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A Fusion Mechanism-Coordinated Dynamic Modeling Approach for Smartphone Battery Depletion Prediction

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Abstract

Accurate time-to-empty (TTE) estimation for smartphones remains challenging because battery electrochemical dynamics interact with highly variable device-level power demands. This study develops the Fusion Mechanism-Coordinated Dynamic Model (FM-CDM), a physics-informed theoretical framework that couples a second-order Thevenin equivalent-circuit model with component-level power consumption, electro-thermal feedback, battery state of health, and stochastic workload generation. TTE is formulated as the first time at which the terminal voltage reaches a 3.2 V cutoff, thereby distinguishing the shutdown condition from SOC = 0%. The algebraic coupling among device power, discharge current, and terminal voltage is resolved using the physically admissible solution of the constant-power load equation. Separate battery and processor thermal states are introduced to represent temperature-dependent internal resistance, battery heat generation, heat dissipation, and processor thermal throttling. Four representative workload classes—Standby, Light, Medium, and Heavy—are considered, with 500 Monte Carlo realizations used for each class to propagate workload and parameter uncertainty. Global sensitivity is evaluated using the Morris elementary-effects method. The illustrative numerical analysis shows that increasing component activity shortens model-estimated runtime and that voltage-triggered shutdown can occur at a nonzero residual SOC, particularly when temperature-dependent resistance and load-induced voltage drop become significant. The framework provides a transparent and reproducible basis for investigating smartphone battery depletion, uncertainty propagation, and mechanism-level energy-management strategies under explicitly defined reference conditions.

Keywords: smartphone battery; time to empty; equivalent-circuit model; electro-thermal coupling; stochastic workload

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1. Introduction

Battery runtime remains a fundamental constraint on smartphone usability and operating-system energy management. A reliable estimate of the remaining operating time is required not only to inform users but also to support workload scheduling, network management, display control, and processor power regulation. Smartphone battery depletion is inherently nonlinear because the available charge, open-circuit voltage, internal resistance, polarization, temperature, and load-dependent conversion losses jointly determine the terminal voltage and shutdown time. Previous studies have demonstrated that device operations and temperature can substantially affect battery behavior [1,2], while

user-centered studies have highlighted the practical importance of battery-runtime information [3]. Consequently, a linear extrapolation of the displayed battery percentage cannot fully represent the physical processes governing TTE.

Coulomb counting is widely used for state-of-charge estimation because of its low computational cost and straightforward implementation. However, its accuracy is affected by current-measurement bias, uncertainty in the initial SOC, and accumulated integration error [4,5]. Data-driven approaches, including machine-learning and neural-network models, can learn nonlinear relationships among voltage, current, temperature, and battery state [6,7]. Their performance, however, depends on the representativeness of the training data and may deteriorate when the operating conditions differ substantially from those encountered during training. Equivalent-circuit models provide an interpretable alternative by representing the dominant ohmic, charge-transfer, and diffusion processes with a limited number of electrical states [8,9]. Temperature-dependent OCV–SOC identification further improves their applicability under varying thermal conditions [10].

Smartphone-level TTE estimation introduces an additional challenge because the battery current is determined by a combination of heterogeneous and time-varying hardware loads. OLED display power depends on both brightness and average pixel level; processor and graphics power varies with activity, frequency, voltage, and thermal throttling; and wireless interfaces exhibit discrete operating states and tail-energy effects. GPS operation, camera activity, background synchronization, and wake-lock events introduce further temporal variability. Recent studies have provided detailed characterizations of smartphone hardware power consumption and user-dependent energy demand [11–13]. Nevertheless, component-level power models are frequently analyzed independently of the battery's internal voltage and thermal states, whereas battery models commonly treat the external load as a prescribed current or power profile.

This separation becomes particularly important when the terminal-voltage cutoff, rather than complete charge depletion, determines the usable runtime. Under a high-power workload, the voltage drop across the internal resistance and polarization branches may cause the terminal voltage to reach the shutdown threshold, while a nonzero amount of charge remains. Low-temperature conditions can further increase internal resistance and intensify this effect. Conversely, processor self-heating and thermal throttling can alter the device-power trajectory during discharge. Battery state of health changes the available capacity and resistance over the device lifetime, but its influence on a single discharge process must be distinguished from long-term degradation. A coherent TTE model should therefore coordinate electrical, thermal, health-related, and device-power mechanisms within a common state-space formulation.

To address these requirements, this study proposes the Fusion Mechanism-Coordinated Dynamic Model (FM-CDM). The objective is to establish a transparent theoretical coupling among a second-order Thevenin equivalent-circuit model, component-level device power, electro-thermal feedback, battery state of health, and a voltage-based TTE event. The model treats TTE as a first-passage problem in which simulation terminates when the terminal voltage reaches a prescribed cutoff. Device power and discharge current are coupled through the terminal voltage, and the resulting constant-power equation is solved using its physically admissible current root. Separate battery and processor thermal states are used so that battery resistance correction and processor thermal throttling are governed by physically distinct temperatures.

The main contributions of this work are summarized as follows. First, TTE is formulated as a terminal-voltage first-passage event, thereby distinguishing the shutdown condition from $\text{SOC} = 0\%$. Second, a physically admissible solution is derived for the algebraic coupling among device power, discharge current, and terminal voltage under constant power loading. Third, a two-node electro-thermal structure is introduced to distinguish

battery temperature from processor temperature and to represent the associated heat-generation and heat-rejection processes. Finally, stochastic workload variability and parameter sensitivity are incorporated through Monte Carlo simulation and Morris screening within a reproducible numerical workflow.

The remainder of this paper is organized as follows. Section 2 presents the model scope, electrical and thermal formulations, component-level power models, stochastic workload definitions, and numerical implementation. Section 3 describes the numerical analysis of scenario-dependent TTE, uncertainty, power attribution, global sensitivity, and thermal coupling. Section 4 summarizes the principal conclusions, discusses the applicability and limitations of the framework, and outlines directions for subsequent device-level evaluation.

2. Methodology

To address the challenge of predicting smartphone battery depletion under stochastic usage, this study proposes the FM-CDM. Unlike black-box regression models that treat the device as a simple energy sink, the FM-CDM is a continuous-time “white-box” approach. It mathematically couples the internal electrochemical dynamics of the lithium-ion battery with the external, non-linear power scheduling logic of the operating system.

2.1. Scope, Assumptions, and State Definitions

The FM-CDM is formulated as a coupled continuous time framework that links battery electrical dynamics, device-level power demand, and electro-thermal feedback. The modeled system comprises a generic single-cell lithium-ion battery and an aggregated smartphone load. For the illustrative numerical analysis, the reference configuration adopts a nominal capacity of 5 Ah (18,000 C) and a terminal-voltage cutoff of 3.2 V. These values define a smartphone-scale theoretical configuration rather than a parameterization of a particular commercial handset. To maintain physical consistency, the open-circuit-voltage curve, equivalent-circuit parameters, and thermal properties used within an individual simulation case are required to correspond to the same reference cell configuration and voltage window.

The model is established under the following assumptions. First, the dominant battery voltage dynamics are represented by a second-order Thevenin equivalent-circuit model with an additional hysteresis state. Second, the battery and the system-on-chip are treated as two spatially lumped thermal nodes with uniform temperatures. Third, the device load is approximated as a constant-power load within each numerical integration interval, while its power demand may vary between intervals according to the prescribed workload process. Fourth, the initial state of health, denoted by (SOH_0), remains fixed during a single TTE simulation. Finally, device shutdown is defined by the first occurrence of the loaded terminal voltage reaching the prescribed cutoff voltage; it is not defined by the SOC reaching zero.

With the battery discharge current defined as positive, the electrical and thermal state vector is written as:

$$x(t) = [z, V_1, V_2, h, T_b, T_s]^T \quad (1)$$

where $z \in [0, 1]$ is the normalized state of charge; V_1 and V_2 are the polarization voltages associated with the fast and slow RC branches, respectively; $h \in [-1, 1]$ is the dimensionless voltage-hysteresis state; T_b is the lumped battery temperature; and T_s is the lumped system-on-chip temperature. Separating T_b from T_s allows the temperature dependence of the battery resistance and the processor thermal-throttling mechanism to be represented independently.

