly during flight, accurate state-of-charge (SOC) estimation by the battery management system (BMS) plays an important role in safe energy management. Accordingly, SOC estimation accuracy is a key performance metric that directly affects flight safety margins and energy management. Underestimation of SOC may cause the pilot to perceive the remaining energy as lower than it actually is, whereas overestimation may lead to an overestimation of the available energy and thereby reduce the flight safety margin.

Voltage-based SOC estimation is simple to implement; however, substantial errors can occur under electric-aircraft operating conditions characterized by continuously varying loads. During discharge, the cell terminal voltage decreases relative to the open-circuit voltage (OCV), and this voltage drop consists of an instantaneous ohmic drop caused by internal resistance and a polarization voltage associated with electrochemical dynamics. In particular, polarization associated with charge-transfer and diffusion processes develops and relaxes over different time scales. Therefore, directly interpreting the terminal voltage under load as the equilibrium OCV can lead to SOC underestimation. After current interruption, these dynamic voltage components gradually relax, resulting in terminal-voltage recovery. Consequently, compensation based solely on ohmic resistance cannot adequately represent the time-dependent polarization voltage, and the dynamic voltage response of the battery must be considered for SOC estimation under actual operating loads.

Previous studies on batteries for electric aircraft have primarily focused on unmanned aerial vehicles or laboratory-scale conditions. Hogge et al. [3] verified algorithms for predicting the remaining flight time of small unmanned aircraft but did not quantify SOC estimation errors at the scale of manned aircraft. For unmanned aerial vehicles, extended Kalman filter (EKF)-based SOC and state-of-power (SOP) estimation [4] and retrospective validation of SOC estimates for small unmanned aircraft using a reverse-time Kalman approach [5] have been reported; however, these studies were limited to small unmanned platforms. Bills et al. [6] developed a battery dataset for electric vertical takeoff and landing

(eVTOL) aircraft, although the dataset was obtained from bench-level testing. Clarke and Alonso [7] proposed a battery model for electric-aircraft applications but did not address SOC estimation errors during actual flight. Yang et al. [8] investigated the high-rate discharge requirements of eVTOL batteries, whereas SOC estimation accuracy was outside the scope of their study. Therefore, within the literature reviewed by the authors, studies that quantitatively analyze load-dependent SOC estimation errors and polarization dynamics using actual telemetry from a manned electric aircraft and subsequently correct these errors through dynamic battery-model-based state estimation remain limited.

The KLA-100X, which served as the research platform in this study, is Korea's first manned electric-propulsion aircraft developed under the leadership of the Korea Aerospace Research Institute (KARI) [9]. On February 8, 2023, it successfully completed its 16.1-min maiden flight at the KARI Goheung Aviation Center. Electrical and thermal telemetry consisting of 191,667 data points acquired during the flight at a temporal resolution of 5 ms, together with bench characterization results obtained using the same LG INR21700M50LT cell model installed in the aircraft, provided the experimental basis for this study.

The main contributions of this study are threefold. First, constant-current discharge tests were conducted at 1.01C, 2.02C, and 3.03C using the same cell model installed in the aircraft. The effective ohmic resistance, R_0 , identified from the instantaneous voltage drop at the onset of discharge was 22.18, 19.04, and 18.03 m Ω , respectively. In addition, effective relaxation time constants of 73.1, 73.9, and 62.0 s were quantified from the post-discharge voltage-relaxation curves. These measurements provide an experimental basis for the ohmic resistance and slow polarization dynamics relevant to the actual flight operating range.

Second, analysis of the KLA-100X maiden-flight telemetry revealed that the difference between voltage-based SOC and coulomb-counting SOC reached an average of 21.4 percentage points (pp) and a maximum of 26.4 pp during cruise. Furthermore, decomposition of the voltage drops using time-aligned OCV showed that, under cruise conditions, the total voltage drop of 32.1 V consisted of an ohmic component of 21.5 V (67.0%) and a dynamic polarization component of 10.6 V (33.0%). This analysis quantitatively identifies the contribution of the dynamic voltage component that cannot be explained by simple ohmic-resistance compensation alone.

Third, a 2RC-EKF incorporating an in-flight effective time constant of 47.7 s, identified from the post-landing voltage relaxation, was applied to the actual flight data. The resulting

cruise SOC error was reduced by 80%, from 21.4 pp to 4.4 pp, while the overall SOC root-mean-square error (RMSE) decreased by 70%, from 12.5 pp to 3.8 pp. In addition, compared with the 1RC-EKF, the 2RC-EKF reduced the pack-voltage prediction RMSE by 28.6% over the actual propulsion-load period, demonstrating the practical benefit of accounting for polarization states with different time scales under actual flight conditions.

2. Battery Modeling and SOC Estimation Framework

2.1 2RC Equivalent Circuit and OCV-SOC Model

The second-order RC (second-order Thevenin) equivalent circuit model (ECM), which is used to represent the dynamic voltage behavior of lithium-ion batteries, consists of an open-circuit voltage source $V_{OCV}(SOC)$, an ohmic resistance R_0 , and two parallel RC elements representing polarization dynamics with different time scales [10, 11]. The cell terminal voltage is expressed as follows.

$$V(t) = V_{OCV}(SOC) - I(t) \cdot R_0 - V_{p1}(t) - V_{p2}(t) \quad (1)$$

where $I(t) > 0$ is defined as the cell current in the discharge direction. The dynamics of each RC state are expressed as follows:

$$\frac{dV_{pi}}{dt} = -\frac{V_{pi}}{\tau_i} + I(t) \cdot \frac{R_i}{\tau_i}, \quad \tau_i = R_i C_i, \quad (i = 1, 2), \quad (2)$$

The time constant of each polarization component is defined as $\tau_i = R_i C_i$ ($i = 1, 2$). Here, V_{p1} and V_{p2} represent the effective polarization voltages associated with the slow and fast time scales, respectively. These states represent lumped electrochemical dynamics and are not directly assigned to specific electrochemical mechanisms in the present study.

Under constant-current conditions, each polarization component approaches its steady-state value, $I \cdot R_i$, and relaxes exponentially after current interruption. Accordingly, the relaxation of the total polarization voltage, ΔV_{relax} , can be expressed as the sum of two exponential responses as follows.

$$\Delta V_{relax}(t) = V_{p1}(0)e^{-t/\tau_1} + V_{p2}(0)e^{-t/\tau_2} \quad (3)$$

A 2RC structure incorporating two distinct time constants is therefore more suitable than a 1RC model for simultaneously representing the short-term transient response to rapid propulsion-load changes and the longer-term polarization behavior during cruise.

The OCV–SOC relationship of the LG INR21700M50LT cell is inherently nonlinear. In

this study, however, the following linear approximation was adopted as a first-step model to evaluate the feasibility of real-time embedded implementation in the BMS of a light electric aircraft.

$$V_{OCV} = 3.0 + 1.2 \cdot SOC \quad (4)$$

Here, SOC is normalized to a range of 0–1. Because the operating SOC range during this flight was limited to approximately 84–95%, a linear OCV–SOC approximation was applied over this range. However, the inherent nonlinearity and temperature dependence of the actual OCV–SOC relationship may contribute to the residual SOC estimation error; their effects are discussed in Section 7. Future work will incorporate a high-resolution OCV–SOC look-up table obtained using the Galvanostatic Intermittent Titration Technique (GITT), together with temperature-dependent model parameters [12–14].

2.2 EKF Formulation and Discrete State-Space Model

The EKF estimates the SOC and polarization states by combining a process model based on coulomb counting with a measurement model based on the observed pack voltage, while accounting for process and measurement uncertainties. The state vector is defined as follows.

$$\mathbf{x}_k = [SOC_k \quad V_{p1,k} \quad V_{p2,k}]^T \quad (5)$$

Here, SOC represents the battery state of charge, while V_{p1} and V_{p2} denote the polarization-voltage states associated with the slow and fast time scales, respectively.

