

Battery State Prediction for Mobile Devices Based on Coupled CETM and ALE-SOH Models

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Abstract: This paper proposes a two-layer coupled model for mobile device battery capacity prediction, integrating the CETM electrothermal model with the ALE-SOH aging model to achieve a coordinated estimation of SOC, temperature, and battery degradation status. The inner layer uses state-space estimation to track real-time load changes, while the outer layer adjusts capacity decay and internal resistance growth based on cycle count and temperature, thereby balancing short-term prediction with long-term degradation characterization. Validated using data from the Samsung Galaxy S8, the model achieved an SOC prediction MAE of 4.231%, an RMSE of 5.673%, and an R^2 of 0.952, with an average absolute error of 0.592°C for temperature. The results indicate that this model is applicable to various scenarios, including web browsing, navigation, 5G data transmission, and gaming, demonstrating good prediction accuracy, stability, and practical value for widespread application.

Keywords: Coupled Electro-Thermal Model, ALE-SOH Model, Battery Aging Modeling.

1. Introduction

As the performance of smart devices continues to improve, processor operations, network communications, and multimedia applications place increasingly higher demands on battery life. Remaining battery capacity is influenced not only by changes in load but also by factors such as temperature, cycle aging, and internal resistance; therefore, it is necessary to develop predictive models capable of reflecting these multifactorial interactions.

Existing battery capacity prediction methods largely rely on empirical formulas, equivalent circuits, or single data-driven models [1]. While these methods have certain practical value, they often struggle to simultaneously account for short-term load fluctuations and long-term battery degradation in complex usage scenarios, resulting in insufficient model adaptability and prediction stability.

To address this, this paper proposes a two-layer coupled prediction framework that integrates a thermoelectric coupling model (CETM) with an aging state-of-health model (ALE-SOH). The former is used to characterize the dynamic relationship among load, state of charge, and temperature, while the latter corrects for capacity degradation and increasing internal resistance, with both models updated collaboratively through parameter feedback. Additionally, a state-space estimation method is introduced to track the battery state in real time [2]. Using a smartphone battery system as an example, this paper analyzes the patterns of state of charge changes under different load scenarios, providing an adaptive algorithmic model framework for battery state prediction and energy management in mobile devices.

2. Construction and Validation of the CETM Electro-Thermal Coupling Model

2.1. Construction of the CETM Model

The remaining battery energy is usually characterized by the State of Charge (SOC), which essentially reflects the ratio

between the currently available capacity and the rated capacity:

$$SOC = \frac{Q_c(t)}{Q_n} \times 100\% \quad (1)$$

Where $Q_c(t)$ denotes the remaining capacity at time t , and Q_n is the rated capacity.

During continuous discharge, SOC changes continuously as current is consumed. Based on the ampere-hour integration principle, the following relationship can be obtained:

$$\frac{dSOC}{dt} = -\frac{I(t)}{C_{ref}} \quad (2)$$

The power consumption of a smartphone does not originate from a single module. Instead, it is jointly contributed by multiple subsystems such as the display, processor, and network communication modules. Therefore, the total load current can be expressed as:

$$I(t) = I_{base} + I_{screen}(t) + I_{CPU}(t) + I_{network}(t) \quad (3)$$

As the operating environment and working conditions vary, the releasable battery capacity does not remain constant. Temperature fluctuations, changes in discharge rate, and cycling aging can all cause the capacity to deviate from its design value. Therefore, the effective capacity is corrected as:

$$C_{ref}(T, I, N) = C_{design} \times \eta_{temp}(T) \times \eta_{rate}(I) \times \eta_{aging}(N) \quad (4)$$

Where $\eta_{temp}(T)$, $\eta_{rate}(I)$, and $\eta_{aging}(N)$ represent the temperature correction factor, rate correction factor, and aging correction factor, respectively.