The time-varying device-level input vector is defined as:

$$u(t) = [\alpha^T, s_{disp}, L, APL, S_{net}, s_{GPS}, s_{cam}, w_{wake}]^T \quad (2)$$

where $u(t)$ is the time-varying device-level input vector; $\alpha = [\alpha_1, \dots, \alpha_{N_{cl}}]^T$ contains the activity factors of the N_{cl} processor or graphics domains; $L \in [0, 1]$ is the normalized display-brightness level; $APL \in [0, 1]$ is the average pixel level; S_{net} is the discrete network operating state; SNR is the received signal-to-noise ratio; $s_{GPS} \in \{0, 1\}$ and $s_{cam} \in \{0, 1\}$ indicate whether the GPS and camera modules are active, respectively; and $w_{wake} \in \{0, 1\}$ denotes the finite-duration background wake-lock state. All quantities on the right-hand side of Equation (2) are evaluated at time t . Their stochastic evolution is specified in Section 2.7.

The nominal capacity Q_{nom} , ambient temperature T_{amb} , initial state of health SOH_0 , and cutoff voltage V_{cut} are treated as case-level conditions rather than time-varying workload inputs. Let θ denote the set of electrical, thermal, and component-power parameters. The FM-CDM can then be expressed in the general state-space form.

$$\begin{aligned} x(t) &= f(x(t), u(t); \theta, T_{amb}, SOH_0) \\ y(t) &= [V_{term}(t), z(t), T_b(t), T_s(t)]^T \end{aligned} \quad (3)$$

where $f(\cdot)$ denotes the nonlinear state-transition function; θ is the parameter vector containing the electrical, thermal, and component-power parameters; $y(t)$ is the model-output vector; and $V_{term}(t)$ is the loaded battery terminal voltage. The detailed expressions governing the individual state variables are developed in the following subsections.

The overall coupling architecture of the FM-CDM is illustrated in Figure 1. The framework links stochastic workload generation, component-level device power, constant-power current calculation, battery electrical dynamics, two-node thermal feedback, and the voltage-cutoff TTE event.

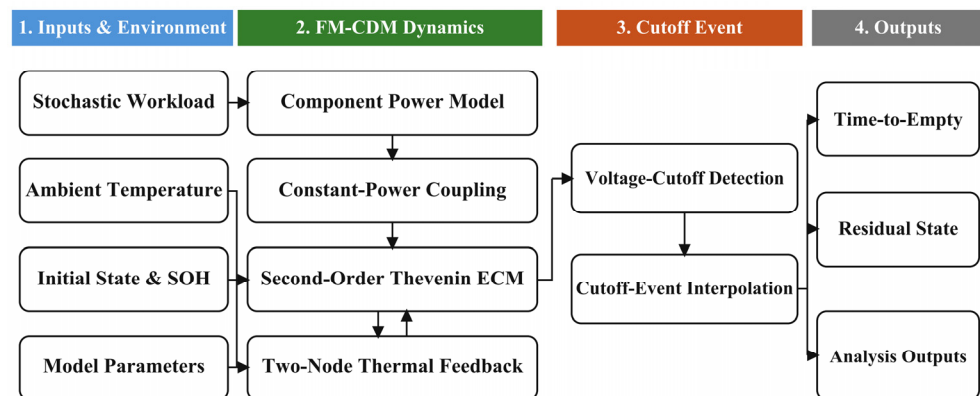


Figure 1. Coupling architecture and voltage-cutoff workflow of the FM-CDM.

2.2. Electrical Model and Voltage-Cutoff TTE

The battery electrical subsystem is represented by a second-order Thevenin equivalent-circuit model, which provides a computationally efficient description of the open-circuit voltage, ohmic voltage drop, polarization dynamics, and voltage hysteresis [8–10]. The open-circuit voltage is represented by a polynomial function of SOC:

$$V_{oc}(z) = \sum_{j=0}^n p_j z^j, \quad z \in [z_{\min}, z_{\max}] \quad (3)$$

where p_j is the j -th polynomial coefficient, n is the polynomial order, and $[z_{\min}, z_{\max}]$ denotes the applicable SOC interval. A sixth-order polynomial, corresponding to $n = 6$, is adopted in the reference formulation. The coefficient vector and applicable SOC interval are summarized in Table 1, and the model is evaluated within this interval.

Table 1. Core parameters of the theoretical reference configuration.

Category	Symbol	Value (Typical)	Unit
Nominal capacity	Q_{nom}	18,000	C
Cutoff voltage	V_{cut}	3.20	V
Reference temperature	T_{ref}	298.15	K
Reference SOH	SOH_0	1.00	-
OCV coefficients	$p_0, \dots, p_6$	3.202466, 5.457440, -26.637712, 72.840195, -108.07222, 81.460741, -24.053131	V
Branch resistances	$R_{0,ref}, R_{1,ref}, R_{2,ref}$	0.058, 0.032, 0.032	Ω
Branch capacitances	C_1, C_2	5460, 18,720	F
RC time constants	τ_1, τ_2	174.72, 599.04	s
Hysteresis parameters	M, γ_h	0.030, 20	V, -
Resistance Activation factor	$E_{a,i} / R_g$	1200	K
SOH resistance coefficients	$\kappa_{R,0}, \kappa_{R,1}, \kappa_{R,2}$	0.80, 0.80, 0.80	-
DC conversion efficiency	η_{dc}	0.92	-
Thermal capacitances	C_b, C_s	120, 180	JK ⁻¹
Thermal resistances	R_{bs}, R_{ba}, R_{sa}	1.50, 8.00, 5.00	KW ⁻¹
Heat-conversion Fractions	ξ_{dev}, ξ_{dc}	0.90, 1.00	-

Note: The values define the theoretical reference configuration used in the numerical analysis. The OCV coefficient order is p_0 to p_6 . Detailed device-component parameters are listed in Appendix A, Table A1.

The discharge current $I(t)$ is defined as positive. To separate short-term battery depletion from long-term aging, the effective available charge capacity for an individual TTE simulation is defined as:

$$Q_{eff} = Q_{nom} SOH_0 \quad (4)$$

where Q_{nom} is the nominal charge capacity in coulombs and SOH_0 is the battery state of health at the beginning of the simulation. The resulting Q_{eff} remains constant during a single discharge simulation. Temperature influences the predicted runtime through the resistance, polarization, terminal-voltage, and thermal-feedback equations; temperature-dependent capacity derating is not included in the present formulation.

Assuming unity discharge coulombic efficiency and negligible self-discharge over a single smartphone-discharge period, charge conservation is expressed as:

$$\frac{dz}{dt} = -\frac{I(t)}{Q_{eff}} \quad (5)$$

where z is the dimensionless SOC, I is expressed in amperes, and Q_{eff} is expressed in coulombs. The negative sign indicates that SOC decreases when the positive discharge current flows from the battery to the device.

The fast and slow polarization processes are represented by two polarization branches, each comprising a parallel resistor–capacitor pair. The voltage dynamics of branch i are governed by:

$$\frac{dV_i}{dt} = -\frac{V_i}{R_i C_i} + \frac{I}{C_i}, \quad i \in \{1, 2\} \quad (6)$$

where R_i , C_i , and V_i denote the resistance, capacitance, and polarization voltage of branch i , respectively. The corresponding time constant is $\tau_i = R_i C_i$. The parameter set $\{R_1, C_1, \tau_1, R_2, C_2, \tau_2\}$ is summarized in Table 1.

To represent the path-dependent voltage difference between charging and discharging, the dimensionless hysteresis state is described by:

$$\frac{dh}{dt} = \gamma_h \frac{|I|}{Q_{eff}} [\text{sgn}(I) - h] \quad (7)$$

where γ_h is the hysteresis-rate coefficient and $\text{sgn}(\cdot)$ denotes the sign function. Under the adopted current convention, h approaches +1 during sustained discharge. When $I = 0$, Equation (8) gives $dh/dt = 0$, and the hysteresis state remains unchanged.

The loaded terminal voltage is calculated as:

$$V_{term} = V_{oc}(z) - V_1 - V_2 - IR_0 - Mh \quad (8)$$

where R_0 is the instantaneous ohmic resistance and M is the maximum hysteresis-voltage magnitude. The ohmic resistance is modeled as a function of SOC, battery temperature, and initial SOH. Its temperature dependence is introduced in Section 2.4. The sign of the hysteresis term is consistent with Equation (8), such that $-Mh$ represents the discharge-side hysteresis contribution as h approaches +1.