The general discrete-time state equation and measurement equation of the EKF are expressed as follows.

$$\mathbf{x}_{k+1} = f(\mathbf{x}_k, I_k) + \mathbf{w}_k, \quad \mathbf{w}_k \sim N(0, Q) \quad (6)$$

$$y_k = h(\mathbf{x}_k, I_k) + n_k, \quad n_k \sim N(0, R) \quad (7)$$

Here, $\mathbf{x}_k$ denotes the state vector, and y_k is the measured pack terminal voltage at the k -th sample. The terms $\mathbf{w}_k$ and n_k represent the process noise and measurement noise, respectively, while Q and R denote the corresponding noise covariance matrices.

The continuous-time differential equations in Equation (2) were discretized using the zero-order hold (ZOH) method, assuming that the current remains constant over each sampling interval. By applying the ZOH formulation, the exponential responses of the RC states can be represented directly in discrete-time state equations. The discrete-time state equations for SOC and the two polarization voltages are given as follows.

$$159 \quad \text{SOC}_{k+1} = \text{SOC}_k - \frac{I_k}{n_p} \cdot \frac{\Delta t}{3600 \cdot Q_{cell}} \quad (8)$$

$$160 \quad V_{p1,k+1} = V_{p1,k} \cdot \exp\left(-\frac{\Delta t}{\tau_1}\right) + R_1 \cdot \left[1 - \exp\left(-\frac{\Delta t}{\tau_1}\right)\right] \cdot \frac{I_k}{n_p} \quad (9)$$

$$161 \quad V_{p2,k+1} = V_{p2,k} \cdot \exp\left(-\frac{\Delta t}{\tau_2}\right) + R_2 \cdot \left[1 - \exp\left(-\frac{\Delta t}{\tau_2}\right)\right] \cdot \frac{I_k}{n_p} \quad (10)$$

162 Here, $I_k > 0$ denotes the pack current in the discharge direction, $n_p = 9$ is the equivalent
 163 number of parallel cells, $Q_{cell} = 4.95 \text{ Ah}$ is the rated cell capacity, and Δt is the sampling
 164 interval. The factor 3600 converts the time unit from seconds to hours (s→h). Dividing the
 165 cell current, $\frac{I_k}{n_p}$, by the cell capacity, Q_{cell} , is mathematically equivalent to dividing the pack
 166 current, I_k , by the pack capacity of 44.55 Ah. This formulation was applied consistently to
 167 both the reference coulomb-counting calculation and the EKF process model.

168 The measurement model uses the measured pack terminal voltage. Considering the
 169 number of series-connected cells in the KLA-100X, $n_s = 156$, the predicted pack voltage is
 170 expressed as follows.

$$171 \quad V_{\text{pack,pred},k} = n_s \left[V_{OCV}(\text{SOC}_k) - \frac{I_k}{n_p} R_0 - V_{p1,k} - V_{p2,k} \right] \quad (11)$$

172 In the prediction step, the SOC and the two polarization states are propagated using
 173 **Equations** (8)–(10). In the update step, the states are corrected using the innovation,
 174 defined as the difference between the measured pack voltage and the predicted voltage
 175 from **Equation** (11). Through this procedure, the polarization voltages V_{p1} and V_{p2} , which
 176 cannot be measured directly, are estimated as internal states, and the influence of dynamic
 177 polarization associated with load variations is reflected in the SOC estimation.

178 The Jacobian of the measurement model is expressed as

$$179 \quad \mathbf{H}_k = \frac{\partial h}{\partial \mathbf{x}} = \left[n_s \frac{\partial V_{OCV}}{\partial \text{SOC}} \quad -n_s \quad -n_s \right] \quad (12)$$

180 For the linear OCV–SOC relationship adopted in **Equation** (4),

$$181 \quad \frac{\partial V_{OCV}}{\partial \text{SOC}} = 1.2 \quad (13)$$

182 Therefore, for $n_s = 156$,

$$183 \quad \mathbf{H}_k = [187.2 \quad -156 \quad -156] \quad (14)$$

This yields Equation (14). Therefore, within the linear OCV–SOC approximation adopted in this study, the measurement Jacobian remains constant. The model error introduced by approximating the inherently nonlinear OCV–SOC relationship as linear may contribute to the residual SOC estimation error, and this limitation is discussed in Section 7. The EKF process- and measurement-noise covariance matrices, Q and R , are key design parameters that affect the Kalman gain, filter convergence, and estimation performance [15]. In addition, ECMs incorporating the temperature dependence of resistance and time constants have been reported to improve estimation accuracy over a wide temperature range [13,14].

In this study, the EKF framework was adopted to allow future implementation of the actual nonlinear OCV–SOC relationship and SOC- and temperature-dependent model parameters. However, under the present assumptions of a linear OCV–SOC approximation and fixed ECM parameters, both the state and measurement equations are linear with respect to the state variables. Consequently, the EKF is mathematically equivalent to a linear Kalman filter under the present formulation. Therefore, the primary focus of this study is not the nonlinear estimation capability of the EKF itself, but rather the correction of voltage-based SOC errors by incorporating polarization dynamics identified from actual flight data into the state-estimation model. The method proposed in this study is referred to as an EKF with this extensibility in mind, allowing the same EKF framework to be retained in future studies incorporating nonlinear OCV relationships or SOC- and temperature-dependent parameters, with the corresponding model functions and Jacobians updated as required.

3. KLA-100X Aircraft and Battery System

3.1 Aircraft and Battery System

The KLA-100X shown in Figure 1 is a single-seat manned electric aircraft developed by replacing the internal-combustion engine of the KLA-100, a two-seat light sport aircraft manufactured by Vessel Aerospace, with a 65 kW-class electric propulsion system. The aircraft was developed under the leadership of the Korea Aerospace Research Institute (KARI) with support from the Korea Evaluation Institute of Industrial Technology (KEIT), Ministry of Trade, Industry and Energy (Project No. 20003470). The electric propulsion system comprises a propulsion motor (AMOTECH, APM151-65, 65 kW PMSM), an inverter (J&S, ITM-22, SiC MOSFET, 96.1% efficiency), and a battery system and BMS supplied by V-Space [9]. On February 8, 2023, the KLA-100X successfully completed its maiden flight

at the Goheung Aviation Center, marking the first flight of a manned electric aircraft in Korea. The key specifications of the KLA-100X aircraft, electric propulsion system, and battery system are summarized in Table 1.



Figure 1. KLA-100X ground and first-flight test scenes: (a) ground motor test at the Goheung Aviation Center, 2022; (b) first-flight takeoff at the Goheung Aviation Center on February 8, 2023.

Table 1. Key specifications of KLA-100X and battery system.

Item	Specification	Source
Aircraft configuration	Modified KLA-100, single-seat	Vessel Aerospace
Propulsion motor	PMSM, 65 kW (APM151-65)	AMOTECH
Inverter	SiC MOSFET, 96.1% efficiency (ITM-22)	J&S
Battery cell	LG INR21700M50LT (21700, 4.95 Ah, 3.7 V)	[16]
Battery pack configuration	156S (front: 156S6P + rear: 156S3P; equivalent 9P)	V-Space Co., Ltd.
Nominal pack voltage / total energy	577.2 V / 25.7 kWh	Calculated
Total number of cells	1,404 (= 156 × 9P)	V-Space Co., Ltd.
BMS	STM32, passive balancing, CAN communication	V-Space Co., Ltd.
First flight	February 8, 2023, Goheung Aviation Center	[9]

3.2 Battery System Architecture

The KLA-100X battery system consists of a total of 1,404 LG INR21700M50LT cylindrical cells, corresponding to an overall equivalent configuration of 156S9P. The battery pack has a nominal voltage of 577.2 V and a total energy capacity of 25.7 kWh. The battery system is physically divided into a front pack (156S6P) and a rear pack (156S3P), which are connected in parallel to the propulsion inverter. Each pack employs an STM32-based BMS

for cell-state monitoring and incorporates passive balancing and CAN communication functions.