The temperature effect is described using an Arrhenius-type formulation:

$$\eta_{temp}(T) = \exp \left[\frac{E_a}{R} \left(\frac{1}{T_{ref}} - \frac{1}{T(t)} \right) \right] \quad (5)$$

The rate correction factor follows the Peukert empirical relationship:

$$\eta_{rate}(I) = \left(\frac{I_{ref}}{I(t)} \right)^\alpha \quad (6)$$

The cycling aging term is written as:

$$\eta_{aging}(N) = 1 - N \times 0.0005 \quad (7)$$

After introducing the capacity correction, the SOC evolution equation can be further rearranged as:

$$\frac{dSOC(t)}{dt} = -\frac{1}{C_{design}} \cdot I_{load}(t) \cdot \left(\frac{I_{load}(t)}{I_{ref}} \right)^{\alpha-1} \cdot \frac{1}{\eta_{temp}(T(t))} \quad (8)$$

At this stage, the SOC variation depends not only on the load current but also on temperature conditions and battery aging.

Besides the change in charge level, the temperature rise during operation cannot be neglected. By considering both the internal Joule heating of the battery and the heat dissipation process between the battery and the environment, the thermal balance equation can be established as:

$$mC_p \frac{dT}{dt} = I(t)^2 R_{in} - hA(T - T_{env}) \quad (9)$$

Where R_{in} denotes the internal resistance and hA

represents the overall heat dissipation capability.

Accordingly, a coupled system consisting of the charge state and thermal state can be obtained:

$$\frac{dSOC(t)}{dt} = -\frac{I_{load}(t)}{C_{eff}(T, I, N)} \quad (10)$$

$$mC_p \frac{dT(t)}{dt} = I_{load}(t)^2 R_{in} - hA[T(t) - T_{env}] \quad (11)$$

The following initial conditions are adopted during model computation: $SOC(0) = 0.983$ and $T(0) = T_{env}$.

2.2. Model Validation

The model prediction accuracy was validated using Samsung Galaxy S8 battery data from the Kaggle Mobile Battery dataset. The test device had been in operation for approximately 821 days, undergoing about 820 charge-discharge cycles. The effective capacity was corrected for aging using:

$$C_{eff} = C_{design} \cdot (1 - \beta \sqrt{N}) \quad (12)$$

Where $C_{design} = 3000$ mAh and $\beta = 0.006$. After correction, the capacity is approximately 2487 mAh. The internal resistance was set to 0.25–0.35 Ω to reflect impedance changes caused by aging.

Figure 1 presents the comparison between predicted SOC and measured SOC curves. During 17.5 hours of continuous discharge, the predicted curve aligns well with the actual trajectory. The mean absolute error (MAE) of SOC prediction is 4.231%, the root mean square error (RMSE) is 5.673%, and the coefficient of determination R^2 reaches 0.952.

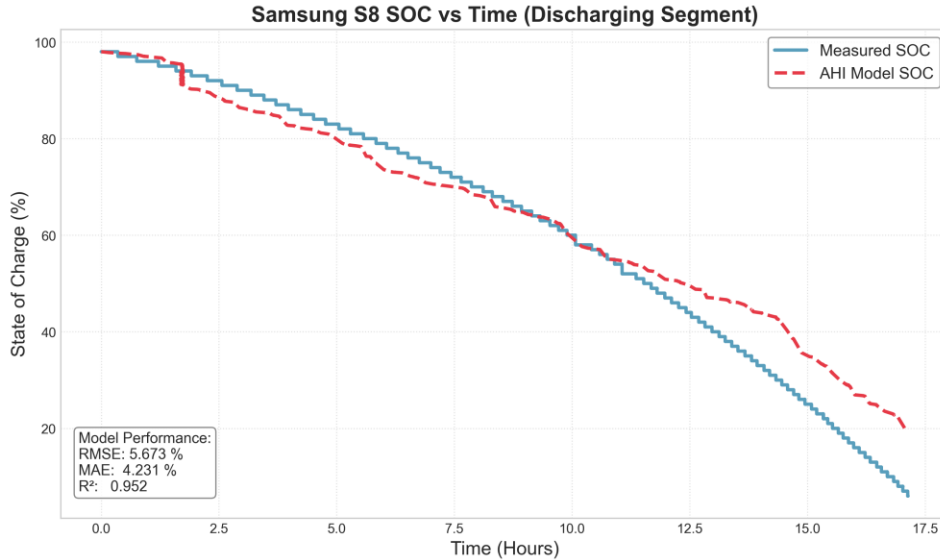


Figure 1. Measured vs. model-predicted SOC trajectory for Samsung Galaxy S8

The SOC curve indicates that the model can stably track the discharge process. Predictions closely match measured values in the early stage of discharge. As capacity decays, local errors slightly increase, but the overall trend remains consistent. Errors are mainly concentrated in intervals with significant load fluctuations, which correspond to background activities and transient power consumption changes during

actual use.