Because the smartphone is represented as a constant-power load within each numerical integration interval, battery current cannot be calculated by dividing the device power by an independently prescribed terminal voltage. The power drawn from the battery terminals and an auxiliary voltage variable are defined as:

$$P_{bat} = \frac{P_{dev}}{\eta_{dc}}, \quad A = V_{oc} - V_1 - V_2 - Mh \quad (9)$$

where P_{dev} is the total device-level power demand, $\eta_{dc} \in (0, 1]$ is the DC conversion efficiency, and P_{bat} is the power drawn from the battery terminals. Substitution of $V_{term} = A - IR_0$ into $P_{bat} = IV_{term}$ gives

$$R_0 I^2 - AI + P_{bat} = 0 \quad (10)$$

The physically admissible current is the smaller positive root of Equation (11):

$$I = \frac{A - \sqrt{A^2 - 4R_0 P_{bat}}}{2R_0} = \frac{2P_{bat}}{A + \sqrt{A^2 - 4R_0 P_{bat}}} \quad (11)$$

The second expression in Equation (12) is algebraically equivalent to the conventional quadratic-form solution and is used in the numerical implementation to avoid subtractive cancellation when R_0 is small. A real-valued current exists when

$$A^2 - 4R_0P_{\text{bat}} \geq 0$$

If this condition is violated, the requested constant power cannot be supplied at the current electrical state. The simulation is then terminated, and the event is recorded as an electrical-load infeasibility rather than a voltage-cutoff event.

The voltage-cutoff time is defined as the first time at which the loaded terminal voltage reaches the prescribed cutoff threshold. The TTE and residual SOC at shutdown are subsequently defined as:

$$\begin{aligned} t_{\text{cut}} &= \inf\{t \geq t_0 : V_{\text{term}}(t) \leq V_{\text{cut}}\} \\ \text{TTE} &= t_{\text{cut}} - t_0, \quad z_{\text{cut}} = z(t_{\text{cut}}) \end{aligned} \quad (13)$$

where t_0 is the initial simulation time, t_{cut} is the voltage-cutoff time, and z_{cut} is the residual SOC at shutdown. In the reference configuration, $V_{\text{cut}} = 3.2$ V. This threshold represents a voltage-based shutdown condition and is not equivalent to $z = 0$. Consequently, the model can produce a nonzero residual SOC at shutdown, particularly under high-power or low-temperature conditions that cause a pronounced load-induced voltage drop.

2.3. Component-Level Device-Power Model

The component-level power model converts the stochastic workload variables defined in Section 2.1 into the electrical power demand applied to the battery model. At the output boundary of the DC–DC converter, the total device power is expressed as:

$$P_{\text{dev}}(t) = P_{\text{disp}}(t) + \sum_{d \in \mathcal{D}} P_d(t) + P_{\text{net}}(t) + P_{\text{GPS}}(t) + P_{\text{cam}}(t) + P_{\text{wake}}(t) + P_{\text{ovh}}(t) \quad (14)$$

where $\mathcal{D} = \{\text{L, M, B, G}\}$ denotes the Little-CPU, Medium-CPU, Big-CPU, and GPU domains, respectively. The DC–DC conversion loss is not included in Equation (14) because it is applied separately through the conversion efficiency in Equation (10).

For the OLED display, the power demand depends on the display-state indicator, normalized brightness, and average pixel level:

$$P_{\text{disp}}(t) = s_{\text{disp}}(t) \left[P_{\text{disp},0} + k_{\text{disp}} L(t)^{a_L} \text{APL}(t)^{b_{\text{APL}}} \right] \quad (15)$$

where $s_{\text{disp}} \in \{0,1\}$, $L \in [0,1]$, and $\text{APL} \in [0,1]$. The quantities $P_{\text{disp},0}$, k_{disp} , a_L , and b_{APL} are the display-driver power, brightness–APL coefficient, brightness exponent, and APL exponent, respectively.

The temperature-dependent throttling multiplier applied to the computational domains is defined as:

$$\vartheta(T_s) = \begin{cases} 1, & T_s \leq T_{\text{on}} \\ [4pt] 1 - \frac{(1 - \vartheta_{\text{min}})(T_s - T_{\text{on}})}{T_{\text{full}} - T_{\text{on}}}, & T_{\text{on}} < T_s < T_{\text{full}} \\ [8pt] \vartheta_{\text{min}}, & T_s \geq T_{\text{full}} \end{cases} \quad (16)$$

where T_s is the system-node temperature, T_{on} is the throttling-onset temperature, T_{full} is the temperature at which the minimum multiplier is reached, and ϑ_{min} is the retained activity multiplier under full throttling.

For computational domain d , the effective activity factor, normalized frequency, and normalized voltage are calculated as:

$$\begin{aligned}
 \alpha_{d,\text{eff}}(t) &= \text{clip}[\vartheta(T_s)\alpha_d(t), 0, 1] \\
 \hat{f}_d(t) &= \rho_{\min} + (1 - \rho_{\min})\alpha_{d,\text{eff}}(t) \\
 \hat{v}_d(t) &= c_{v,0} + c_{v,1}\hat{f}_d(t).
 \end{aligned} \tag{17}$$

Here, α_d is the commanded workload activity, $\rho_{\min}$ is the normalized frequency intercept, and $c_{v,0}$ and $c_{v,1}$ define the normalized voltage–frequency relation. The operator $\text{clip}(x, 0, 1)$ restricts x to the interval $[0, 1]$.

The power of computational domain d is the sum of dynamic and temperature-dependent leakage contributions:

$$\begin{aligned}
 P_d(t) &= P_{d,\max}\alpha_{d,\text{eff}}(t)\hat{f}_d(t)\hat{v}_d(t)^2 \\
 &\quad + P_{d,\text{leak}}^{\text{ref}} \exp[\beta_{\text{leak}}(T_s - T_{\text{ref}})] [g_0 + g_1 \mathbb{I}(\alpha_d > \alpha_{\text{gate}})]
 \end{aligned} \tag{18}$$

where $P_{d,\max}$ is the maximum dynamic-power coefficient, $P_{d,\text{leak}}^{\text{ref}}$ is the reference leakage power at T_{ref} , and β_{leak} is the leakage-temperature coefficient. The indicator function $\mathbb{I}(\cdot)$ distinguishes active and inactive computational domains, while g_0 , g_1 , and α_{gate} define the leakage-power gate.

Network interface power is determined by its discrete operating state:

$$P_{\text{net}}(t) = \begin{cases} P_{\text{net,idle}}, & S_{\text{net}}(t) = \text{Idle} \\ P_{\text{net,tail}}, & S_{\text{net}}(t) = \text{Tail} \\ P_{\text{net,active}}, & S_{\text{net}}(t) = \text{Active} \end{cases} \tag{19}$$

The Tail state represents the finite elevated-power interval following an Active event. The stochastic state transitions and state durations are defined in Section 2.7. No additional signal-quality correction is applied in the reference configuration.

The GPS and camera contributions are:

$$\begin{aligned}
 P_{\text{GPS}}(t) &= P_{\text{GPS,act}} s_{\text{GPS}}(t) \\
 P_{\text{cam}}(t) &= P_{\text{cam,act}} s_{\text{cam}}(t)
 \end{aligned} \tag{12}$$

where $s_{\text{GPS}}, s_{\text{cam}} \in \{0, 1\}$, and $P_{\text{GPS,act}}$ and $P_{\text{cam,act}}$ are their active-state powers.

Wake-lock activity and the remaining system overhead are represented independently as:

$$\begin{aligned}
 P_{\text{wake}}(t) &= P_{\text{wake,act}} w_{\text{wake}}(t) \\
 P_{\text{ovh}}(t) &= P_{\text{base}} + k_{\alpha} \max_{d \in \mathcal{D}} \alpha_{d,\text{eff}}(t) + k_{\text{disp,on}} s_{\text{disp}}(t)
 \end{aligned} \tag{13}$$

where $w_{\text{wake}} \in \{0, 1\}$ is the finite-duration wake-lock state. The overhead term accounts for power-management quiescent consumption, memory and storage activity, sensor-hub operation, and activity-dependent supporting circuitry that is not assigned to the explicitly modeled components.

All power terms in Equations (14)–(21) are nonnegative and expressed in watts. Their sum is evaluated at each numerical time step, converted to battery-terminal power through Equation (10), and used to determine the physically admissible battery current from Equation (12).