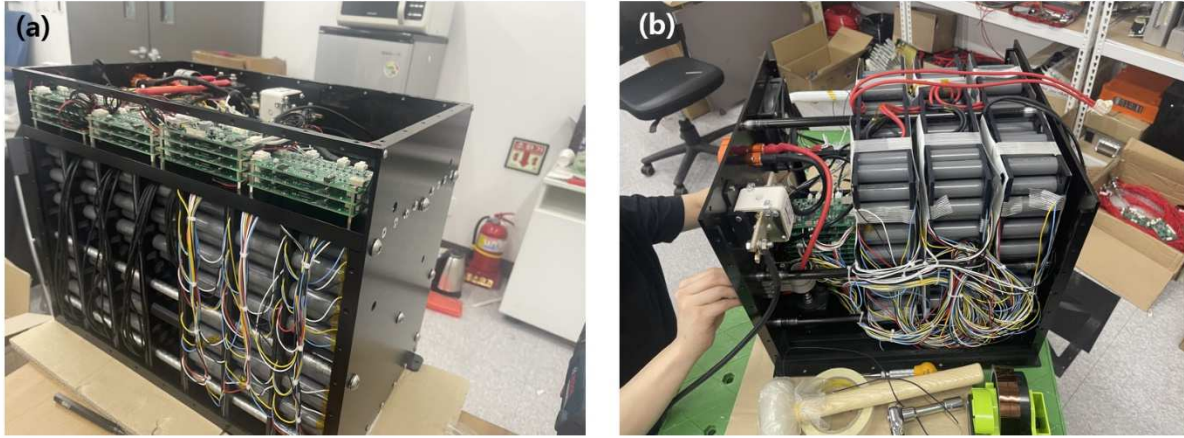


Figure 2. Internal configuration of the KLA-100X battery pack (LG INR21700M50LT cells, 156S configuration): (a) front pack (156S6P); (b) rear pack (156S3P).

To satisfy the aircraft center-of-gravity (CG) balance and structural space constraints, the front and rear packs adopt asymmetric parallel configurations of 6P and 3P, respectively. Both packs have the same 156S series configuration and are connected in parallel to the DC bus of the propulsion inverter. **Figure 2** shows the internal configurations of the front and rear battery packs of the KLA-100X, including the arrangement of the cylindrical cells and the placement of the BMS boards. In the present SOC estimation model, however, the front and rear packs are treated as a single equivalent 9P pack, and the current distribution between the two packs is beyond the scope of this study.

4. Cell Characterization and Parameter Identification

4.1 Test Conditions and Ohmic Resistance Identification

The objective of the bench tests was to experimentally characterize the 2RC ECM parameters over the C-rate range relevant to KLA-100X operation, including the cruise condition of approximately 1.26C per cell, and thereby establish an experimental basis for EKF parameterization. Methodologies for identifying the SOC-, current-, and temperature-dependent characteristics of equivalent-circuit parameters from current-step responses have been widely applied to lithium-ion cells [17]. The test cell was an LG INR21700M50LT, identical to the cell model installed in the aircraft. The charging protocol consisted of constant-current (CC) charging at 0.3C to 4.20 V followed by constant-voltage (CV) charging at 4.20 V in a 25 °C chamber. Charging was terminated when the current

decreased to 50 mA, after which the cell was allowed to rest for 30 min. Cell voltage and surface temperature were recorded simultaneously at 100 Hz. Each test dataset included 30 min of pre-stabilization logging before the onset of discharge. An automatic discharge-onset detection procedure was applied to define the start of discharge in each test as $t = 0$, and the average of the five samples immediately preceding discharge initiation was used as V_{OCV} . The three test conditions are summarized in Table 2.

Table 2. Discharge test conditions.

Test	Current	C-rate	Initial V_{OCV}	Cut-off Voltage	Relaxation Duration	Relevance to Flight Operation
T-1	5 A	1.01C	4.202 V	2.5 V	34.2 min	Lower bound of cruise condition (1.26C)
T-2	10 A	2.02C	4.196 V	2.5 V	20.4 min	Upper bound encompassing cruise condition (1.26C)
T-3	15 A	3.03C	4.186 V	2.5 V	33.9 min	Above maximum takeoff load

The instantaneous voltage-drop method calculates R_0 from the difference between V_{OCV} immediately before current application and the terminal voltage $V_t(0^+)$ immediately after current application, as follows:

$$R_0 = \frac{V_{OCV} - V_t(0^+)}{I} \quad (15)$$

Assuming that the initial polarization voltage is small after a sufficiently long pre-test rest period, the voltage drop immediately after current application primarily reflects the ohmic resistance component. However, because $V_t(0^+)$ is obtained at a finite sampling interval, it may include part of the very fast electrochemical transient response. Therefore, the R_0 value calculated here is interpreted as an experimentally identified effective ohmic resistance.

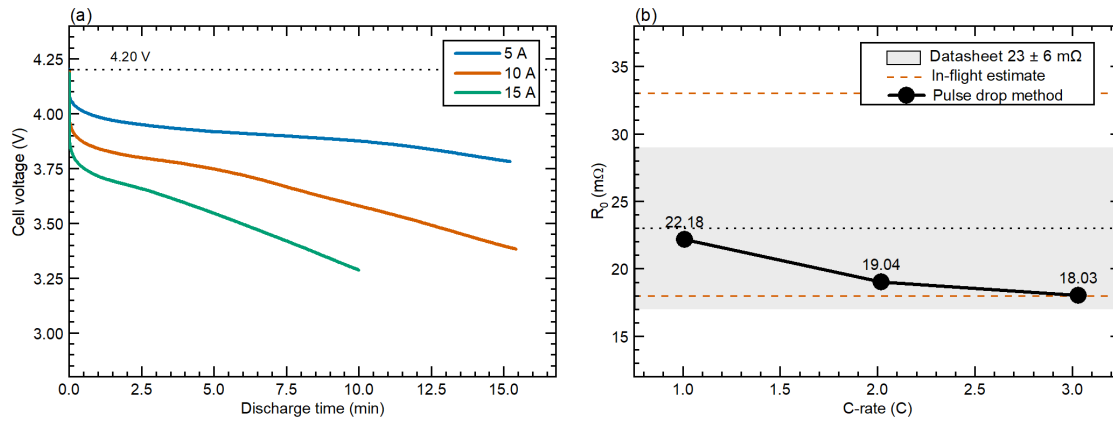


Figure 3. C-rate-dependent discharge behavior and R_0 estimation: (a) cell voltage profiles; (b) R_0 estimated using the instantaneous voltage-drop method.

As shown in **Figure 3(a)**, the voltage drop immediately after current application and the subsequent voltage decrease during discharge became more pronounced as the C-rate increased. The R_0 values estimated using the instantaneous voltage-drop method were 22.18, 19.04, and 18.03 m Ω at 1.01C, 2.02C, and 3.03C, respectively, as shown in **Figure 3(b)**. All values lie within the resistance range of 17–29 m Ω specified in the datasheet, confirming the validity of the measurement procedure. Although the measured R_0 values showed a slight decreasing trend with increasing C-rate, this trend was not interpreted as an intrinsic C-rate dependence because of differences in the initial measurement timing and SOC conditions among the tests. The increase in cell temperature during the subsequent discharge process was not directly used in determining R_0 immediately after current application and was instead examined together with the relaxation behavior in **Section 4.2**.

The R_0 values obtained using the instantaneous voltage-drop method under the different C-rate conditions are summarized in **Table 3**. For the 5 A test, the earliest valid post-discharge voltage value at $t = 0.1$ s was used, whereas $t = 0.01$ s was used for the 10 and 15 A tests. Therefore, considering the possible influence of differences in measurement timing on the estimated values, the results were interpreted primarily as an experimentally observed range rather than as quantitative evidence of an intrinsic C-rate dependence among the three tests.

Table 3. R_0 estimated using the instantaneous voltage-drop method at different C-rates.

