Research on State of Charge Modeling and Multi-Scenario Endurance Prediction of Lithium-Ion Batteries in Smartphones Based on Continuous-Time Dynamics

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Abstract. Battery-life uncertainty remains one of the most significant factors affecting smartphone user experience. This study develops a continuous-time dynamic model for the state of charge (SOC) of lithium-ion batteries in smartphones and applies it to multi-scenario endurance prediction. The model is established using ordinary differential equations grounded in the Coulomb counting principle, while incorporating component-level current consumption, including screen brightness, processor load, wireless communication, GPS, Bluetooth, and standby power. Temperature correction and battery aging effects are also introduced to improve physical realism and practical applicability. Numerical integration is then used to simulate SOC evolution under different usage scenarios, and endurance time is defined as the moment when SOC drops to the cut-off threshold. The results show substantial differences in battery life across scenarios, with heavy-use conditions leading to rapid depletion and standby conditions providing the longest endurance. Furthermore, Monte Carlo simulation is employed to quantify uncertainty in endurance prediction, while sensitivity analysis identifies CPU load, screen brightness, and battery capacity as the most influential factors. The study not only provides a mathematically interpretable framework for smartphone battery modeling, but also offers a theoretical basis for power optimization strategies and intelligent battery management.

Keywords: Continuous-time model, Battery life prediction, Sensitivity analysis, Monte Carlo simulation, Power consumption optimization.

1 Introduction

Smartphones have become indispensable infrastructure in contemporary digital society, supporting communication, navigation, entertainment, mobile payment, health monitoring, and emergency response. As their functional integration deepens, user dependence on stable battery performance has increased accordingly. Battery-life uncertainty remains one of the most persistent constraints on user experience. Under seemingly similar patterns of use, the same device may last an entire day in one case but discharge rapidly in another. This inconsistency is not merely inconvenient [1]. In some circumstances, it can also undermine reliability in safety-critical or time-sensitive situations.

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From a technical perspective, battery modeling has a long history rooted in electrochemical theory. Classical high-fidelity models, especially porous-electrode formulations such as the pseudo-two-dimensional framework, offer strong descriptive power for internal battery processes by representing mass transfer, charge conservation, and reaction kinetics in detail [2]. However, such models are computationally expensive and therefore difficult to deploy in real-time smartphone battery management or endurance prediction [3]. For smartphone applications, where usage conditions change continuously and system-level decision making must remain efficient, a middle-ground framework is needed.

Against this background, state of charge (SOC) serves as the most suitable core variable for endurance analysis. SOC directly reflects the remaining usable energy of a battery and links physical discharge mechanisms with user-visible device lifetime. The project is formulated around the construction of a continuous-time mathematical model that captures SOC evolution under realistic smartphone operating conditions [4]. Rather than treating battery discharge as a simple uniform process, the model connects user behavior to component-level current draw and then to dynamic SOC variation. Screen usage, processor load, wireless communication, GPS activity, Bluetooth, and background tasks are all treated as explicit contributors to total current consumption.

A further challenge is that smartphone battery behavior is not determined solely by instantaneous power consumption. Environmental temperature, battery aging, and scenario-dependent usage variability also shape endurance outcomes. At the macroscopic level, the battery is represented as a finite-capacity storage unit governed by Coulomb counting; at the component level, total current is decomposed into additive consumption modules; and at the environmental level, correction factors are introduced to account for temperature effects and capacity degradation [5]. This structure reduces model complexity while retaining essential physical meaning. It also allows the framework to move beyond deterministic discharge curves and toward broader tasks such as uncertainty quantification, sensitivity analysis, and user-oriented energy-saving recommendations.

2 Related Work

Flores-Martin et al. [6] develop a deep-learning model for smartphone battery-life enhancement using user-specific application behavior, screen time, network type, network usage, and battery temperature, while Ghaeminezhad et al. [7] organize SOC methods from a control perspective into open-loop, closed-loop, and hybrid approaches.

Another important trend is the move from isolated SOC estimation to joint estimation of multiple battery states, especially SOC and state of health (SOH). Huang et al. [8] propose an integrated SOC–SOH estimation framework for whole-life-cycle lithium-ion batteries and explicitly address the coupling between charge state and health degradation. Liu et al. [9] survey deep-learning-based SOC estimation and classify the field into architecture-focused and accuracy-enhancement directions. Madani et al. [10] review thermal modeling of lithium-ion batteries and emphasize that temperature strongly affects battery performance, safety, and lifespan. They also note that standalone thermal models are often coupled with electrochemical or equivalent-circuit models to improve fidelity.