2.4. Electro-Thermal Coupling

The electrical and thermal subsystems are coupled through battery heat generation, temperature-dependent electrical resistance, and device-level heat dissipation. Because the battery cell and the system-on-chip have different heat-generation mechanisms and

thermal time constants, they are represented by two lumped thermal nodes. The battery node has temperature T_b and thermal capacitance C_b , whereas the system node has temperature T_s and thermal capacitance C_s .

The energy balance of the battery thermal node is written as:

$$C_b \frac{dT_b}{dt} = \dot{Q}_b + \frac{T_s - T_b}{R_{bs}} - \frac{T_b - T_{amb}}{R_{ba}} \quad (14)$$

where $\dot{Q}_b$ is the heat-generation rate within the battery, R_{bs} is the thermal resistance between the battery and the system node, R_{ba} is the thermal resistance between the battery and the ambient environment, and T_{amb} is the prescribed ambient temperature. A positive value of $(T_s - T_b)/R_{bs}$ represents heat transfer from the system node to the battery.

The energy balance of the system thermal node is:

$$C_s \frac{dT_s}{dt} = \dot{Q}_s - \frac{T_s - T_b}{R_{bs}} - \frac{T_s - T_{amb}}{R_{sa}} \quad (15)$$

where $\dot{Q}_s$ is the heat-generation rate associated with the device components and DC conversion loss, and R_{sa} is the thermal resistance between the system node and the ambient environment. The heat-transfer term between the two nodes appears with opposite signs in Equations (22) and (23), thereby conserving energy within the coupled thermal system.

The heat generated in the RC polarization branches can be derived directly from Equation (7). Multiplying the branch equation by $C_i V_i$ gives

$$\frac{d}{dt} \left(\frac{1}{2} C_i V_i^2 \right) = I V_i - \frac{V_i^2}{R_i}, \quad i \in \{1, 2\} \quad (16)$$

where $C_i V_i^2 / 2$ is the energy temporarily stored in the polarization capacitor and V_i^2 / R_i is the irreversible heat-dissipation rate in the corresponding polarization resistance. This relation distinguishes energy storage in the capacitors from irreversible thermal loss in the resistors.

For the discharge-only TTE simulations, the total battery heat-generation rate is defined as:

$$\dot{Q}_b = I^2 R_0 + \frac{V_1^2}{R_1} + \frac{V_2^2}{R_2} + IMh \quad (17)$$

where $I^2 R_0$ is the ohmic heat-generation rate, V_1^2 / R_1 and V_2^2 / R_2 are the polarization-loss terms, and IMh represents the irreversible contribution associated with the discharge-side hysteresis overpotential. The reference discharge cases use $I \geq 0$ and $h(t_0) = 0$; consequently, h remains nonnegative, and all terms in Equation (25) are nonnegative. Reversible entropic heat is not included because the OCV formulation in Equation (4) does not contain a temperature-dependent entropic coefficient.

The heat-generation rate of the system node is expressed as:

$$\dot{Q}_s = \xi_{dev} P_{dev} + \xi_{dc} (P_{bat} - P_{dev}) \quad (18)$$

where $\xi_{dev} \in [0, 1]$ is the fraction of device-level electrical power converted into heat within the lumped system node, and $\xi_{dc} \in [0, 1]$ is the fraction of DC conversion loss dissipated within the same node. The difference $P_{bat} - P_{dev}$ is nonnegative because $P_{bat} = P_{dev} / \eta_{dc}$ and $0 < \eta_{dc} \leq 1$. Energy leaving the modeled thermal node as display

light, radio-frequency radiation, acoustic output, or mechanical work is represented by the fraction $1 - \xi_{\text{dev}}$.

The resistances of the ohmic and polarization branches depend on SOC, battery temperature, and initial SOH. For $i \in \{0, 1, 2\}$, the resistance is expressed as:

$$R_i(z, T_b, \text{SOH}_0) = R_{i,\text{ref}}(z) g_{R,i}(\text{SOH}_0) \exp \left[\frac{E_{a,i}}{R_g} \left(\frac{1}{T_b} - \frac{1}{T_{\text{ref}}} \right) \right] \quad (19)$$

where $R_{i,\text{ref}}(z)$ is the SOC-dependent resistance at the reference temperature T_{ref} and reference health state, $g_{R,i}(\text{SOH}_0)$ is the resistance-scaling function associated with battery health, $E_{a,i}$ is the activation energy, and R_g is the universal gas constant. The SOH scaling function is defined in Section 2.5.

Both T_b and T_{ref} in Equation (27) are expressed in kelvin. The units of $E_{a,i}$ and R_g are J mol^{-1} and $\text{J mol}^{-1} \text{K}^{-1}$, respectively, making the exponential argument dimensionless. For $E_{a,i} > 0$, a battery temperature below T_{ref} increases R_i , thereby increasing the ohmic voltage drop and advancing the voltage-cutoff event under a given power demand. The polarization capacitances C_1 and C_2 are treated as constant reference parameters in the present formulation.

Adding Equations (22) and (23) eliminates the internal heat-transfer term and gives the overall transient thermal-energy balance:

$$C_b \frac{dT_b}{dt} + C_s \frac{dT_s}{dt} = \dot{Q}_b + \dot{Q}_s - \frac{T_b - T_{\text{amb}}}{R_{\text{ba}}} - \frac{T_s - T_{\text{amb}}}{R_{\text{sa}}} \quad (20)$$

Equation (28) shows that the thermal coupling between the battery and the system redistributes heat internally but does not create or remove energy. At thermal equilibrium, the stored-energy terms on the left-hand side vanish, and the combined heat generation equals the heat rejected from the battery and system nodes to the ambient environment. All thermal capacitances and thermal resistances are positive, and their reference values are summarized in Table 1.

The battery resistance obtained from Equation (27) is used in the terminal-voltage equation and constant-power current solution at every numerical time step. Simultaneously, the system temperature obtained from Equation (23) determines the processor frequency limit in Equation (17). These two feedback paths complete the electro-thermal coupling of the FM-CDM.

2.5. State of Health and Aging Scope

Battery state of health affects TTE through two distinct mechanisms: a reduction in available charge capacity and an increase in internal resistance. In the FM-CDM, SOH is treated as a case-level condition that characterizes the battery at the beginning of a discharge simulation. It is not included as a time-varying state during the several-hour TTE calculation.

A capacity-based definition of the initial SOH is adopted:

$$\text{SOH}_0 = \frac{Q_{\text{max}}(t_{\text{age}})}{Q_{\text{nom}}}, \quad 0 < \text{SOH}_0 \leq 1 \quad (21)$$

where $Q_{\text{max}}(t_{\text{age}})$ is the maximum available charge capacity at battery age t_{age} , and Q_{nom} is the beginning-of-life nominal capacity. Therefore, $\text{SOH}_0 = 1$ represents the reference beginning-of-life condition, whereas $\text{SOH}_0 < 1$ represents a capacity-degraded battery.

According to Equation (5), the effective charge capacity used in the SOC dynamics is:

$$Q_{\text{eff}} = Q_{\text{nom}} \text{SOH}_0$$

A decrease in SOH_0 therefore increases the SOC depletion rate for a given discharge current through Equation (6). This constitutes the capacity-related pathway by which battery aging affects TTE.

The resistance-related effect of SOH is represented by the scaling function introduced in Equation (27):

$$g_{R,i}(\text{SOH}_0) = 1 + \kappa_{R,i}(1 - \text{SOH}_0), \quad i \in \{0, 1, 2\} \quad (22)$$

where $\kappa_{R,i} \geq 0$ is the resistance-growth coefficient of the ohmic or polarization branch i . This formulation satisfies $g_{R,i}(1) = 1$, so that the resistance reduces to its reference healthy-state value when $\text{SOH}_0 = 1$. For $\text{SOH}_0 < 1$, the scaling factor exceeds unity and increases the corresponding resistance. The resulting resistance increase produces a larger load-induced voltage drop and can cause the terminal voltage to reach V_{cut} at a higher residual SOC.

During an individual TTE simulation, the health state is held constant:

$$\frac{d\text{SOH}}{dt} = 0, \quad \text{SOH}(t) = \text{SOH}_0, \quad t_0 \leq t \leq t_{\text{cut}} \quad (23)$$

Consequently, capacity loss and resistance growth are introduced only through the initial condition SOH_0 , Equation (5), and Equation (30). No additional capacity-fade or solid-electrolyte-interphase growth equation is integrated during the same discharge simulation. This separation prevents the degradation represented by SOH_0 from being counted a second time within the TTE calculation.