C-rate / Reference	Current, I (A)	V_{OCV} (V)	$V_t(0^+)$ (V)	R_0 (m Ω)	Remarks
1.01C	5	4.202	4.091	22.18	Measured at $t = 0.1$ s
2.02C	10	4.196	4.006	19.04	Measured at $t = 0.01$ s
3.03C	15	4.186	3.916	18.03	Measured at $t = 0.01$ s
Datasheet [16]	0.5C	—	—	23 ± 6	Reference at 50% SOC

4.2 Relaxation and Polarization Time-Constant Identification

After completion of discharge, the effective time constant τ was obtained by nonlinear least-squares fitting of a single-exponential model to the voltage-recovery curve

measured from the instant of current interruption, and the results are summarized in Table 4. In this study, the purpose of the single-exponential fitting was not to directly separate individual electrochemical processes, but rather to quantify the dominant time scale of the voltage-relaxation behavior following current interruption. The voltage-recovery model was defined as

$$V_{\text{relax}}(t_{\text{rel}}) = V_{\infty} - \Delta V_{\text{rel}} e^{-t_{\text{rel}}/\tau} \quad (16)$$

where V_{∞} is the estimated equilibrium voltage after sufficient relaxation, ΔV_{rel} is the voltage-recovery amplitude, t_{rel} is the elapsed time after current interruption, and τ is the effective relaxation time constant.

For reproducibility, the same fitting interval from immediately after current interruption ($t_{\text{rel}} = 0$) to 600 s was used for all three test conditions, and no initial-sample exclusion or weighting was applied (unweighted least-squares fitting). When the fitting interval was changed to 300 or 900 s, the estimated τ varied by up to approximately $\pm 15\%$, depending on the test condition. Therefore, the τ values obtained in this study are interpreted as effective time constants associated with the selected fitting window rather than as intrinsic electrochemical constants.

Table 4. Results of single-exponential fitting for the voltage relaxation curves.

C-rate	Voltage Recovery Amplitude, ΔV_{rel} (V)	Time Constant, τ (s)	R^2	Temperature Rise During Discharge ($^{\circ}\text{C}$)
1.01C (5 A)	0.163	73.1 ± 0.7	0.8964	+4.8
2.02C (10 A)	0.313	73.9 ± 0.1	0.9654	+18.3
3.03C (15 A)	0.427	62.0 ± 0.1	0.9515	+29.4

Figure 4 presents the voltage-recovery curves after discharge termination together with the corresponding single-exponential fitting results. The identified time constants ranged from 62.0 to 73.9 s under the three test conditions, indicating a common slow voltage-recovery time scale on the order of tens of seconds despite the differences in C-rate. However, the time constant obtained from single-exponential fitting alone cannot be directly attributed to a specific electrochemical mechanism, such as diffusion or charge transfer. Therefore, in this study, it was treated as an effective polarization-relaxation time constant representing the overall voltage-recovery behavior. As an auxiliary analysis, a bi-exponential model can separate relatively fast and slow components; however, because no independent physical identification based on electrochemical impedance spectroscopy (EIS) or the galvanostatic intermittent titration technique (GITT) was performed, the individual

time constants were not directly assigned to specific electrochemical processes. The existence of these two characteristic time scales was subsequently used as the basis for representing effective polarization states with different dynamic responses in the 2RC model.

The voltage-recovery amplitude increased with C-rate, from 0.163 V to 0.313 V and 0.427 V. This indicates that a larger dynamic voltage deviation was established immediately before current interruption under the higher-discharge-current conditions. However, all three tests were conducted after discharge to 2.5 V, and the temperature rise during discharge also differed substantially among the test conditions. Therefore, the resulting values were not directly transferred to the high-SOC operating range of the maiden flight for quantitative polarization estimation. Instead, these results were used as an experimental basis for the existence of a slow relaxation component on the order of tens of seconds and for selecting the initial parameter range. A quantitative comparison with the flight data is discussed in [Section 7](#).

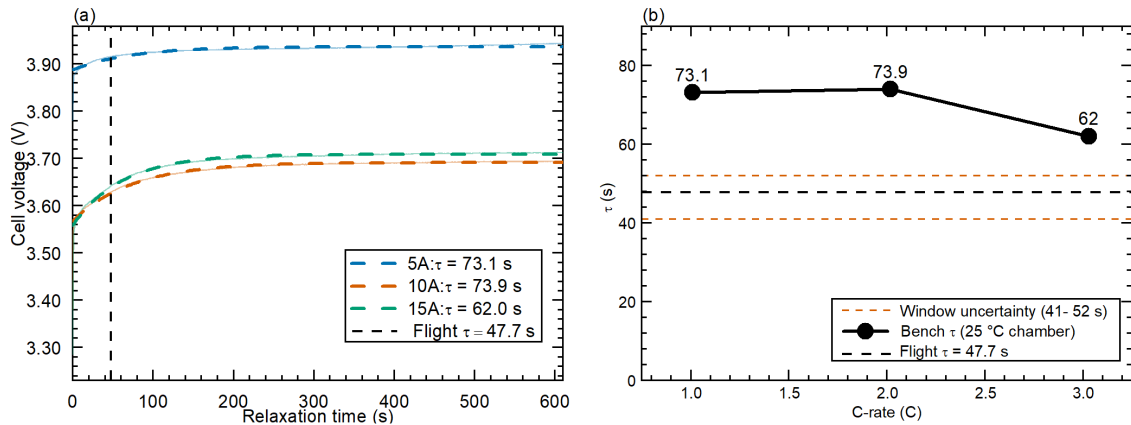


Figure 4. Voltage relaxation and time-constant characteristics: (a) voltage relaxation curves and single-exponential fits; (b) relaxation time constant versus C-rate.

5. First-Flight SOC Mis-estimation and Polarization Analysis

5.1 First-Flight Conditions and SOC Mis-estimation

The maiden flight was conducted on February 8, 2023, at the Goheung Aviation Center under an ambient temperature of 13.4 °C and an atmospheric pressure of 1,012 hPa. During the flight, 191,667 data points were acquired at a sampling interval of 5 ms (200 Hz). The measured channels included pack terminal voltage, front- and rear-pack branch currents, motor winding temperature, and inverter board temperature. Based on the electrical load characteristics during flight, the operating profile was divided into four

phases: Ground/Taxi, Takeoff/Climb, Cruise, and Descent/Landing. The average operating conditions for each phase are summarized in [Figure 5](#) and [Table 5](#).

[Figure 5](#) shows the temporal variations in pack voltage, battery current, propulsion power, and motor/inverter temperatures during the maiden flight. [Table 5](#) summarizes the corresponding average values for each flight phase. During the Ground/Taxi phase, the average current and power remained low at 1.7 A and 1.1 kW, respectively. During Takeoff/Climb, the current and power increased transiently to maximum values of 74.5 A and 44.9 kW. During Cruise, a sustained high-load condition was maintained, with an average current of 55.9 A, an average power of 33.2 kW, and a cell C-rate of 1.26C; under this condition, the average pack voltage decreased to its minimum value of 594.2 V. At the same time, the motor and inverter temperatures increased, reaching maximum values of 63.3 °C and 34.5 °C, respectively. During Descent/Landing, the average current and power decreased to 11.1 A and 6.6 kW, while the pack voltage recovered to 609.4 V. These load-dependent voltage drops and recovery characteristics were subsequently used in [Section 5.2](#) as the basis for separating the ohmic voltage drop from the dynamic polarization component.