The temperature prediction results are shown in Figure 2. The prediction deviation is small, not exceeding $\pm 0.70^\circ\text{C}$, with an average absolute error of 0.592°C . The temperature curve captures the heating and cooling characteristics during device operation, providing a reliable basis for subsequent temperature coupling and thermal throttling analysis.

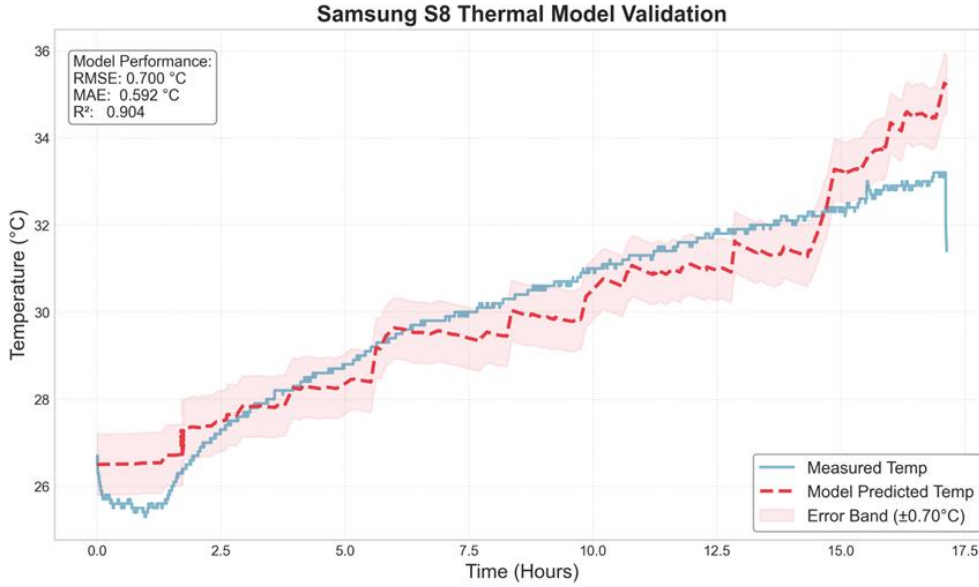


Figure 2. Temperature prediction validation for Samsung Galaxy S8

2.3. Scenario Analysis

To examine the model performance under different usage patterns, four typical scenarios were constructed, including Normal Browsing, GPS Navigation, 5G Streaming, and

Gaming. The SOC variation process was then simulated.

Figure 3 shows the SOC evolution curves under different scenarios. SOC decreases over time in all working conditions, but the decay rates show clear differences.