Long-term calendar and cycle aging occur on a time scale substantially longer than a single smartphone discharge. They are therefore treated as an outer process that determines the value of SOH_0 before each TTE simulation. Discharge cases with different health conditions are evaluated by repeating the FM-CDM calculation with different fixed values of SOH_0 while keeping the short-term electrical, thermal, and workload equations unchanged.

This treatment produces two identifiable SOH-to-TTE pathways. First, a lower SOH_0 reduces Q_{eff} and accelerates SOC depletion. Second, it increases R_0 , R_1 , and R_2 through $g_{R,i}$, thereby increasing the ohmic and polarization voltage drops. The first pathway affects the available charge inventory, whereas the second affects the voltage-cutoff time. Both effects are included once and remain mathematically separated in the model.

2.6. Reference Parameters and Traceability

To define a reproducible baseline for the numerical analysis, the FM-CDM parameter vector is divided into electrical, thermal, component-power, and state-of-health subsets:

$$\theta_{\text{ref}} = \{\theta_{\text{elec}}, \theta_{\text{thermal}}, \theta_{\text{power}}, \theta_{\text{SOH}}\} \quad (24)$$

The configuration represents a generic smartphone-scale single-cell battery coupled to a generic mobile-device load. It is defined as a theoretical reference configuration and is not associated with a named commercial handset. The core electrical, thermal, and SOH parameters are summarized in Table 1. Detailed display, processor-domain, network, and auxiliary-module parameters are provided in Appendix A, Table A1.

The nominal capacity is set to $Q_{\text{nom}} = 18000 \text{ C}$, corresponding to 5 Ah, and the terminal-voltage cutoff is $V_{\text{cut}} = 3.2 \text{ V}$. The reference OCV relation is represented by the sixth-order polynomial in Equation (4). Over $z \in [0, 1]$, the selected coefficient vector produces a smooth monotonic increase from approximately 3.202 V to 4.198 V. The curve serves as an analytical reference relation for the theoretical numerical analysis rather than as an empirical fit to a particular smartphone cell.

The reference resistances and capacitances define the fast and slow polarization dynamics. Their time constants are obtained directly from $\tau_i = R_i C_i$:

$$\tau_1 = R_1 C_1 = 174.72 \text{ s}, \quad \tau_2 = R_2 C_2 = 599.04 \text{ s} \quad (25)$$

Thus, the two RC branches represent distinct polarization time scales while preserving dimensional consistency between resistance, capacitance, and time. The capacitance values in Table 1 are expressed in farads.

The temperature-dependent resistance factor in Equation (27) is parameterized using $E_{a,i} / R_g = 1200 \text{ K}$ for $i \in \{0, 1, 2\}$. Reporting the ratio in kelvin distinguishes it from an activation energy reported in J mol^{-1} . The resistance-growth coefficients in Equation (30) are identical for the three electrical branches in the reference configuration, giving a common first-order resistance increase as SOH decreases.

The two-node thermal parameters define the transient heat storage, internal heat exchange, and heat rejection represented by Equations (22) and (23). The battery and system thermal capacitances are $C_b = 120 \text{ J K}^{-1}$ and $C_s = 180 \text{ J K}^{-1}$, respectively. The three thermal resistances separately represent battery-to-system, battery-to-ambient, and system-to-ambient heat-transfer paths. The thermal parameters are positive, ensuring a dissipative and asymptotically stable thermal subsystem under bounded heat input.

The baseline parameter vector remains fixed during each deterministic simulation. In the uncertainty analysis, selected parameters are sampled around these reference values using the bounded distributions defined in Section 2.8. Workload-dependent quantities, including display activity, processor utilization, network states, and module activation, are not included as fixed parameters in Table 1; their scenario-specific definitions are provided in Section 2.7.

The reference values in Table 1 define the baseline case rather than a population distribution of smartphone batteries. Accordingly, numerical results obtained from this configuration are interpreted as model responses under the stated assumptions. The influence of parameter variation is evaluated separately through Monte Carlo uncertainty propagation and Morris sensitivity analysis.

2.7. Stochastic Workload Scenarios

The stochastic workload model converts the scenario class into time-varying inputs for the component-power equations. Four reference classes are considered:

$$c \in \{\text{Standby, Light, Medium, Heavy}\}$$

These classes define theoretical workload conditions rather than population-level statistics for smartphone users. A scenario class remains fixed during one TTE realization, while its display, processor, network, and auxiliary-module states vary stochastically over time.

The general workload vector for class c is sampled at discrete command intervals:

$$\mathbf{u}_k^{(c)} \sim \mathcal{P}_c, \quad \mathbf{u}(t) = \mathbf{u}_k^{(c)}, \quad k\Delta t_w \leq t < (k+1)\Delta t_w \quad (26)$$

where $\mathcal{P}_c$ is the class-dependent joint distribution and $\Delta t_w = 60 \text{ s}$ is the workload-command interval. Display brightness, APL, processor activity, SNR, GPS state, and

camera state are held constant within one command interval and resampled at the beginning of the next interval. Network-state transitions and wake-lock events are updated at a finer time resolution.

The command-level variables are sampled according to:

$$\begin{aligned}
 s_{\text{disp},k} &\sim \text{Bernoulli}(p_{\text{disp},c}) \\
 L_k | s_{\text{disp},k} = 1 &\sim \mathcal{U}(L_c^-, L_c^+) \\
 \text{APL}_k | s_{\text{disp},k} = 1 &\sim \mathcal{U}(A_c^-, A_c^+) \\
 \alpha_{d,k} &\sim \mathcal{U}(\alpha_{d,c}^-, \alpha_{d,c}^+), \quad d \in \mathcal{D} \\
 s_{\text{GPS},k} &\sim \text{Bernoulli}(p_{\text{GPS},c}) \\
 s_{\text{cam},k} &\sim \text{Bernoulli}(p_{\text{cam},c})
 \end{aligned} \tag{27}$$

The sampled values remain constant throughout the corresponding 60 s command interval. When $s_{\text{disp},k} = 0$, Equation (15) gives $P_{\text{disp}} = 0$, irrespective of the sampled brightness and APL values. The processor activities are converted into effective activities, normalized frequencies, and normalized voltages using Equation (17); therefore, no separate commanded-frequency equation is required in this section.

Network activity is updated at the finer interval $\Delta t_{\text{net}} = 1$ s. When no Active transfer is in progress, the network-event indicator is sampled as:

$$b_{\text{net},n}^{(c)} \sim \text{Bernoulli}\left(\frac{\lambda_{\text{net},c} \Delta t_{\text{net}}}{3600}\right)$$

The network state is updated according to

$$S_{\text{net},m} = \begin{cases} \text{Active,} & b_{\text{net},m} = 1, \\ \text{Tail,} & b_{\text{net},m} = 0 \text{ and } 0 < (m - m_{\text{last}}) \Delta t_{\text{net}} \leq t_{\text{tail},c}, \\ \text{Idle,} & \text{otherwise,} \end{cases} \tag{28}$$

where $\lambda_{\text{net},c}$ is the class-dependent event-arrival rate in events per hour. A new event places the network interface in the Active state for $d_{\text{act},c}$ seconds. After the Active interval has elapsed, the interface enters the Tail state for $d_{\text{tail}} = 8$ s. An event arriving during the Tail interval restarts the Active state, whereas the interface returns to Idle when the Tail counter reaches zero. The resulting state $S_{\text{net}}(t)$ determines the network power through Equation (19).

The Medium workload uses a higher network-event rate than the Heavy workload because the former represents a communication-intensive condition, whereas the latter is defined as a computation-dominant condition. This distinction is reflected in the component-level energy attribution discussed in Section 3.3.

Wake-lock starts are generated independently at the 1 s update interval:

$$w_{\text{wake},n}^{(c)} = \max_{\substack{j \leq n \\ n-j < N_{\text{wake}}}} b_{\text{wake},j}^{(c)}, \quad N_{\text{wake}} = \frac{d_{\text{wake}}}{\Delta t_{\text{net}}} = 30. \tag{29}$$

Thus, each wake-lock event produces a 30 s binary pulse, and overlapping events are represented by the union of their active intervals. The resulting $w_{\text{wake}}(t)$ determines the independent wake-lock power in Equation (21) and does not modify the processor activity factors.