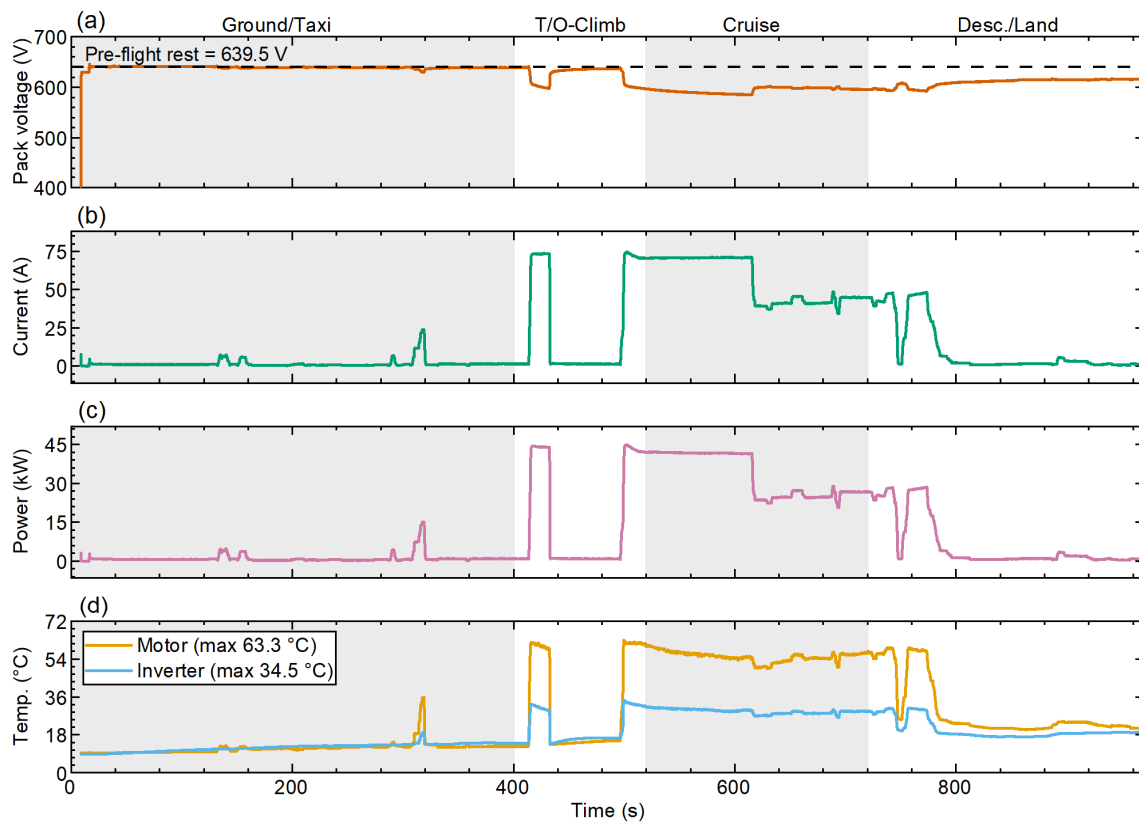


Figure 5. Electrical and thermal profiles during the first flight of the KLA-100X: (a) pack voltage; (b) battery current; (c) propulsion power; (d) motor and inverter temperatures.

Table 5. Electrical and thermal characteristics during different flight phases.

Flight Phase	Time (s)	V_{avg} (V)	I_{avg} (A)	P_{avg} (kW)	Cell C-rate	T_{motor} (°C)
Ground/Taxi	0–400	639.2	1.7	1.1	0.04C	11.6
Takeoff/Climb	400–520	624.7	24.7	14.9	0.55C	29.7
Cruise	520–720	594.2	55.9	33.2	1.26C	55.1
Descent/Landing	720–967	609.4	11.1	6.6	0.25C	29.7

Figure 6 shows the variations in voltage-based SOC and coulomb-counting SOC during the maiden flight, together with the SOC estimation error between the two methods. The voltage-based SOC was calculated by applying the linear OCV–SOC relationship to the cell voltage ($V_{pack}/156$), whereas the coulomb-counting SOC was obtained by setting the initial SOC to approximately 95% and integrating the pack current over time using the pack capacity of 44.55 Ah (= 4.95 Ah × 9P). In this study, the coulomb-counting SOC was used as the reference SOC for evaluating the voltage-based SOC error.

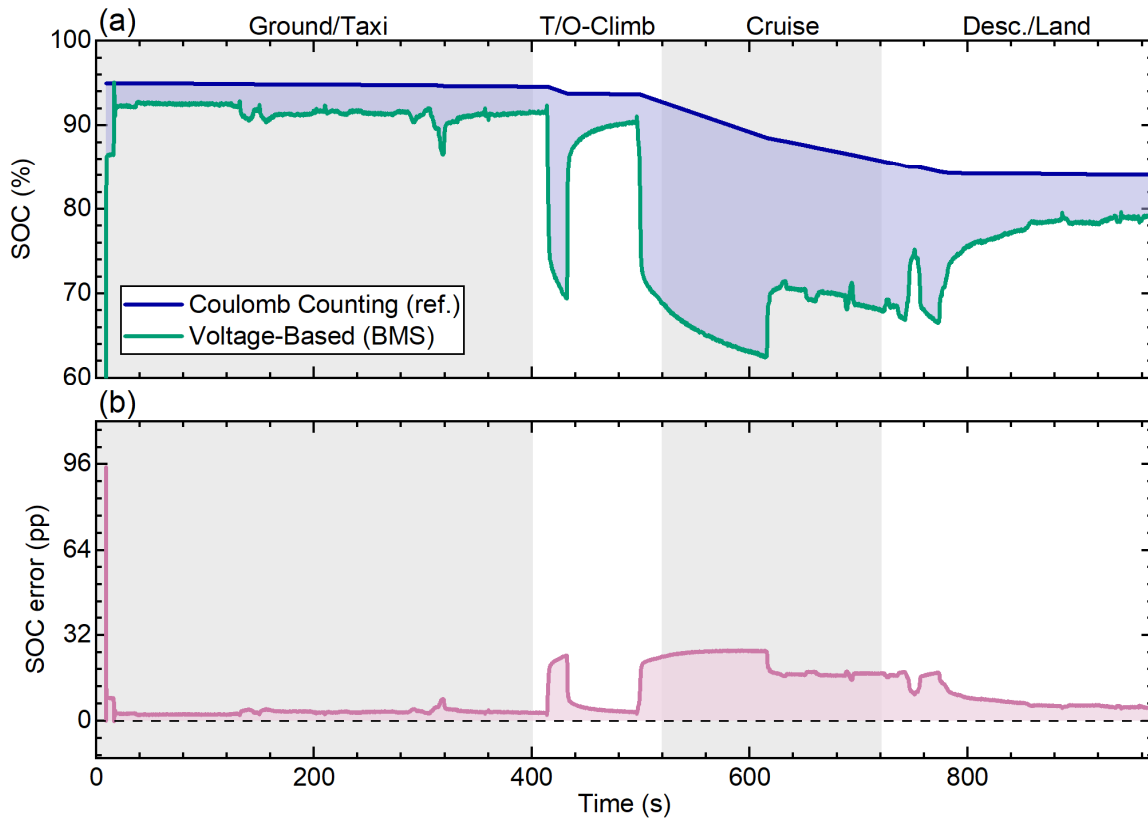


Figure 6. SOC estimation and error during the first flight of the KLA-100X: (a) voltage-based and coulomb-counting SOC; (b) SOC estimation error.

During the initial Ground/Taxi phase, the two SOC estimates remained relatively close. However, as the load increased during Takeoff/Climb, the voltage-based SOC decreased rapidly, and the discrepancy from the coulomb-counting SOC increased. During Cruise, the coulomb-counting SOC remained at an average of 88.8%, whereas the voltage-based SOC decreased to an average of 67.4%, resulting in a mean error of 21.4 percentage points (pp) and a maximum error of 26.4 pp. During Descent/Landing, the reduction in load caused the voltage-based SOC to increase again, thereby decreasing the estimation error. The phase-wise SOC differences are summarized in **Table 6**.

Table 6. SOC comparison and polarization interpretation across flight phases.

Flight Phase	SOC _{vol} (%)	SOC _{cc} (%)	Error (pp)	Polarization Interpretation
Ground/Taxi	91.5	94.8	3.3	Low current: negligible polarization
Takeoff/Climb	83.7	93.8	10.1	Increasing current: polarization buildup
Cruise (average)	67.4	88.8	21.4	Sustained high load: large and relatively stable SOC error
Descent/Landing	75.5	84.4	8.8	Decreasing current: polarization relaxation
After complete stop	79.0	84.1	5.1	Further voltage recovery after current removal

The phase-wise error variation summarized in **Table 6** is qualitatively consistent with the polarization dynamics described by **Equation (2)**. While the SOC error increased to an average of 21.4 pp during Cruise, the voltage-based SOC recovered by approximately 3.5 pp, from 75.5% to 79.0%, after landing when the propulsion current was nearly removed. During the same period, the coulomb-counting SOC remained nearly unchanged at approximately 84.1%. Therefore, this SOC recovery can be interpreted as resulting from terminal-voltage recovery following load removal rather than from an actual increase in the remaining charge. This observation supports the contribution of dynamic polarization to the voltage-based SOC estimation error.

