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SMARTPHONE BATTERY POWER PREDICTION BASED ON CONTINUOUS-TIME AND USAGE PATTERN MODELS

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Abstract: This paper develops a smartphone battery power prediction framework based on the continuous-time model and the usage pattern model. The continuous-time model decomposes useful power into screen, CPU, network, GPS, and RAM components, then incorporates temperature-dependent Joule heating, active thermal management, and self-discharge into a coupled thermal-energy differential system. This structure describes how hardware settings, usage behavior, ambient conditions, and temperature jointly determine real-time power drain and battery energy decay. The usage pattern model further characterizes seven typical scenarios, including idling, gaming, web browsing, navigation, communication, multimedia playback, and camera operation. Based on a public dataset covering the daily feature usage of Android devices, model parameters are divided into usage pattern parameters, static hardware parameters, and power-type hardware parameters. The Trust Region Reflection Algorithm is used to invert hardware coefficients that cannot be directly obtained, while the Analytic Hierarchy Process evaluates the relative intensity of ten core variable parameters across the seven usage patterns. The analysis shows that screen power dominates most screen-on modes except Idle, making display power reduction a priority for power saving. Thermal management alleviates overheating but shortens battery life; in Navigation mode, it reduces the maximum temperature from about 43°C to 39°C while decreasing battery life by about half an hour.
Keywords: Smartphone battery; Continuous-time model; Usage pattern; Thermal-energy coupling; Power consumption prediction

1 INTRODUCTION

Smartphone battery life is one of the most important factors affecting mobile user experience. Modern smartphones integrate multiple energy-consuming subsystems, from display and computing units to communication, sensing, memory, and thermal-control modules. These components operate under changing workloads and interact with user behavior in complex ways. As a result, battery discharge is not determined by any single hardware parameter, but by the joint effect of component-level consumption, thermal evolution, usage scenarios, and system efficiency [1-2]. Accurate power prediction is therefore important for battery management, performance optimization, and user-oriented energy-saving strategies.

Traditional battery estimation methods often rely on simple empirical discharge curves or average power consumption under fixed scenarios. Such methods are easy to implement, but they may fail to capture real-time changes in workload and environmental conditions. For example, active modes such as media playback, gaming, navigation, browsing, and communication impose different workload patterns across display, computing, wireless, positioning, and memory resources [3-5]. Temperature further complicates the problem because high power consumption may increase heat generation, while thermal control may alter system performance and energy efficiency. Therefore, a useful prediction model should connect component-level power decomposition with thermal-energy coupling and scenario-specific usage patterns.

These observations motivate a modeling structure with two complementary perspectives. The first is a continuous-time perspective, in which instantaneous power is decomposed into the main hardware power terms and coupled with temperature feedback. This approach is suitable for describing real-time discharge and thermal response. The second is a usage-pattern perspective, in which typical smartphone activities are represented by different parameter combinations. This approach is more practical for user-level prediction because it links power consumption to recognizable behavioral scenarios. Combining these two perspectives can improve both physical interpretability and application relevance.

This paper develops a smartphone battery power prediction framework based on continuous-time and usage pattern models. First, useful power is decomposed at the component level and represented by key operating variables instead of repeatedly enumerating each hardware unit. Second, a thermal-energy coupling equation is introduced to describe the interaction between power consumption, temperature rise, and battery discharge. Third, a usage pattern model is constructed for typical smartphone scenarios, and scenario parameters are calibrated using dataset-driven estimation and analytic hierarchy process weighting. Fourth, the two models are connected so that physical power estimates can be adjusted according to user behavior. Finally, the framework is used to predict battery consumption and evaluate the contribution of different components and usage modes. The proposed method provides a structured basis for smartphone energy prediction, thermal-aware management, and personalized battery optimization.

2 CONTINUOUS-TIME MODEL

2.1 Model Overview

This continuous-time model predicts smartphone power consumption and battery discharge by linking hardware operating states with thermal dynamics. The model is organized around a coupled thermal-energy framework: the useful-power module estimates component-level consumption, and the thermal-energy module adds temperature-dependent Joule heating, active thermal management, and self-discharge to obtain total system power [6-8].

2.2 Useful Power Breakdown Equation

The system's total useful power can be expressed as the sum of the primary power-consuming electronic units:

$$P_{useful} = P_{screen} + P_{CPU} + P_{network} + P_{GPS} + P_{RAM} \tag{1}$$

In Equation (1), P_{useful} denotes the total useful power drawn by active hardware components; P_{screen}, P_{CPU}, $P_{network}$, P_{GPS}, and P_{RAM} represent the power consumed by the display, processor, network interfaces, positioning module, and memory module, respectively.