The complete time-varying workload trajectory is formed by combining the 60 s command-level variables with the 1 s network and wake-lock processes. The class-dependent distributions and event parameters are summarized in Table 2.

Table 2. Definitions of the stochastic reference workload classes. (a) Display and processor activity; (b) Network and auxiliary-module activity.

(a)						
Scenario Class	P_{disp}	Brightness and APL	Processor Activity			
I. Standby	0.05	L : $\mathcal{U}(0.05, 0.15)$ APL : $\mathcal{U}(0.10, 0.30)$	$\alpha = [\text{U}(0, 0.05), \text{U}(0, 0.03), \text{U}(0, 0.01), 0]^T$			
II. Light	0.65	L: $\mathcal{U}(0.20, 0.50)$ APL: $\mathcal{U}(0.20, 0.60)$	$\alpha = [\text{U}(0.05, 0.25), \text{U}(0, 0.15), \text{U}(0, 0.05), \text{U}(0, 0.05)]^T$			
III. Medium	0.90	L: $\mathcal{U}(0.45, 0.80)$ APL: $\mathcal{U}(0.30, 0.70)$	$\alpha = [\text{U}(0.20, 0.55), \text{U}(0.15, 0.45), \text{U}(0.05, 0.30), \text{U}(0.05, 0.35)]^T$			
IV. Heavy	1.00	L: $\mathcal{U}(0.70, 1.00)$ APL: $\mathcal{U}(0.40, 0.90)$	$\alpha = [\text{U}(0.50, 0.90), \text{U}(0.40, 0.80), \text{U}(0.30, 0.75), \text{U}(0.40, 0.95)]^T$			
(b)						
Scenario Class	p_{net}	$t_{\text{tail}}(s)$	SNR (dB)	p_{GPS}	p_{cam}	λ_{wake}
I. Standby	0.002	10	$\mathcal{U}(10, 30)$	0	0	2
II. Light	0.010	10	$\mathcal{U}(10, 30)$	0.02	0	4
III. Medium	0.050	10	$\mathcal{U}(8, 28)$	0.15	0.05	8
IV. Heavy	0.100	10	$\mathcal{U}(8, 28)$	0.30	0.10	12

2.8. Uncertainty and Sensitivity Analysis

Two sources of uncertainty are considered in the FM-CDM. Aleatory uncertainty originates from the time-varying workload processes defined in Section 2.7, including display activity, processor utilization, network-state transitions, auxiliary-module activation, and wake-lock arrivals. Parametric uncertainty represents variation around the theoretical reference configuration defined in Table 1 and Appendix A, Table A1. These two sources are propagated jointly within the Monte Carlo framework.

For realization r , a parameter vector $\theta^{(r)}$ is sampled once at the beginning of the simulation and remains fixed until the termination event. A stochastic workload trace $\mathbf{u}^{(r)}(t)$ is then generated from the selected workload class. Positive parameter multipliers are sampled using bounded lognormal distributions:

$$\xi_j^{(r)} = \exp\left(\varepsilon_j^{(r)} - \frac{\sigma_{\ln,j}^2}{2}\right), \quad \varepsilon_j^{(r)} \sim \mathcal{N}(0, \sigma_{\ln,j}^2) \quad (30)$$

where ξ_j is a dimensionless multiplicative factor and $\sigma_{\ln,j} = \sqrt{\ln(1 + CV_j^2)}$ is determined from the prescribed coefficient of variation CV_j . Samples outside their physical bounds are rejected and resampled. Bounded scalar variables are represented by uniform or truncated-normal distributions. The complete factor definitions, distribution parameters, and physical bounds are provided in Appendix A, Table A2.

Group multipliers are applied to physically related parameters. The same resistance factor ξ_R multiplies R_0 , R_1 , and R_2 , thereby preserving their relative ratios. Common multipliers are also applied to the polarization capacitances, thermal resistances, thermal capacitances, and component-power coefficients. The OCV polynomial coefficients are not

perturbed independently because independent coefficient variation could destroy the monotonicity of the reference curve. Instead, an additive offset δV_{oc} is applied to the complete OCV relation.

For each of the four workload classes, $N = 500$ independent Monte Carlo realizations are performed. The pseudorandom number generator uses the fixed seed 20250724. In each realization, the parameter vector is sampled first, followed by the generation of an independent stochastic workload trace. The coupled electrical and thermal equations are then integrated until either the voltage-cutoff event or an electrical-load infeasibility occurs.

Each realization records the termination time, termination category, residual SOC, maximum battery temperature, and maximum system temperature. Let $\mathcal{R}_{\text{cut}} = \{r : V_{\text{term}}^{(r)} \text{ reaches } V_{\text{cut}}^{(r)}\}$ denote the set of voltage-cutoff realizations and let $N_{\text{cut}} = |\mathcal{R}_{\text{cut}}|$ be the corresponding number of valid TTE outcomes. The mean and standard deviation of TTE are calculated over this set:

$$\overline{\text{TTE}} = \frac{1}{N_{\text{cut}}} \sum_{r \in \mathcal{R}_{\text{cut}}} \text{TTE}^{(r)}, \quad s_{\text{TTE}} = \sqrt{\frac{1}{N_{\text{cut}} - 1} \sum_{r \in \mathcal{R}_{\text{cut}}} (\text{TTE}^{(r)} - \overline{\text{TTE}})^2} \quad (31)$$

The corresponding coefficient of variation is $\text{CV}_{\text{TTE}} = \frac{s_{\text{TTE}}}{\overline{\text{TTE}}}$. The empirical 95% prediction interval is defined as:

$$\text{PI}_{95} = [q_{0.025}(\text{TTE}), q_{0.975}(\text{TTE})] \quad (32)$$

where $q_{0.025}$ and $q_{0.975}$ are the empirical 2.5th and 97.5th percentiles of the voltage-cutoff TTE samples. This interval characterizes the distribution of model outcomes under the prescribed workload and parameter assumptions. It is therefore interpreted as a prediction interval for the theoretical model rather than as a confidence interval for measured smartphone performance.

Electrical-load infeasibility is treated as a separate termination category. Let $D^{(r)}(t) = [A^{(r)}(t)]^2 - 4R_0^{(r)}(t)P_{\text{bat}}^{(r)}(t)$ denote the discriminant of the constant-power current equation. The estimated infeasibility probability is:

$$\hat{P}_{\text{inf}} = \frac{1}{N} \sum_{r=1}^N \mathbb{I}[\min_t D^{(r)}(t) < 0] \quad (33)$$

where $\mathbb{I}[\cdot]$ is the indicator function. Voltage-cutoff and electrical-infeasibility outcomes are reported separately so that an infeasible constant-power request is not interpreted as an ordinary voltage-cutoff TTE.

Sample-size convergence is evaluated using nested sample sizes $N = 100, 250, 500$, and 1000 drawn from the same seeded sequence. The convergence analysis compares the mean, standard deviation, and empirical 2.5th and 97.5th percentiles. The sample-size convergence results are presented in Section 3.2.

Morris Sensitivity Analysis

Global parameter screening is performed using the Morris elementary-effects method. The 14 uncertain factors listed in Appendix A, Table A2 are mapped to the normalized domain $[0, 1]$. For factor j and Morris trajectory q , the elementary effect is defined as:

$$\text{EE}_j^{(q)} = \frac{Y(\boldsymbol{\psi}^{(q)} + \Delta \mathbf{e}_j) - Y(\boldsymbol{\psi}^{(q)})}{\Delta} \quad (34)$$

where ψ is the normalized factor vector, e_j is the unit vector associated with factor j , Y is the mean TTE at the parameter point, and Δ is the normalized Morris step.

The Morris design uses six grid levels, $p = 6$, and $r_M = 20$ trajectories. The normalized step is $\Delta = \frac{p}{2(p-1)} = 0.6$. With 14 factors, the design contains $r_M(14+1) = 300$ 300 parameter points for the Heavy workload class. At each parameter point, Y is calculated from 20 workload realizations. Common random numbers are used within each trajectory, so paired evaluations use identical workload traces and differ only in the perturbed parameter. Parameter points that produce an electrical-infeasibility event are recorded separately and are not included in the elementary-effect statistics for voltage-cutoff TTE.