Meanwhile, the coulomb-counting SOC is obtained by integrating the measured flight current and therefore does not constitute a fully independent SOC reference. However, the SOC uncertainty estimated by accumulating the current-sensor measurement uncertainty ($\pm 0.5\%$) over the flight duration was approximately 0.2 pp, which is substantially smaller

than the mean error of 21.4 pp observed during Cruise. Thus, the large SOC deviation observed in this flight cannot be explained solely by current-measurement uncertainty. Future work should perform independent SOC validation using the post-flight recharge capacity or OCV measurements after a sufficiently long rest period.

5.2 Polarization Decomposition and Flight Relaxation

The total voltage drop during Cruise was decomposed into ohmic and polarization components. To separate the OCV decrease associated with SOC depletion from the polarization component, the equilibrium OCV at the mean cruise SOC (88.8%) was estimated as 626.3 V using the local OCV–SOC slope of 2.21 V/pp connecting two quasi-static OCV anchor points: the pre-flight open-circuit condition (639.5 V at SOC 94.8%) and the post-landing relaxed condition (615.8 V at SOC 84.1%). Based on this value, the total voltage drop during Cruise was defined as

$$\Delta V_{total} = 626.3 - 594.2 = 32.1 \text{ V} \quad (17)$$

The ohmic voltage drop was calculated as

$$\Delta V_{ohmic} = I_{avg} \cdot R_{pack} = 55.9 \times \left(156 \times 22.18 \times \frac{10^{-3}}{9} \right) = 21.5 \text{ V (67.0\%)} \quad (18)$$

and the remaining polarization component was

$$\Delta V_{polar} = 32.1 - 21.5 = 10.6 \text{ V (33.0\%)} \quad (19)$$

After time alignment of the OCV, the polarization component accounted for 33.0% (10.6 V) of the total voltage drop, whereas the ohmic component accounted for 67.0% (21.5 V). The magnitude of the polarization component was comparable to the voltage recovery observed in the post-landing relaxation curve ($\Delta V = 8.3 \text{ V}$), showing consistency between two separate post-landing and in-flight observations. In contrast, if the pre-flight open-circuit voltage of 639.5 V were directly used as the cruise OCV without accounting for SOC depletion, the apparent total voltage drop would increase to 45.3 V. This indicates that the time alignment procedure is necessary to remove the equilibrium OCV decrease caused by SOC depletion. The polarization component of 10.6 V/pack (0.068 V/cell) corresponds to an SOC difference of approximately 5.7 pp based on the linear OCV–SOC slope of Equation (4), indicating that a dynamic polarization model is required to account for the voltage component that cannot be eliminated by ohmic-resistance compensation alone.

A single-exponential fit was applied to the pack-voltage recovery curve during the low-load post-landing relaxation period ($t_{rel} = 790 - 940$ s; the shutdown transient at the end of the record was excluded; average residual taxi current = 2.0 A).

$$V_{pack}(t_{rel}) = 615.83 - 8.34 \cdot \exp\left(-\frac{t_{rel}}{47.7}\right), \quad R^2 = 0.946 \quad (20)$$

The flight-identified effective time constant, $\tau = 47.7 \pm 0.2$ s, was approximately 35% shorter than the 25 °C bench-test value of approximately 73.3 s interpolated for the same C-rate (1.26C) from the 0–600 s fitting results at 1.01C and 2.02C. Depending on the selection of the start and end points of the in-flight fitting interval, τ_1 varied within the range of 41–52 s, mainly owing to residual taxi-current fluctuations and treatment of the end-of-record data. The influence of this uncertainty on the EKF was therefore examined through a sensitivity analysis.

The shorter time constant observed during flight suggests that the temperature and load conditions during actual operation differed from those of the 25 °C bench tests. However, because the cell temperature was not measured directly during the flight, the increase in cell temperature cannot be quantified accurately using only the measured motor temperature (maximum 63.3 °C) and inverter temperature (maximum 34.5 °C). The possible temperature dependence of the time constant is discussed quantitatively in [Section 7](#). Accordingly, the measured value is interpreted not as an intrinsic electrochemical constant under a fixed 25 °C condition, but as an effective dynamic parameter obtained under the actual flight environment. From the perspective of EKF design, this actual operating-condition parameter should therefore be reflected preferentially.

6. 2RC-EKF Correction and Flight-Data Evaluation

6.1 2RC-EKF Parameterization and Sensitivity

The 2RC-EKF parameters used in this study and the basis for their selection are summarized in [Table 7](#). The key design decision was to use the flight-identified value of τ_1 (47.7 s), rather than the 25 °C bench-interpolated value (approximately 73.3 s). Use of the bench value would underestimate the polarization-relaxation rate under the flight environment, potentially leading to an excessive residual polarization voltage and, consequently, an SOC estimation error. Therefore, the use of the flight-identified τ_1 is not simply a matter of parameter tuning; rather, it is intended to reflect differences in effective

dynamics arising from the temperature and actual load conditions of the flight environment.

Specifically, the ohmic resistance R_0 was identified using the instantaneous voltage-drop method described in Section 4.1, while the slow polarization time constant τ_1 was set to the effective value of 47.7 s obtained from the single-exponential fitting of the post-landing voltage-relaxation curve in Section 5.2. R_1 was selected to reproduce the quantified in-flight polarization magnitude. In contrast, because the fast polarization parameters R_2 and τ_2 could not be independently identified from the flight data alone, representative values within the acceptable range confirmed through the sensitivity analysis in Table 8 were selected as 3.0 mΩ and 5.0 s, respectively.

Table 7. 2RC-EKF parameters and basis for parameter selection.

Parameter	Symbol	Value	Basis for Selection
Ohmic resistance	R_0	22.18 mΩ	Instantaneous voltage-drop method, bench test T-1 (1.01C $\approx$ cruise condition)
Slow polarization resistance	R_1	8.0 mΩ	Representative value based on slow-polarization voltage-response decomposition
Slow polarization time constant	τ_1	47.7 s	Post-flight relaxation fit (Equation (20)); in-flight effective time constant
Fast polarization resistance	R_2	3.0 mΩ	Representative value selected from sensitivity analysis
Fast polarization time constant	τ_2	5.0 s	Representative value selected from sensitivity analysis
OCV–SOC model	V_{OCV}	$3.0 + 1.2 \cdot \text{SOC}$	Linear approximation
Pack capacity	Q	44.55 Ah = 4.95 $\times$ 9P	Cell specification $\times$ pack configuration
Process-noise covariance	Q_{proc}	$diag[5 \times 10^{-9} \ 10^{-9} \ 10^{-9}]$	Tuning
Measurement-noise covariance	R_{meas}	1.5 V ²	Tuning

The cruise segment of the present flight profile can be regarded as a quasi-steady-state discharge condition compared with the rapid current fluctuations occurring during other flight phases. Because the current was sustained for a period sufficiently longer than the fast time constant, $\tau_2 \approx 5$ s, V_{p2} is expected to approach its steady-state value, $I_{cell} \cdot R_2$, during most of the cruise segment. Accordingly, the influence of uncertainty in τ_2 is expected to be limited. To quantitatively assess this effect, the sensitivity of the 2RC-EKF

SOC RMSE was evaluated for combinations of $R_2 \in \{1, 3, 5, 8\}$ m Ω and $\tau_2 \in \{2, 5, 10, 20\}$ s, as summarized in [Table 8](#).

Table 8. Sensitivity analysis of 2RC-EKF SOC RMSE with respect to R_2 and τ_2 .