Tran et al. [11] provide a complementary review of thermal runaway modeling and diagnosis, highlighting the importance of prediction and detection for safe battery operation. Recent work also shows growing interest in application-level and user-specific battery prediction for smartphones themselves. Zhao et al. [12] similarly argue that machine-learning-based SOC estimation is now a structured pipeline involving data preparation, model selection, training, and evaluation rather than a single algorithmic step.

Despite these advances, recent literature still reveals a methodological gap. Data-driven methods often improve predictive accuracy, but their performance depends heavily on data quality, coverage, and generalization across operating conditions. At the same time, thermal and integrated SOC–SOH studies show that physically meaningful variables such as temperature and degradation remain indispensable for battery analysis.

3 Methodologies

3.1 Continuous-Time SOC Dynamic Modeling

To capture the battery discharge behavior of a smartphone under realistic operating conditions, this study constructs a continuous-time state-of-charge (SOC) model with SOC as the core state variable. This design preserves physical interpretability while avoiding the excessive complexity of full electrochemical models. The fundamental SOC evolution equation is written as Equation 1.

$$\frac{dSOC(t)}{dt} = -\frac{\eta\, I_{\text{eff}}(t)}{1000\, C_{\text{eff}}}. \tag{1}$$

Equation 1 describes the continuous decline of battery charge during discharge. Negative sign indicates that SOC decreases as current is drawn from the battery, while the model scales the discharge rate by Coulombic efficiency and effective battery capacity.

In this expression, $SOC(t)$ denotes the state of charge at time t, η is the Coulombic efficiency coefficient during discharge, $I_{\text{eff}}(t)$ is the effective discharge current, and C_{eff} is the effective battery capacity after accounting for aging. The factor $1000$is used for unit conversion so that the relationship between current, time, and capacity remains dimensionally consistent.

This treatment is important because battery performance is influenced not only by usage intensity but also by environmental conditions. By introducing an explicit temperature factor, the model can explain why discharge behavior differs across thermal conditions even under otherwise similar usage scenarios. The temperature-corrected current is expressed as Equation 2.

$$I_{\text{eff}}(t) = \phi(T)\, I_{\text{tot}}(t), \tag{2}$$

where $I_{\text{tot}}(t)$ is the total current consumed by all active components, and $\phi(T)$ is the temperature correction factor. $\phi(T)$ is modeled linearly to represent the influence of ambient temperature on discharge behavior, and the temperature coefficient is calibrated from the assumed battery-performance response.

To represent smartphone usage more concretely, the total current is decomposed into additive component currents. This additive structure is central to the methodology because it converts qualitative user behavior into quantitative electrical demand. The total current is modeled as Equation 3.

$$I_{\text{tot}}(t) = I_{\text{base}} + I_{\text{scr}}(b) + I_{\text{cpu}}(u) + s_w I_w + s_c I_c + s_g I_g + s_b I_b. \tag{3}$$

where I_{base} is the standby base current, $I_{\text{scr}}(b)$ is the screen current as a function of brightness b, and $I_{\text{cpu}}(u)$ is the processor current as a function of load u. The binary variables $s_w, s_c, s_g, s_b \in \{0,1\}$ indicate whether WiFi, cellular network, GPS, and Bluetooth are active, and I_w, I_c, I_g, I_b are the corresponding module currents.

Ignoring this factor would cause the model to overestimate endurance for older batteries. Therefore, the capacity term is not treated as a fixed nominal constant but as a degradation-dependent quantity. The effective capacity is written as Equation 4.

$$C_{\text{eff}} = C_0(1 - \alpha N - \beta A), \tag{4}$$

where C_0 is the nominal rated capacity of a new battery. This formulation captures the basic idea that both cycle aging and calendar aging reduce the usable amount of stored charge. N denotes the number of charge and discharge cycles, A denotes calendar age, α and β are degradation coefficients reflecting the sensitivity of capacity to these two aging channels.

3.2 Multi-Scenario Endurance Prediction and Numerical Solution

The core output variable for endurance prediction is the time to empty (TTE), defined as the first time when SOC reaches the cut-off threshold. In other words, endurance is not assigned arbitrarily but determined by the moment at which the battery trajectory intersects the shutdown boundary. This definition is consistent with the practical assumption that the smartphone stops operating when the remaining charge falls to about 5%. The TTE is therefore defined by Equation 5.

$$TTE = \inf\{\, t > 0 \mid SOC(t) \le SOC_{\text{cut}} \,\}. \tag{5}$$

where SOC_{cut} is the cut-off SOC threshold, and $SOC(t)$ is the dynamic trajectory obtained by solving the continuous-time model.

Equation 5 provides a mathematically precise criterion for endurance prediction and allows both analytical approximation and numerical simulation. It also makes the model compatible with variable usage patterns.