The signed mean, mean absolute effect, and standard deviation of the elementary effects are calculated as:

$$\begin{aligned}\mu_j &= \frac{1}{r_M} \sum_{q=1}^{r_M} \text{EE}_j^{(q)}, \\ \mu_j^* &= \frac{1}{r_M} \sum_{q=1}^{r_M} |\text{EE}_j^{(q)}|, \quad \sigma_j = \sqrt{\frac{1}{r_M-1} \sum_{q=1}^{r_M} (\text{EE}_j^{(q)} - \mu_j)^2}\end{aligned}\quad (35)$$

A large μ_j^* indicates a strong overall influence on TTE, whereas a large σ_j indicates nonlinear behavior or interactions with other factors. Morris screening is performed for the Heavy workload class using the factor ranges listed in Table A2.

2.9. Numerical Implementation

The coupled FM-CDM equations are integrated using a fixed-step trapezoidal scheme, also referred to as the Tustin or bilinear method. The baseline integration step is $\Delta t = 1$ s. This value is consistent with the 1 s network-state update interval in Section 2.7, whereas the 60 s workload commands remain piecewise constant over 60 consecutive integration steps. All calculations are performed using double-precision floating-point arithmetic.

Let $\tau_{i,k+\frac{1}{2}} = R_{i,k+\frac{1}{2}} C_i$, $i \in \{1, 2\}$, where $R_{i,k+\frac{1}{2}}$ is evaluated at the midpoint

SOC and battery temperature within the current integration step. The Tustin coefficients for polarization branch i are

$$a_{i,k} = \frac{1 - \frac{\Delta t}{2\tau_{i,k+\frac{1}{2}}}}{1 + \frac{\Delta t}{2\tau_{i,k+\frac{1}{2}}}}, \quad b_{i,k} = \frac{\frac{\Delta t}{2C_i}}{1 + \frac{\Delta t}{2\tau_{i,k+\frac{1}{2}}}} \quad (36)$$

The polarization-voltage update is therefore:

$$V_{i,k+1} = a_{i,k} V_{i,k} + b_{i,k} (I_k + I_{k+1}), \quad i \in \{1, 2\} \quad (37)$$

The SOC equation is discretized using the same trapezoidal rule:

$$z_{k+1} = z_k - \frac{\Delta t}{2Q_{\text{eff}}} (I_k + I_{k+1}) \quad (38)$$

For the hysteresis and thermal states, define F_h , F_b , and F_s as the right-hand sides of Equations (8), (22), and (23), respectively, after division by their corresponding state coefficients. Their updates can be written in the common form

$$q_{k+1} = q_k + \frac{\Delta t}{2} [F_{q,k} + F_{q,k+1}], \quad q \in \{h, T_b, T_s\} \quad (39)$$

Because I_{k+1} depends on the updated polarization voltages, temperatures, processor power, resistance, and terminal voltage, Equations (44)–(47) form an implicit coupled system. A fixed-point iteration is used within each time step. The iteration index is denoted by ℓ , and the initial guess is set to $\mathbf{x}_{k+1}^{(0)} = \mathbf{x}_k, I_{k+1}^{(0)} = I_k$.

At iteration $\ell + 1$, the component powers are evaluated first. The processor frequency is constrained using Equation (17), the temperature-dependent resistances are calculated using Equation (27), and the battery current is obtained from the physically admissible root in Equation (12). The electrical and thermal states are then updated using Equations (44)–(47).

The fixed-point iteration terminates when $|I_{k+1}^{(\ell+1)} - I_{k+1}^{(\ell)}| \leq 10^{-6} \text{ A}$, $|V_{\text{term},k+1}^{(\ell+1)} - V_{\text{term},k+1}^{(\ell)}| \leq 10^{-6} \text{ V}$, and $\max\{|T_{b,k+1}^{(\ell+1)} - T_{b,k+1}^{(\ell)}|, |T_{s,k+1}^{(\ell+1)} - T_{s,k+1}^{(\ell)}|\} \leq 10^{-5} \text{ K}$.

A maximum of 20 fixed-point iterations is used for one integration step. When the convergence conditions are not satisfied within this limit, the step is repeated using $\Delta t / 2$. Up to four consecutive step halvings are permitted. A persistent failure after the fourth halving is recorded as a numerical-convergence failure and is not classified as a voltage-cutoff or electrical-infeasibility event.

Cutoff-Event Interpolation

A voltage-cutoff event occurs when $V_{\text{term},k} > V_{\text{cut}}, V_{\text{term},k+1} \leq V_{\text{cut}}$.

To reduce the dependence of TTE on the integration grid, the cutoff position within the final step is calculated as:

$$\chi_{\text{cut}} = \frac{V_{\text{term},k} - V_{\text{cut}}}{V_{\text{term},k} - V_{\text{term},k+1}}, \quad 0 \leq \chi_{\text{cut}} \leq 1 \quad (40)$$

The cutoff time and residual SOC are then interpolated as:

$$t_{\text{cut}} = t_k + \chi_{\text{cut}} \Delta t, \quad z_{\text{cut}} = z_k + \chi_{\text{cut}} (z_{k+1} - z_k) \quad (41)$$

The TTE is subsequently calculated from Equation (13b). The same interpolation principle is applied to the discriminant $D = A^2 - 4R_0 P_{\text{bat}}$ when an electrical-load infeasibility occurs within an integration step.

Time-step independence was examined using $(\Delta t = 2, 1, 0.5, \text{ and } 0.25 \text{ s})$. The baseline step size of $\Delta t = 1 \text{ s}$ was considered converged when the relative difference in TTE with respect to the 0.5 s solution was below 0.5%, while the corresponding difference in the cutoff SOC was below 0.1%. All simulations were performed in double precision using the same initialization, workload realization, model parameters, and cutoff-event detection procedure.

3. Results and Discussion

This section presents the numerical results obtained using the FM-CDM under the reference configuration defined in Section 2. The analysis focuses on reference-case discharge dynamics, stochastic TTE uncertainty, component-level energy attribution, global sensitivity, and thermal-coupling effects.

3.1. Reference-Case Results and Cutoff Dynamics

Reference-case simulations were first conducted to characterize the discharge behavior of the FM-CDM under the four workload classes defined in Table 2. The common

initial conditions were $z(0) = 1$, $V_1(0) = V_2(0) = h(0) = 0$, $T_b(0) = T_s(0) = T_{\text{amb}} = 298.15 \text{ K}$, and $\text{SOH}_0 = 1$. The cutoff voltage was fixed at $V_{\text{cut}} = 3.20 \text{ V}$. For each workload class, one reproducible workload realization was generated using the random seed and simulated using the reference parameterization reported in Tables 1 and A1.

Time-step independence was evaluated using the Heavy reference case. For time steps of 2, 1, 0.5, and 0.25 s, the corresponding TTE values were 4.31637, 4.31652, 4.31659, and 4.31663 h, respectively. Relative to the 0.5 s solution, the 1 s baseline produced a TTE difference of 0.0017% and a cutoff-SOC difference of 0.0016 percentage points. Both differences were substantially below the convergence criteria specified in Section 2.9. Therefore, $\Delta t = 1 \text{ s}$ was used for the subsequent simulations.

As summarized in Table 3, the reference-case TTE decreased monotonically from 58.64 h in Standby to 22.53 h in Light, 8.99 h in Medium, and 4.32 h in Heavy. Over the same sequence, the mean device-level power increased from 0.292 to 0.754, 1.852, and 3.765 W, respectively. The resulting endurance ordering is therefore consistent with the progressively higher display, processor, network, and auxiliary-module activity prescribed by the four reference workloads.

Table 3. Reference-case numerical outcomes under the four workload classes.

Scenario Class	TTE (h)	Mean Device Power (W)	Cutoff SOC (%)	Battery Temperature at Cutoff (°C)	Device Temperature at Cutoff (°C)
Standby	58.64	0.292	0.91	25.76	25.89
Light	22.53	0.754	1.28	26.83	27.11
Medium	8.99	1.852	2.40	29.82	30.59
Heavy	4.32	3.765	3.38	35.08	36.46

Figure 2a shows that the terminal-voltage trajectories contain short-timescale fluctuations associated with workload-state transitions, whereas the SOC trajectories in Figure 2b remain comparatively smooth because charge depletion integrates the instantaneous current over time. The voltage decline becomes more pronounced as the workload increases because higher battery current amplifies the ohmic drop and the two polarization-voltage contributions.