R_2 (m Ω)	$\tau_2 = 2$ s	$\tau_2 = 5$ s	$\tau_2 = 10$ s	$\tau_2 = 20$ s
1	4.17	4.17	4.17	4.16
3 (Baseline)	3.78	3.78	3.78	3.76
5	3.42	3.42	3.42	3.40
8	2.97	2.97	2.96	2.94

Across all parameter combinations, the RMSE ranged from 2.94 to 4.17 pp. The effect of varying τ_2 from 2 to 20 s was less than 0.05 pp for all values of R_2 , indicating a practically negligible influence. Variation of R_2 from 1 to 8 m Ω produced an RMSE change of up to approximately 0.84 pp relative to the baseline value of 3.78 pp, which is limited compared with the overall 8.7 pp improvement relative to the voltage-based SOC method. These results indicate that, under the quasi-steady polarization behavior observed during flight, the influence of the slow polarization component (R_1, τ_1) is relatively greater than that of the fast component (R_2, τ_2), and that precise identification of R_2 and τ_2 has only a limited effect on the main conclusions of this study. This sensitivity analysis was not intended to optimize the parameters to minimize RMSE using the same flight dataset, but rather to assess the robustness of the estimation results with respect to the selected parameter values.

In addition, when τ_1 was varied over the flight-fitting-window uncertainty range of 41–52 s, the RMSE remained essentially unchanged at 3.78 pp. This confirms that the uncertainty associated with the fitting-window selection in [Equation \(20\)](#) does not materially affect the main EKF results.

6.2 Flight-Data Evaluation of the 2RC-EKF

For a fair comparison, the voltage-based (VB) method, the first-order RC EKF (1RC, single-polarization-state model), and the second-order RC EKF (2RC) were evaluated using the same dataset and common parameter conditions. The 1RC-EKF employed the state vector $[\text{SOC } V_{p1}]^T$ with the same $\tau_1 = 47.7$ s. Although previous studies have proposed pack-level SOC estimation methods that combine representative-cell selection and data-driven correction [\[18\]](#), the present study applied the ECM-based EKF structure to all measurement data in order to evaluate the effects of polarization-state modeling under actual flight conditions. All three estimators were evaluated on the same 0.5 s time grid.

As shown in **Figures 7(a)** and **7(b)**, the voltage-based SOC deviated substantially from the reference SOC after the propulsion load increased during Takeoff/Climb, and the maximum discrepancy persisted during Cruise. In contrast, the 1RC- and 2RC-EKF methods tracked the reference SOC more stably by representing the load-dependent dynamic voltage drop through polarization states. **Figure 7(c)** shows that the polarization voltages increased after takeoff; during Cruise, the slow effective polarization component V_{p1} developed predominantly, whereas the fast effective polarization component V_{p2} responded mainly to rapid load variations. After landing, both components gradually relaxed. These behaviors are consistent with the phase-wise variation in SOC estimation error.

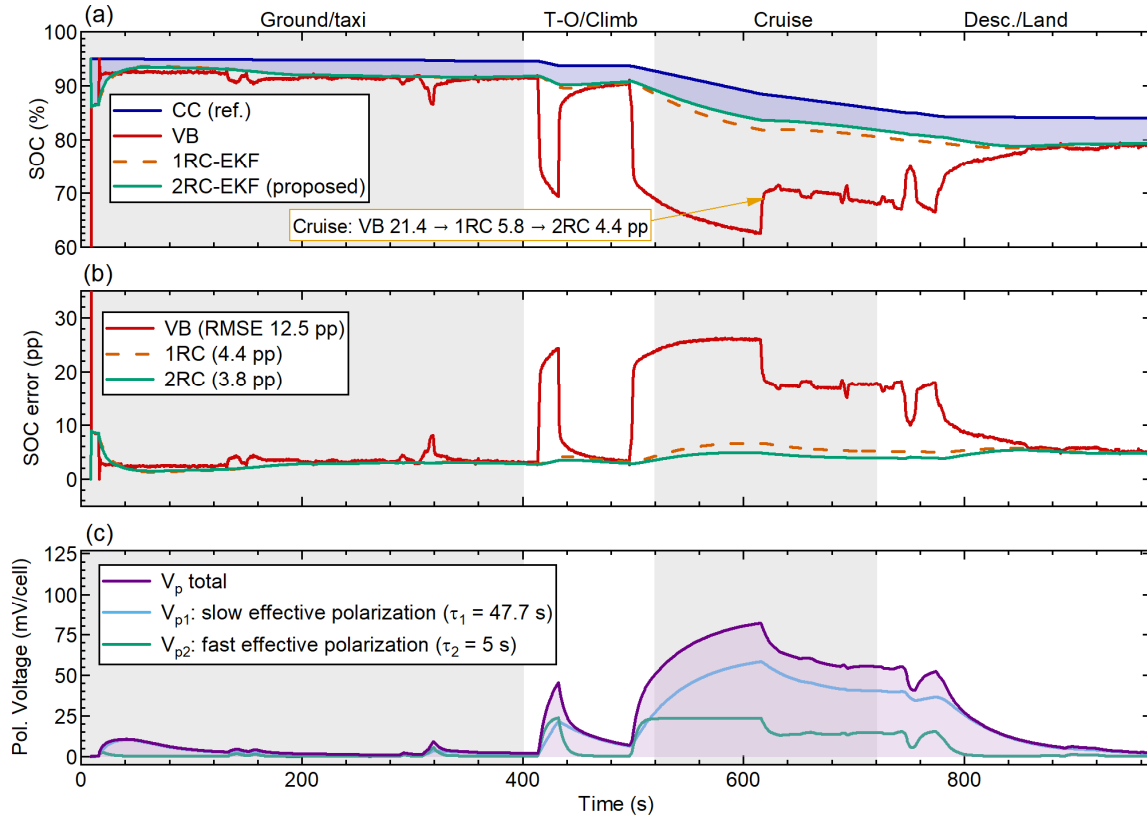


Figure 7. SOC estimation performance and polarization-voltage components during the first flight: (a) SOC estimates; (b) SOC estimation errors; (c) 2RC-EKF polarization-voltage components.

Table 9. Comparison of SOC estimation errors for VB, 1RC-EKF, and 2RC-EKF across flight phases.

Flight Phase	VB (pp)	1RC-EKF	2RC-EKF	Improvement:	Improvement:
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		(pp)	(pp)	VB→1RC	VB→2RC
Ground/Taxi	3.4	2.7	2.7	22%	22%
Takeoff/Climb	10.1	3.5	3.2	65%	69%
Cruise	21.4	5.8	4.4	73%	80%
Descent/Landing	8.8	5.2	4.7	41%	47%
Overall RMSE	12.5	4.4	3.8	65%	70%

As shown in Table 9, even the 1RC-EKF reduced the overall SOC RMSE by 65%, from 12.5 pp to 4.4 pp, demonstrating the substantial benefit of modeling the slow effective polarization state. By additionally accounting for the fast polarization component, the 2RC-EKF further reduced the overall RMSE to 3.8 pp and, in particular, decreased the cruise-phase error from 5.8 pp to 4.4 pp. Consequently, compared with the voltage-based method, the 2RC-EKF reduced the cruise SOC error by 80% and the overall RMSE by 70%, exhibiting the lowest SOC estimation error among the three methods for the present flight dataset.

In addition to SOC estimation performance, the ability of the 1RC and 2RC models to reproduce the pack-voltage dynamics was evaluated by calculating the RMSE between the measured pack voltage and the model-predicted pack voltage, as summarized in Table 10. The first sample, for which the predicted value was not valid during initialization, was excluded using the same criterion for both models. When this sample was included, the overall RMSE increased to approximately 9.3–9.4 V for both models because a single initial sample disproportionately increased the overall RMSE.

Table 10. RMSE of V_{pack} prediction with the initial invalid sample excluded.

Flight Phase	1RC Voltage RMSE (V)	2RC Voltage RMSE (V)	2RC Improvement
Ground/Taxi	1.67	1.53	8.5% ↓
Takeoff/Climb	3.42	2.04	40.5% ↓
Cruise	2.18	1.34	38.6% ↓
Descent/Landing	1.08	1.41	Slightly worse
Flight-load period ($t \geq 400$ s)	2.16	1.54	28.6% ↓
Overall	1.97	1.54	22.2% ↓

As shown in Table 10, the overall pack-voltage prediction RMSE of the 2RC model was 1.54 V, representing a 22.2% reduction from the 1.97 V obtained with the 1RC model. Over the actual propulsion-load period ($t \geq 400$ s), the improvement increased to 28.6%, with reductions of 40.5% and 38.6% during the Takeoff/Climb and Cruise phases, respectively. In contrast, during Descent/Landing, the 2RC model exhibited a slightly higher

RMSE than the 1RC model. This may be attributed to the reduced contribution of polarization voltage under low-current conditions, which increases the relative influence of OCV–SOC model error and state-estimation error. Therefore, the Descent/Landing result alone should not be interpreted as indicating an inherent performance degradation of the 2RC structure; further improvement may be achievable by incorporating a more accurate OCV–SOC relationship.