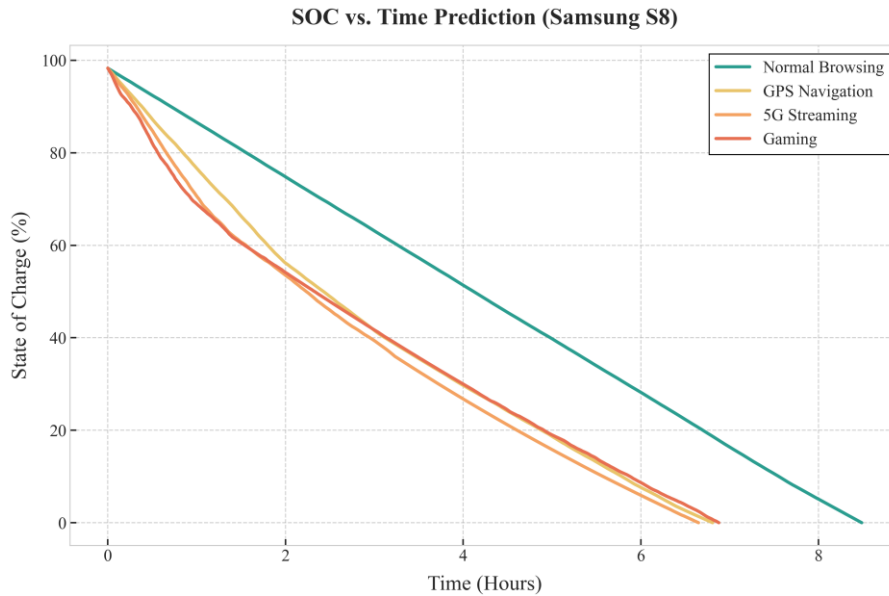


Figure 3. SOC evolution across different smartphone usage profiles

Among them, the Gaming scenario has the fastest discharge rate, with the battery nearly depleted after about 6.5 hours. In this scenario, the CPU and GPU maintain high loads for a long time, and the current demand keeps increasing. As a result, the SOC curve shows a steeper downward slope.

The Normal Browsing scenario presents a relatively gentle discharge process. Since user operations are intermittent, the processor can frequently enter low-power states. The average system power consumption therefore stays at a low level, and the battery life exceeds 8 hours.

The GPS Navigation and 5G Streaming scenarios fall between the two cases above. Navigation tasks require continuous use of location services, while 5G communication increases the data transmission load. Both working conditions raise system energy consumption. However, compared with continuous high-performance computing, their load intensity is still relatively limited, so the SOC decline is smoother.

From the curve shapes, the differences among scenarios are not only reflected in power consumption levels, but are also related to load duration and the way hardware resources are called. The model can reflect the discharge characteristics corresponding to different usage behaviors, and the obtained results are generally consistent with the battery endurance observed in real devices.

3. ALE-SOH Aging Model and State-Space Estimation Method

3.1. ALE-SOH Aging Model

The ALE-SOH model describes the capacity degradation and internal resistance increase of a battery under cyclic charge–discharge operation and different temperatures [3]. The model uses a layered design: the outer layer describes long-term aging, while the inner layer is used for real-time

SOC estimation.

The outer-layer parameters are calibrated using the CALCE battery dataset. Parameter identification can be carried out by nonlinear least squares, genetic algorithms, or LM/PSO methods, with the objective of minimizing the squared error between the model voltage and the measured voltage [4].

Battery aging is mainly driven by the formation and growth of the SEI film, which leads to the decay of capacity $Q(N)$ and the increase of internal resistance $R(N)$ with the number of cycles N . When SOH falls below 80%, the battery is considered to have reached its end of life (EOL).

Based on the diffusion-controlled mechanism, capacity loss can be expressed as:

$$Q_{loss}(t, T) = Q_{nominal} \cdot A_{sei} \cdot \exp\left(-\frac{E_{a,aging}}{R \cdot T}\right) \cdot t^{0.5} \quad (13)$$

Where $Q_{nominal}$ is the nominal capacity, A_{sei} is the proportional coefficient, $E_{a,aging}$ is the activation energy, R is the gas constant, T is the absolute temperature, and t denotes time or the equivalent cycle period.

Since the time constant of the battery aging process is assumed to be much larger than the time scale of real-time SOC monitoring, the capacity and resistance can be treated as constants during short-time Kalman filter iterations. The long-term update is completed asynchronously by the outer layer, forming a two-layer coupled structure.

3.2. State-Space Estimation Model

The inner-layer state-space model performs real-time SOC estimation while quantifying prediction uncertainty through process noise and covariance matrix evolution [5]:

$$SOC_k = SOC_{k-1} - \eta_i \frac{i_{k-1} \Delta t}{C_n} + W_k \quad (14)$$

Where C_n can be replaced by $C_{ref}(T, I, N)$ to achieve coupling among capacity, temperature, and cycle aging.

The noise is modeled as Gaussian white noise. The covariance matrix P_k is updated iteratively to generate dynamic prediction error bounds. Figure 4 shows the SOC estimation results and the 3σ uncertainty bounds for a Samsung Galaxy S8 battery (effective capacity of 2487 mAh

and 821 cycles). The light blue region represents the dynamic confidence interval derived by the EKF, reflecting the influence of background loads and system noise on SOC estimation.