Screen power consumption is modeled by linearly integrating backlight lighting and pixel refresh display. The theoretical formula is:

$$P_{screen} = c_{bl} \cdot A \cdot L + c_{ref} \cdot N_{pixels} \cdot f_r \cdot g(APL) \tag{2}$$

In Equation (2), c_{bl} and c_{ref} are display power coefficients, A is the active screen area, L is the brightness level, N_{pixels} is the number of active pixels, f_r is the screen refresh rate, and $g(APL)$ is the correction function for the average pixel level.

Network power is modeled as the sum of cellular and Wi-Fi power:

$$P_{network} = P_{mobile} + P_{Wi\text{-}Fi} \tag{3}$$

In Equation (3), $P_{network}$ is the total network power, while P_{mobile} and $P_{Wi\text{-}Fi}$ denote cellular-network and Wi-Fi power consumption, respectively.

Table 1 Network Standard Coefficient

Network Standard	Efficiency factor ηRAT
2G (EDGE)	0.4-0.6
3G (HSPA)	0.6-0.8
4G (LTE)	0.8-1.0
5G (NR)	1.0-1.3

The network standard coefficient is shown in Table 1.

$$P_{mobile} = \frac{1}{\eta_{RAT}}(P_{mobile,base} + \alpha_{mobile,tx} \cdot R_{tx} + \alpha_{mobile,rx} \cdot R_{rx}) \tag{4}$$

$$P_{mobile} = \frac{1}{\eta_{RAT}}(P_{mobile,base} + \alpha_{mobile} \cdot (R_{tx} + R_{rx}/2)) \tag{5}$$

$$P_{Wi\text{-}Fi} = P_{Wi\text{-}Fi,base} + (\alpha_{Wi\text{-}Fi,tx} \cdot R_{Wi\text{-}Fi,tx} + \alpha_{Wi\text{-}Fi,rx} \cdot R_{Wi\text{-}Fi,rx}) \cdot \exp(\alpha_{RSSI} \cdot (RSSI_{ref} - RSSI)) \tag{6}$$

$$P_{Wi\text{-}Fi} = P_{Wi\text{-}Fi,base} + (\alpha_{Wi\text{-}Fi} \cdot (R_{Wi\text{-}Fi,tx} + R_{Wi\text{-}Fi,rx}/2)) \cdot \exp(\alpha_{RSSI} \cdot (RSSI_{ref} - RSSI)) \tag{7}$$

$$P_{CPU} \approx P_{dynamic} = \alpha_{CPU} \cdot C_{CPU} \cdot V_{CPU}^2 \cdot f_{CPU} \tag{8}$$

$$P_{GPS} = f_{GPS} \cdot S \tag{9}$$

$$P_{RAM} = \alpha_{RAM} C_{RAM} f_{REF} \tag{10}$$

$$f_{REF}(T) = f_{REF}(85) \cdot 2^{\frac{T-85}{10}} \tag{11}$$

In Equations (4)-(11), η_{RAT} denotes the efficiency factor of the radio access technology; R_{tx} and R_{rx} are uplink and downlink data rates; alpha terms denote empirical rate, signal-strength, CPU, and RAM coefficients; $RSSI$ and $RSSI_{ref}$ describe received signal strength and its reference level; C_{CPU}, V_{CPU}, and f_{CPU} are processor capacitance, voltage, and frequency; f_{GPS} and S describe GPS activation and signal-search intensity; C_{RAM} and f_{REF} denote RAM capacitance and refresh frequency, and T represents battery temperature.

2.3 Integrated Thermal-Energy Model

The energy change rate of a mobile phone battery is determined by total power consumption:

$$\frac{dE(t)}{dt} = -P_{total}(t) \tag{12}$$

$$E(t) = E(0) - \sum_0^t P_{total}(\tau)d\tau \tag{13}$$

$$P_{total}(t) = P_{heat}(t) + P_{thermal}(t) = P_{useful}(t) + I^2 \cdot r_d + P_{thermal}(t) \tag{14}$$

$$r_d(T) \approx r_{ct,25} \cdot \exp\left(\frac{E_a}{R}\left(\frac{1}{T+273.15} - \frac{1}{298.15}\right)\right), T < 40 \tag{15}$$