However, TTE must be computed numerically from the simulated trajectory. Under a constant-current scenario, the endurance approximation can be written as Equation 6.

$$TTE = \frac{1000\, C_{\mathrm{eff}}\,(SOC_0 - SOC_{\mathrm{cut}})}{\eta\, I_{\mathrm{eff}}}, \tag{6}$$

which directly reveals the main determinants of battery life. Equation 6 explains that endurance is proportional to the available SOC range and effective capacity, and inversely proportional to the effective discharge current.

In Equation 6, SOC_0 is the initial state of charge at the start of prediction, and the difference $SOC_0 - SOC_{\mathrm{cut}}$ represents the usable charge window before shutdown. I_{eff} is the temperature-corrected current load, while C_{eff} reflects battery health.

4 Experiments

4.1 Experimental Setup

The experimental setup was designed to ensure that the proposed model could be evaluated under both deterministic and uncertain usage conditions. Following the document, eight representative smartphone scenarios were defined, including standby, music playback, normal use, web browsing, video playback, navigation, gaming, and heavy use, with each scenario specified by a fixed combination of screen brightness, CPU load, and wireless-module states. Battery endurance was computed until the SOC dropped to the 5% cut-off threshold, and both analytical approximation and numerical integration were used for comparison under constant-load conditions.

4.2 Experimental Analysis

Figure 1 presents the results of the global sensitivity analysis by illustrating the relationships between four key input parameters and smartphone battery time-to-empty (TTE): screen brightness, CPU load, ambient temperature, and battery capacity. Each subplot combines a scatter plot with a polynomial fitted curve to show the overall trend between the parameter and endurance time.

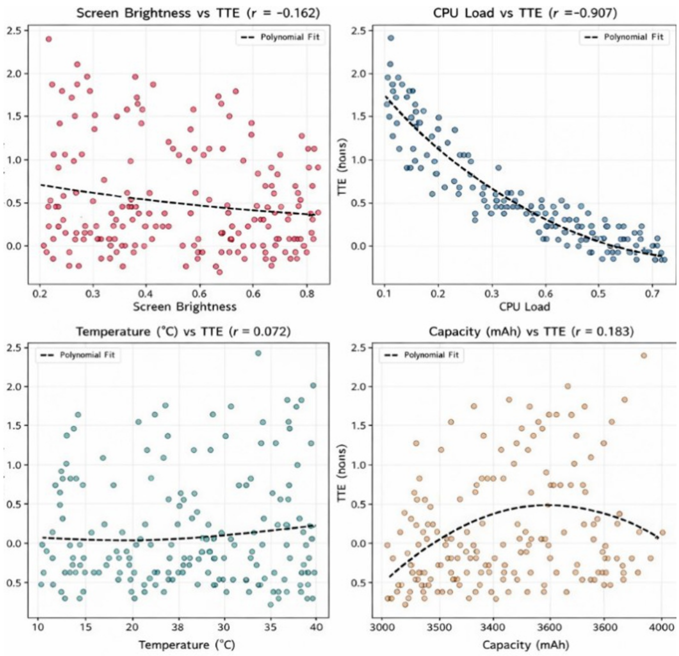

Fig. 1. Correlations Between Key Parameters and Smartphone Battery Time-to-Empty.

Figure 2 presents a three-dimensional parameter response analysis of three key variables affecting smartphone battery performance: screen brightness, CPU load, and ambient temperature. The variation along the CPU load direction is more pronounced than that along the screen brightness direction, suggesting that processor activity has a stronger influence on the battery response.

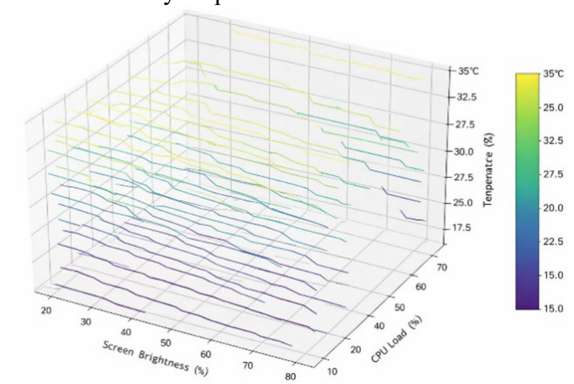

Fig. 2. Joint Effects of Screen Brightness, CPU Load, and Temperature.

5 Conclusion

In conclusion, this study developed a continuous-time SOC dynamic model for smartphone lithium-ion batteries and systematically analyzed battery endurance through multi-scenario simulation, sensitivity analysis, and uncertainty evaluation. The results show that CPU load is the dominant factor affecting time-to-empty, while temperature and capacity degradation also play important regulatory roles in endurance prediction. Future work can incorporate real user behavior data, online parameter identification, and machine learning techniques to build a more adaptive and accurate battery-life prediction model for intelligent energy management and personalized power-saving strategies.

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