7. Bench-to-Flight Consistency and Discussion

To evaluate whether the battery parameters identified from the bench tests remain physically consistent under the actual flight environment, a quantitative comparison was performed between the bench-test and maiden-flight data for R_0 , the polarization time constant τ_1 , and the dominant polarization behavior. The main comparison results are summarized in Table 11. The in-flight effective R_0 was back-calculated for each flight phase by dividing the instantaneous voltage drop associated with load changes during Ground/Taxi, Takeoff/Climb, Cruise, and Descent/Landing by the corresponding phase current. The resulting values ranged from 18 to 33 m Ω .

Table 11. Summary of bench-to-flight consistency.

Parameter	Bench Test	Flight Data	Difference / Agreement	Remarks
R_0	18.03–22.18 m Ω (25 °C)	18–33 m Ω (phase-wise estimates)	Range agreement	Combined dependence on SOC, temperature, and C-rate
τ (interpolated at 1.26C)	73.3 s at 25 °C	47.7 s	–35%	Consistent with Arrhenius behavior

The 35% difference between the bench-interpolated time constant, $\tau = 73.3$ s at 25 °C, and the flight-identified value, $\tau = 47.7$ s, was further examined using an Arrhenius relationship:

$$\tau(T) = \tau_{ref} \cdot \exp \left[\frac{E_a}{k_B} \cdot \left(\frac{1}{T} - \frac{1}{T_{ref}} \right) \right] \quad (21)$$

Based on the Arrhenius temperature dependence of lithium-ion cell parameters [10], and assuming a representative activation energy of $E_a \approx 0.3$ eV within the commonly reported range of 0.2–0.5 eV for diffusion-related processes, the effective cell temperature corresponding to the in-flight time constant was estimated to be approximately 36 °C. This

is approximately 23 °C higher than the ambient temperature of 13.4 °C and is qualitatively consistent with a change in the thermal environment when considering the temperature increases observed in the motor and inverter during flight. However, because neither the internal nor surface temperature of the battery cells was measured directly, this result should only be interpreted as indicating that the reduction in the in-flight time constant is consistent with an increase in temperature; it does not establish a direct causal relationship.

The main limitations of this study are summarized as follows.

(i) **Linear OCV–SOC approximation.** The actual OCV–SOC relationship of the cell is nonlinear and temperature dependent. Therefore, the linear approximation adopted in this study may increase measurement-model error, particularly during the Descent/Landing phase, where the SOC variation is relatively large. This may partly explain why the improvement during this phase (47%) was lower than that during Cruise (80%). Future work should incorporate a high-resolution GITT-based OCV–SOC look-up table.

(ii) **Fixed model parameters.** In this study, R_0 , τ_1 , and τ_2 were treated as fixed parameters, and their variations with SOC and temperature were therefore not explicitly represented. Future work should establish SOC- and temperature-dependent parameter maps over a temperature range of 0–45 °C and develop a method for updating the parameters in real time according to the operating conditions during flight.

(iii) **Initial EKF convergence transient.** The maximum 2RC-EKF error of 9.0 pp during the Ground/Taxi phase resulted from a convergence transient caused by a relatively large initial innovation associated with the pre-flight covariance initialization. This initial transient error could be reduced in future work by applying OCV-based SOC initialization and polarization-state initialization after a sufficiently long pre-flight rest period.

(iv) **Single-flight dataset.** The present evaluation is based on a single maiden-flight dataset and therefore has limitations in terms of statistical generalization. In particular, because the flight-identified τ_1 was applied to the EKF using the same flight dataset, the evaluation cannot be regarded as fully independent validation. Future work should perform independent validation by applying the same parameter set to separate flight datasets.

8. Conclusions

This study analyzed voltage-based SOC mis-estimation, resistive voltage drop, and dynamic polarization components using the maiden-flight telemetry of the KLA-100X, Korea's first manned electric aircraft, together with bench-test data obtained from the

same cell model installed onboard. A 2RC-EKF was then applied to evaluate SOC estimation performance. The main conclusions are as follows.

(1) The ohmic resistance and polarization-relaxation characteristics were quantitatively identified over the C-rate range relevant to the KLA-100X operating conditions. The effective ohmic resistance R_0 , obtained from the instantaneous voltage drop immediately after discharge initiation, was 22.18, 19.04, and 18.03 m Ω at 1.01C, 2.02C, and 3.03C, respectively. All values were within the datasheet resistance range of 17–29 m Ω . Single-exponential fitting of the post-discharge voltage-recovery curves yielded effective slow polarization-relaxation time constants ranging from 62.0 to 73.9 s. These results do not directly identify specific electrochemical mechanisms but provide an experimental basis for defining effective polarization states with different time scales in the 2RC model.

(2) The maiden-flight data confirmed voltage-based SOC mis-estimation associated with increasing propulsion load and quantitatively demonstrated the contribution of dynamic polarization. During Cruise, the mean error between the voltage-based SOC and the reference coulomb-counting SOC reached 21.4 pp, with a maximum error of 26.4 pp. After landing, the SOC error decreased as the terminal voltage recovered. After time-aligning the equilibrium OCV decrease associated with SOC depletion, the total voltage drop during Cruise was evaluated as 32.1 V, of which 21.5 V (67.0%) was attributed to the ohmic component and 10.6 V (33.0%) to dynamic polarization. The polarization component corresponded to an SOC difference of approximately 5.7 pp based on the linear OCV slope, demonstrating that simple resistance compensation alone is insufficient to eliminate voltage-based SOC estimation errors.

(3) The polarization-relaxation characteristics under actual flight conditions differed substantially from those obtained under the 25 °C bench-test conditions, confirming the need for parameterization that reflects the flight environment. The effective time constant identified from post-landing voltage recovery was $\tau = 47.7$ s, approximately 35% shorter than the 25 °C bench-interpolated value of 73.3 s. This reduction suggests that the temperature and load conditions during actual flight differed from the bench-test conditions. Arrhenius-based analysis was also qualitatively consistent with a reduction in the time constant associated with increased temperature. However, because the battery cell temperature was not measured directly during flight, a direct causal relationship with temperature cannot be established. Therefore, incorporating the flight-identified τ_1 into the model was important for representing the effective dynamics under the actual operating environment.

(4) The 2RC-EKF substantially improved SOC estimation and pack-voltage prediction performance on the actual flight dataset. The 1RC-EKF reduced the overall SOC RMSE by 65%, from 12.5 pp to 4.4 pp, whereas the 2RC-EKF further reduced it to 3.8 pp, corresponding to a 70% reduction relative to the voltage-based method. In particular, the cruise SOC error decreased by 80%, from 21.4 pp to 4.4 pp. In addition, compared with the 1RC model, the 2RC model reduced the overall pack-voltage prediction RMSE by 22.2% and achieved improvements of 40.5% and 38.6% during Takeoff/Climb and Cruise, respectively. Sensitivity to variations in R_2 and τ_2 was limited, indicating that the slow polarization component played a relatively greater role under the quasi-steady cruise condition of this flight and that uncertainty in the fast polarization parameters had only a minor influence on the main SOC estimation results.

Future work should incorporate a high-resolution GITT-based OCV–SOC look-up table, SOC- and temperature-dependent model parameters, real-time parameter updating according to flight operating conditions, and independent SOC validation using post-flight recharge capacity or sufficiently relaxed OCV measurements. In addition, because the flight-identified τ_1 was applied to the EKF using the same flight dataset in the present study, fully independent validation will require applying the same parameter set to additional flight datasets.

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Data Availability Statement:

The original contributions presented in this study are included in the article. Further inquiries can be directed to the corresponding author.

Conflicts of Interest:

The authors declare no conflicts of interest.

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