To relate the internal state to voltage observations, an OCV–SOC mapping is established:

$$OCV = a_1 e^{a_2 SOC} + a_3 e^{a_4 SOC} + \dots \quad (15)$$

A hysteresis and polarization model is introduced to simulate the rapid voltage variation following short-term load transients:

$$h_k = \sum_{j=1}^{k-1} \exp(-\eta_{ij} \Delta t / C_n) \gamma h_j \quad (16)$$

The terminal voltage is expressed as:

$$V_k = OCV(SOC_k) - R_{in} \cdot i_k \quad (17)$$

This equation explains why the instantaneous voltage may fall below the shutdown threshold V_{cutoff} under high-load or low-temperature conditions, even when the SOC still indicates remaining battery capacity.

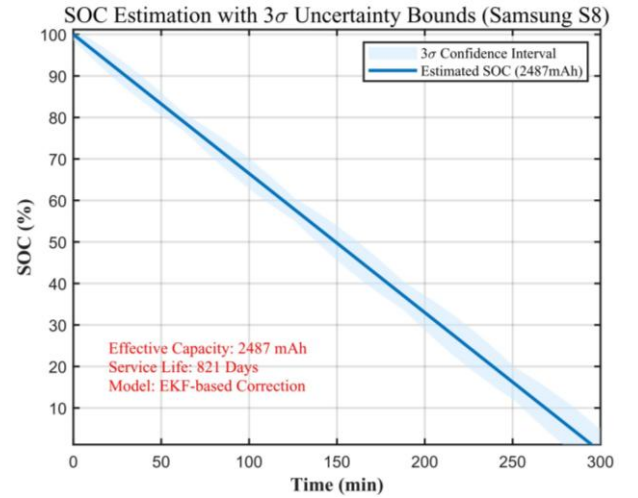


Figure 4. 3σ uncertainty bounds in SOC estimation (Samsung S8)

Figure 5 presents the distribution of SOC prediction errors. Most errors fall within the range of 0–3%, and nearly all samples remain below 4%, indicating that the model maintains good robustness under dynamic load and aging conditions.

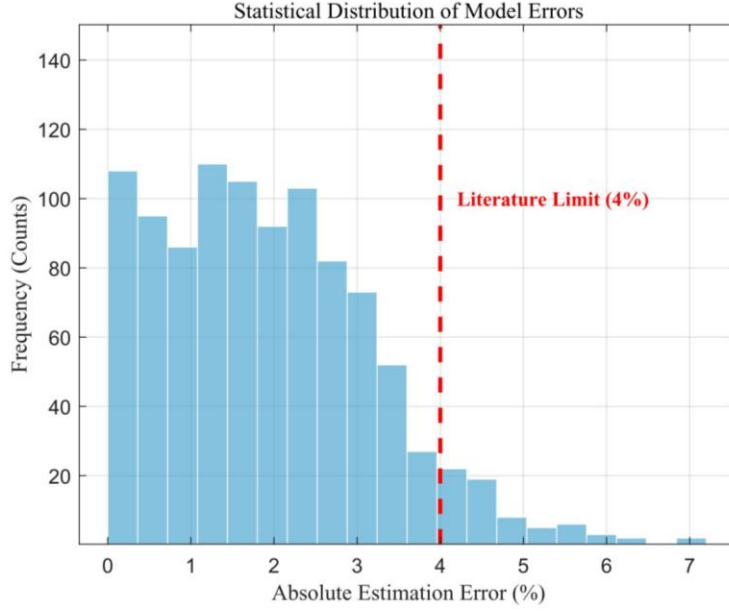


Figure 5. SOC estimation error distribution vs. 4% accuracy threshold

3.3. Dual-Layer Model Coupling Mechanism

Information exchange between ALE-SOH and CETM is achieved through capacity and impedance parameters. Capacity degradation and internal resistance growth are described by ALE-SOH and updated according to cycle count and operating temperature. The corrected parameters are then introduced into the CETM model for SOC estimation and terminal voltage calculation.

The model parameters are first calibrated using the CALCE dataset to obtain the initial capacity and impedance values. As the number of cycles increases, capacity loss and impedance growth continue to accumulate, while SOC estimation is updated in real time under the current aging condition. Since the two processes operate on significantly different time scales, capacity and impedance are updated through periodic corrections, whereas state estimation remains continuously iterative.

This strategy separates long-term aging effects from short-term dynamic processes, preserving aging characteristics while reducing the computational burden of real-time estimation [6]. Test results show that when both capacity degradation and impedance growth are present, the prediction error remains below 4% in most cases.