$$C_{th}\frac{dT}{dt} = P_{heat} - \frac{T-T_0}{R_{ja}} + \begin{cases} \xi P_{thermal}, T < T_{low} \\ -\xi P_{thermal}, T > T_{high} \\ 0, otherwise \end{cases} \tag{16}$$

$$P_{thermal} = \begin{cases} \kappa_h(T_{low} - T), T < T_{low} \\ \kappa_c(T - T_{high}), T > T_{high} \\ 0, otherwise \end{cases} \tag{17}$$

$$P_{self} = I_{sd} \cdot V_{loss} \tag{18}$$

$$I_{sd}(T) = I_{sd,25} \cdot 2^{\frac{T-25}{10}} \tag{19}$$

$$P_{heat} = P_{useful} + \left(\frac{P_{useful}}{U}\right)^2 r_d + P_{self} \tag{20}$$

In Equations (12)-(20), $E(t)$ is the remaining battery energy at time t, P_{total} is total system power, P_{heat} is heat-related power, $P_{thermal}$ is the power used by active thermal control, I is current, $r_d(T)$ is temperature-dependent internal resistance, C_{th} is thermal capacitance, T and T_0 are battery and ambient temperatures, R_{ja} is thermal resistance to ambient air, ξ indicates the sign and effect of heating or cooling control, κ_h and κ_c are heating and cooling coefficients, T_{low} and T_{high} are thermal-control thresholds, P_{self} is self-discharge power, I_{sd} is self-discharge current, V_{loss} is voltage loss, and E_a and R are the activation energy and gas constant used in the Arrhenius-type resistance term.

By incorporating thermal effects and energy variables, the model formulates a system of differential equations that describes the link between energy and time together with thermal effects.

3 USAGE PATTERN MODEL

3.1 Model Overview

After building power consumption submodels for each core component, the model characterizes seven typical user usage patterns: idling, gaming, web browsing, navigation, communication, multimedia playback, and camera. Each scenario is characterized by component activation states and operating-intensity characteristics, which are used to build the system's instantaneous power consumption model. The model compares power consumption intensity under equal initial charge and operating voltage settings, and identifies major driver components through their fractional energy contribution [9-10].

3.2 Model Building

To develop a computable power consumption model, a comprehensive dataset detailing the daily use of features in Android devices [11], hosted on Mendeley Data, is utilized to estimate and calibrate the model parameters. Parameters are grouped into usage pattern parameters, static hardware parameters, and power-type hardware parameters. Usage pattern parameters describe the scenario-dependent operating intensity of the device, such as display activity, processor load, communication demand, positioning use, and battery state. Static hardware parameters represent device configuration constants, while power-type hardware parameters denote intrinsic coefficients that cannot be directly obtained from the dataset and must be inferred through model inversion.

The parameter estimation procedure consists of three stages. The framework first estimates power-type hardware parameters by assuming full operational capacity and using the Trust Region Reflection Algorithm to minimize the discrepancy between predicted and observed power values. It then separates measurable continuous variables from binary operating states. The former describe workload intensity, whereas the latter indicate whether major modules such as display, network interfaces, and positioning are active. The Analytic Hierarchy Process is finally used to assess the relative strengths of ten core variable parameters across seven usage patterns, with all judgment matrices passing the consistency-ratio requirement below 0.1.

3.3 Data Analysis

The power consumption distribution among components in different modes is shown in Figure 1.

Specifically, Figures 1(a)-1(f) correspond to browsing, camera operation, gaming, communication, idle operation, and multimedia playback, respectively. In the later comparison, Figures 1(a), 1(c), 1(d), and 1(f) represent typical screen-on usage modes, Figure 1(e) represents the idle state dominated by network/background activity, and Figure 1(b) represents camera operation with a dominant display load.