4. Endurance Prediction and Sensitivity Analysis under Temperature-Load Coupling

4.1. Key Drivers of Battery Consumption

Figure 6 illustrates the influence of different factors on the

remaining battery time (TTE). These factors do not act independently; there is a clear coupling among load level, temperature variation, and internal battery state, with high-load conditions having the most pronounced impact.

When 5G communication and high-demand games run simultaneously, the display, processor, and network modules all operate at high loads, causing the total current to increase rapidly. The rate effect further reduces the effective capacity C_{ref} , shortening the battery life by an amount greater than that corresponding to the increase in power consumption alone. Simulation results show that the 5G-related load alone can cause a TTE loss of approximately 4.31 hours.

Sustained high-load operation also leads to temperature rise. In the “Heavy Use” scenario shown in Figure 6, the battery temperature reaches a maximum of 35.3°C. As the temperature increases, the heat generation term in the thermal model:

$$mC_p \frac{dT}{dt} \quad (18)$$

gradually dominates. Although the system dynamically throttles the processor to reduce power consumption, the internal resistance does not recover synchronously, so the terminal voltage drops faster than the SOC changes. In some cases, the device triggers shutdown protection before the remaining capacity is fully discharged.

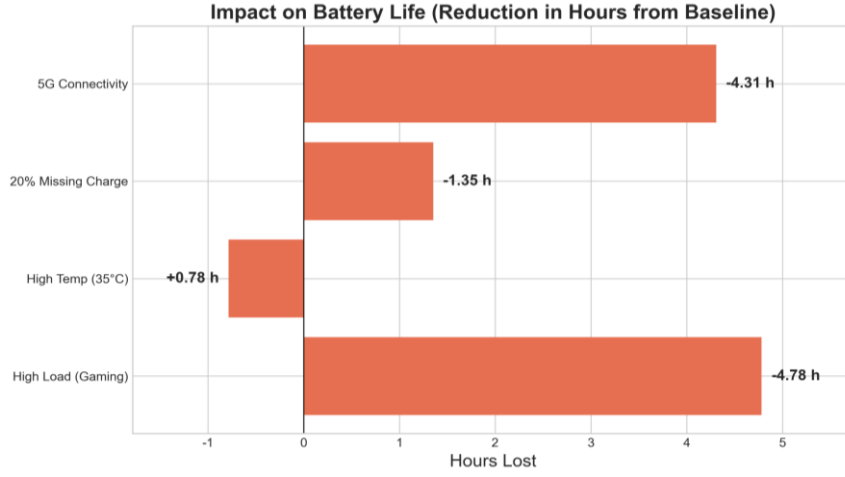


Figure 6. Driver analysis chart

Some factors have a relatively limited effect on battery life. During standby, maintaining a 5G connection signal continues, but the corresponding load level is low. Under normal signal conditions, this mainly acts as background disturbance, causing less than 0.8% impact on TTE.

When the ambient temperature is within 20–35°C, the temperature correction factor η_{temp} changes slightly, and internal resistance remains basically stable. Therefore, battery life does not fluctuate noticeably. For most daily usage scenarios, load intensity and initial SOC remain the primary factors affecting endurance.

4.2. Temperature–Load Coupling Analysis

When both ambient temperature and load power vary simultaneously, the battery life exhibits clear nonlinear characteristics. Parameter scanning was performed within the ranges $T_{env} \in [-10^\circ\text{C}, 40^\circ\text{C}]$ and $P_{load} \in [0.5\text{W}, 5.0\text{W}]$, revealing a typical low-temperature, high-load region. This region mainly occurs under conditions of $T_{env} < 0^\circ\text{C}$ and $P_{load} > 4\text{W}$, where the battery state shows pronounced voltage collapse.

As the ambient temperature decreases, the internal resistance R_{in} continuously increases. When a large load current passes through the battery, the internal voltage drop: $I \cdot R_{in}$.

Rises rapidly, causing the terminal voltage to approach the shutdown threshold prematurely. At this point, part of the chemical energy inside the battery remains, but the device can no longer maintain normal operation.

Under an environment of -5°C , the predicted TTE for a high-load gaming scenario ($P_{load} \approx 5\text{W}$) is about 25 minutes, while SOC remains above 60%. This phenomenon closely resembles abnormal battery drain observed during winter usage and demonstrates that SOC does not always correspond directly to the actual available time.