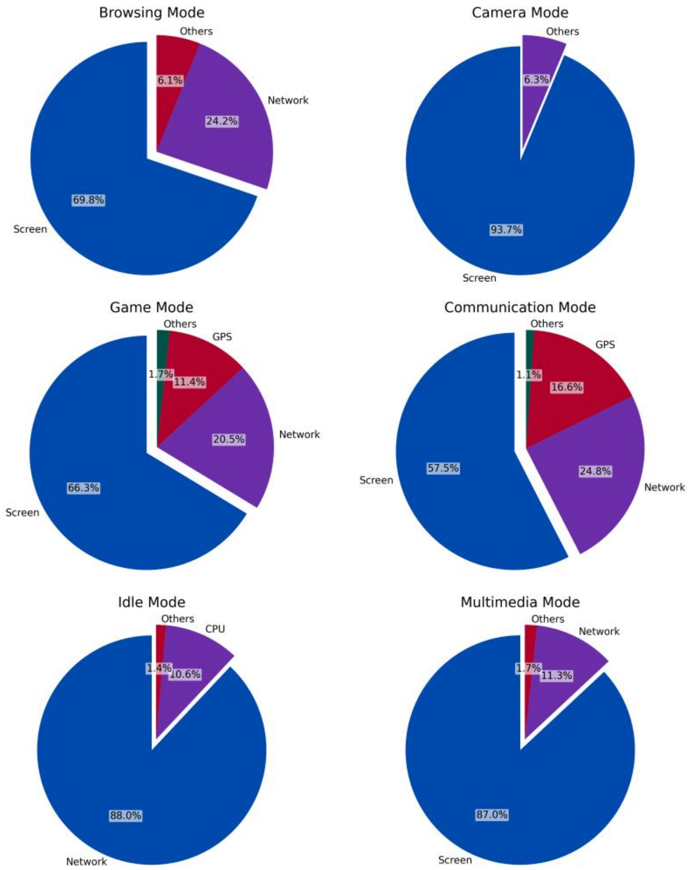

Figure 1 Power Consumption Distribution Among Components in Different Modes ((a) Browsing Mode, (b) Camera Mode, (c) Game Mode, (d) Communication Mode, (e) Idle Mode, (f) Multimedia Mode; Left to Right, Top to Bottom)

The fitted model parameters allow the power equations for all hardware modules to be evaluated. The pie charts show that screen power accounts for the largest proportion in all screen usage modes except Idle. Therefore, reducing screen power consumption should be the top priority for power saving.

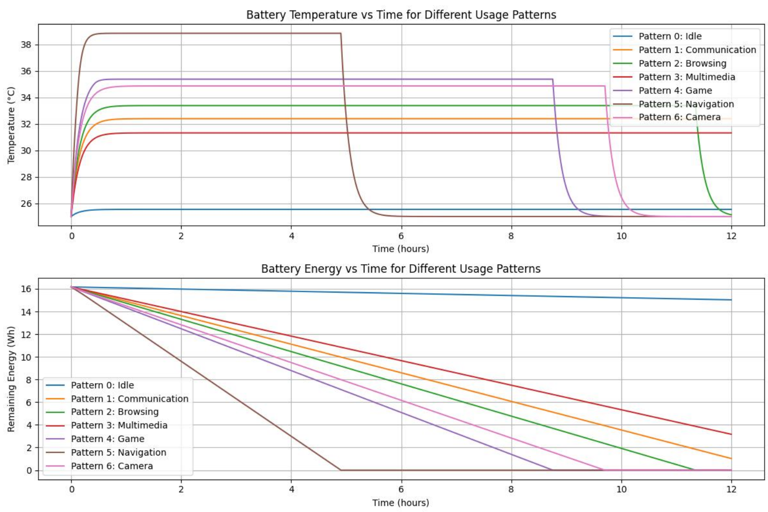

Figure 2 Time Curve of Temperature and Energy Not Enabling Thermal Management

The time curves for temperature and energy without thermal management are shown in Figure 2.

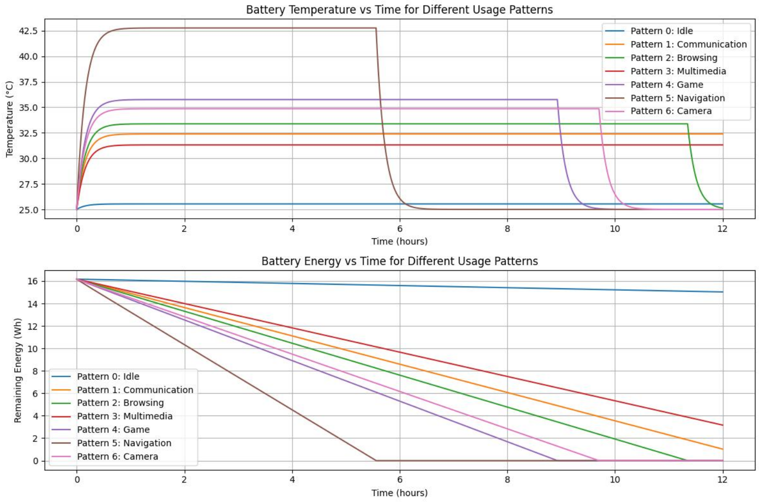

Figure 3 Time Curve of Temperature and Energy Enabling Thermal Management

"The time curves for temperature and energy with thermal management enabled are shown in Figure 3.
Enabling thermal management significantly alleviates overheating issues, but also reduces battery life to some extent. Taking Pattern 5: Navigation as an example, enabling thermal management lowers the maximum temperature from approximately 43°C to 39°C. Correspondingly, battery life is reduced by about half an hour.

4 SENSITIVITY ANALYSIS

A comprehensive sensitivity analysis was conducted to evaluate how key hardware, operational, and environmental parameters influence the total power consumption model (P_{total}) and the subsequent time-to-empty predictions ($t_{predict}$) across seven distinct usage scenarios. By perturbing specific variables, we identified distinct patterns of influence that validate the model's robustness and highlight critical energy drivers.
Here, P_{total} denotes the total power consumption model and $t_{predict}$ denotes the predicted time to empty. The symbols f_{GPS}, U, f_r, c_{bl}, and T_{env} in the following analysis denote GPS activation intensity, battery terminal voltage, screen refresh rate, brightness-level power coefficient, and ambient temperature, respectively.

4.1 Impact of Hardware and Operational Parameters

The analysis indicates that GPS power (f_{GPS}) variations have the most pronounced effect on the Navigation mode, which is consistent with the high operational intensity of positioning modules in that scenario. In contrast, changes in battery voltage (U) demonstrate a minimal impact on the total power consumption across all usage modes. This finding is significant as it justifies the model's simplification in Section 3, where battery terminal voltage is approximated as a constant to reduce computational complexity without sacrificing predictive accuracy.
The simplification is reasonable because the sensitivity results show that voltage perturbations produce much smaller runtime changes than display, GPS, and thermal parameters. In addition, smartphone power-management circuits usually regulate the terminal-voltage output within a narrow normal operating window, so treating U as quasi-constant is acceptable for scenario-level prediction.
Screen-related parameters were found to be highly sensitive in modes characterized by active display usage. A $\pm 50\%$ variation in the screen refresh rate (f_r) notably shifts the predicted runtime for Communication, Browsing, Multimedia, Game, and Camera modes, whereas the Idle mode remains entirely unaffected. Similarly, the power coefficient per brightness level (c_{bl}) primarily governs the variance in battery life during Multimedia and Camera operations, underscoring the dominance of backlight and pixel-refresh energy in these scenarios.

4.2 Environmental Temperature and Thermal Dynamics

The ambient temperature (T_{env}) exhibits a complex, non-linear impact on the device's operational time due to the coupling between battery energy and the integrated thermal management module. Under elevated temperatures (e.g., $32^{\circ}C$), the thermal management system is activated to mitigate overheating risks, which effectively lowers the device temperature but reduces battery life across all modes. For example, in Navigation mode, enabling thermal control can reduce the maximum temperature from $43^{\circ}C$ to $39^{\circ}C$ at the cost of approximately 30 minutes of runtime.
Under extreme cold conditions, such as $0^{\circ}C$, the impact of thermal management becomes catastrophic for low-load states. Because the system must consume significant energy to maintain the battery within an acceptable operating range, the predicted Idle mode operation time can plummet from a standard 7 days to approximately 10 hours. This 94% reduction in standby time highlights the critical trade-off between device safety and energy efficiency in extreme environments.

5 CONCLUSION

This study constructs a smartphone battery power prediction framework from the specified continuous-time and usage pattern models. The continuous-time model decomposes useful power into screen, CPU, network, GPS, and RAM components and then couples useful power with temperature-dependent Joule heating, thermal management, and self-discharge through energy and heat-balance equations. The usage pattern model calibrates scenario-specific power behavior for seven typical modes with the aforementioned daily feature usage dataset, applies Trust Region Reflection to infer hardware coefficients, and uses AHP to evaluate the intensity of core variable parameters. The analysis indicates that screen power dominates most screen-on usage modes except Idle, while thermal management lowers overheating risk but reduces runtime, as shown by the Navigation example. The limitation of the present model is that several component expressions rely on simplified physical or empirical approximations and scenario intensities derived from the available dataset. Future work may further refine parameter estimation with broader device samples and more detailed real-world traces to strengthen robustness across different smartphone platforms.

COMPETING INTERESTS

The authors have no relevant financial or non-financial interests to disclose.

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