When temperature and load change simultaneously, their effects are not simply additive. Compared with changing ambient temperature or load power alone, the combination of low temperature and high load results in a more pronounced reduction in battery life.

4.3. Parameter Sensitivity Analysis

Local sensitivity analysis shows that different parameters

have varying degrees of influence on battery life, with changes in ambient temperature, internal resistance, and heat dissipation capability being the most significant.

The effect of ambient temperature is the most direct. When the temperature drops by approximately 20%, the predicted battery life decreases by more than 35%. Under low-temperature conditions, the reaction rates inside the battery slow down, reducing the releasable capacity and shortening endurance.

Changes in internal resistance mainly affect high-load conditions. When R_{in} exceeds $0.35\ \Omega$, the terminal voltage drops faster, and the usable voltage range is further compressed. For batteries that have already aged, the device may trigger shutdown protection early even if SOC still indicates remaining capacity.

The impact of heat dissipation is concentrated during high-power operation. Under normal usage, different dissipation levels do not significantly affect TTE. However, when the system operates under high load for extended periods, reduced thermal efficiency causes heat accumulation and can trigger thermal protection. Thermal throttling can lower power consumption and extend battery life, but device performance decreases correspondingly.

Among these three parameters, ambient temperature and internal resistance have more direct effects, while heat dissipation mainly influences endurance indirectly through temperature changes.

4.4. Thermally-Regulated Endurance Analysis

To further investigate the influence of ambient temperature T_{env} on system battery life, joint simulations of initial SOC and environmental temperature were conducted under a high-load gaming scenario ($P_{load} \approx 5\text{W}$), using the remaining battery time (Time-to-Empty, TTE) as the evaluation metric.

Figure 7 shows the TTE distribution under different temperature conditions. Overall, when the ambient temperature is between 0°C and 30°C , the relationship between TTE and initial SOC remains approximately linear. The color variation in this region is relatively smooth, indicating limited differences in battery life across temperatures. For an initial SOC of 100%, TTE remains near 2.44 hours.



Figure 7. Thermodynamically-regulated TTE distribution

Within this temperature range, the system has not entered significant protection states, and load power remains the main factor affecting energy consumption. Although temperature changes influence capacity utilization and internal resistance, their impact is relatively limited, so overall battery life remains stable.

When ambient temperature rises above 35°C, the TTE distribution begins to show noticeable changes. Under $T_{env} = 40^{\circ}\text{C}$, TTE increases from about 2.44 hours at 30°C to 8.34 hours, exhibiting a clear nonlinear growth trend.

This change does not come from an increase in battery capacity, but from the activation of the system's thermal protection mechanism. Under the combined effect of environmental temperature and load-induced heat, the battery temperature quickly approaches the safety threshold, prompting the processor to throttle. System load power drops from approximately 5 W to around 1.5 W. Consequently, the energy consumption per unit time decreases, resulting in longer runtime.

However, device performance is limited under this condition. The TTE increase corresponds to operation under reduced power consumption, not an enhancement of battery storage capacity.

Temperature affects not only internal battery parameters but also the system's operating strategy. Low-temperature conditions are more prone to voltage collapse and early shutdown, while high temperatures trigger thermal throttling. Both phenomena follow different protection pathways but alter the device's actual battery life.

5. Conclusions

This paper presents a two-layer coupled model that integrates electrothermal characteristics and aging features for predicting the state of charge (SOC) of mobile device batteries. The results indicate that the model effectively captures SOC changes, temperature fluctuations, and capacity degradation processes under various load scenarios, while also reflecting the impact of conditions such as low

temperatures and high loads on battery life. Validation using data from the Samsung Galaxy S8 showed that the SOC prediction had a Mean Absolute Error (MAE) of 4.231%, a Root Mean Square Error (RMSE) of 5.673%, and an R^2 of 0.952, while the temperature prediction had a Mean Absolute Error of 0.592°C, indicating that the model possesses good accuracy and stability. The research findings can serve as a reference for battery management, runtime evaluation, and energy consumption optimization in mobile devices. Future research could further incorporate online learning and additional device data to enhance the model's adaptability.

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