Importantly, all four simulations reach the 3.20 V cutoff before the modeled charge state becomes zero. The residual SOC at cutoff increases from 0.91% in Standby to 3.38% in Heavy. This trend demonstrates the distinction between charge inventory and voltage-limited availability: under a larger power demand, the terminal-voltage threshold can be reached while a greater fraction of charge remains in the cell. The temperatures at cutoff also increase with workload, reaching 35.08 °C for the battery node and 36.46 °C for the device node in the Heavy case. Together, these trends demonstrate how workload intensity, voltage cutoff, and electro-thermal feedback jointly determine the simulated discharge endpoint.

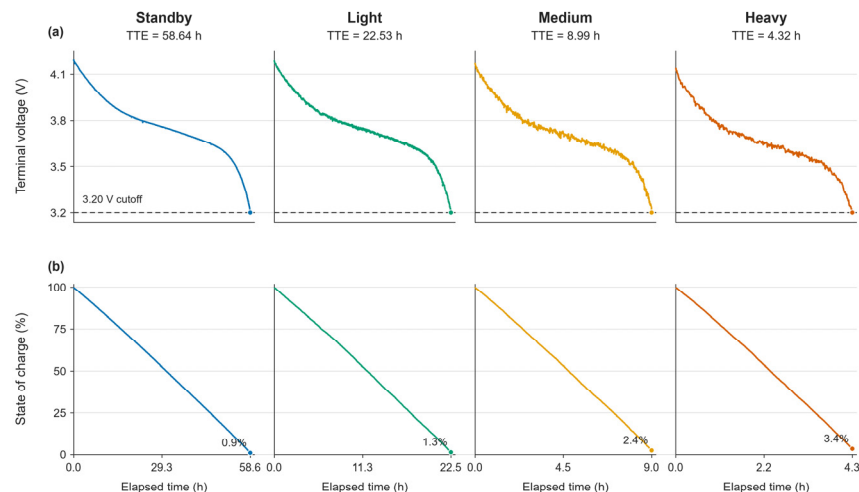


Figure 2. Simulated discharge trajectories for the four reference workloads: (a) terminal voltage and (b) SOC.

3.2. Stochastic TTE Uncertainty

Monte Carlo simulations were conducted to quantify the combined effects of workload variability and parameter uncertainty on TTE. For each workload class, 500 realizations were generated using the distributions specified in Table A2 and the master random seed 20250724. All 2000 reported simulations reached the voltage-cutoff event within the simulation horizon. No electrically infeasible power-coupling event or numerical-convergence failure occurred.

Figure 3 shows the resulting TTE distributions. For Standby, the mean TTE was 55.88 h with a standard deviation of 2.55 h, a coefficient of variation of 4.56%, and a 95% prediction interval from 51.26 to 61.08 h. The corresponding results were 21.75 ± 1.13 h for Light, 8.63 ± 0.51 h for Medium, and 4.18 ± 0.27 h for Heavy, where the values following the plus-minus sign denote one standard deviation. Their 95% prediction intervals were 19.67 to 24.07 h, 7.74 to 9.71 h, and 3.67 to 4.73 h, respectively.

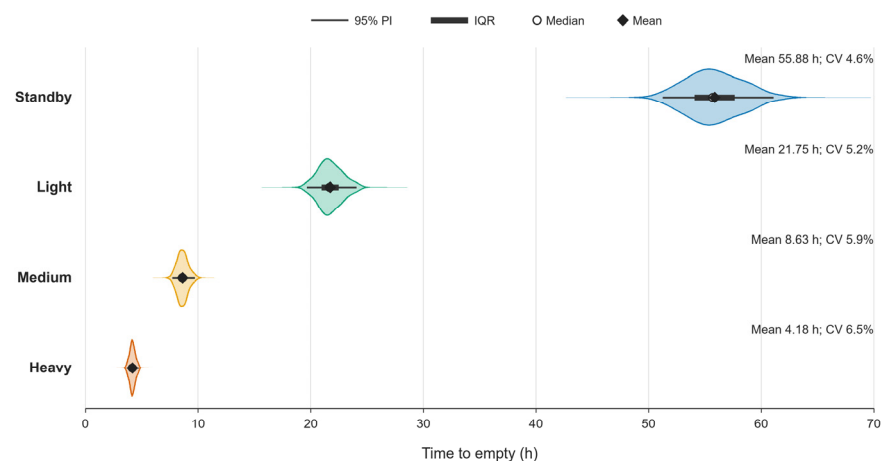


Figure 3. Monte Carlo TTE distributions for the four workload classes.

The Standby class exhibited the largest absolute standard deviation because its longer discharge duration allows small variations in capacity and background power to

accumulate over a longer period. In contrast, relative variability increased with workload intensity: the coefficient of variation rose from 4.56% in Standby to 5.21% in Light, 5.90% in Medium, and 6.51% in Heavy. Thus, the high-load scenarios did not produce the largest absolute dispersion, but they exhibited greater dispersion relative to their mean TTE. This trend is consistent with the stronger influence of current-dependent voltage losses and the voltage-cutoff event at higher power levels.

The Monte Carlo means are lower than the corresponding reference-case TTE values reported in Section 3.1 because the uncertainty ensemble includes SOH values from 0.90 to 1.00 together with bounded variations in capacity, resistance, component power, ambient temperature, conversion efficiency, and cutoff voltage. The reference cases, by comparison, use the nominal parameter values and an initial SOH of 1.

Sample-size convergence was examined using 100, 250, 500, and 1000 realizations per workload class. Increasing the sample size from 500 to 1000 changed the estimated mean TTE by less than 0.25% for every class. Over the same comparison, the largest change in either endpoint of the 95% prediction interval was 0.22 h and occurred in Standby. These results support the use of 500 realizations for the reported uncertainty analysis.

3.3. Component-Level Energy Attribution

Component-level energy consumption was obtained by integrating each device-power term from the initial time to the voltage-cutoff event. The corresponding mean power was then calculated over the scenario-specific TTE. For clarity in Figure 4, the Little, Medium, and Big CPU domains and the GPU domain are combined into the CPU/GPU category, while their individual parameters remain separately defined in Table A1. GPS and camera power are similarly combined as auxiliary sensing and imaging loads.

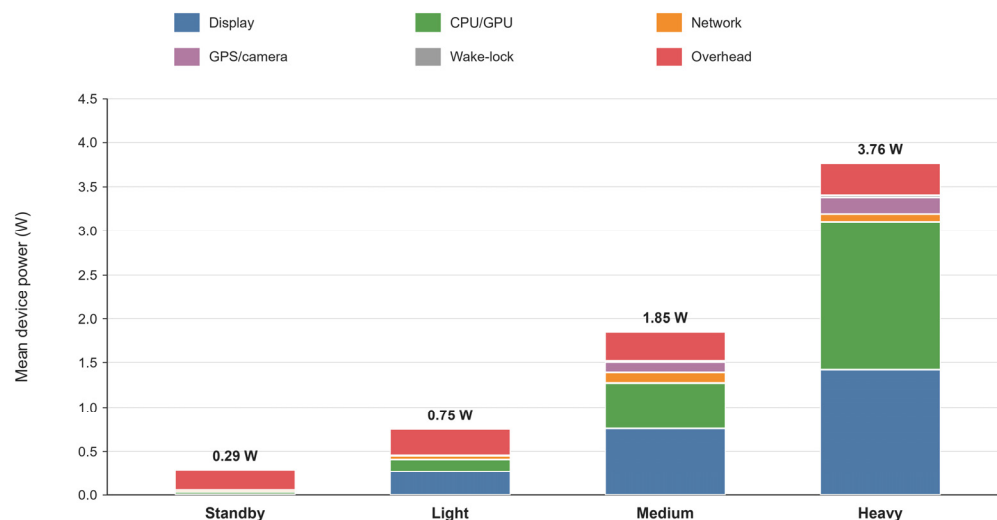


Figure 4. Mean device-power attribution across the four reference workloads.

The mean device power increased from 0.292 W in Standby to 0.754 W in Light, 1.852 W in Medium, and 3.765 W in Heavy. In Standby, system overhead was the dominant contribution, accounting for 81.4% of the total power, while CPU/GPU and network activity contributed 9.5% and 7.2%, respectively. This composition reflects a low-activity state in which the display and auxiliary modules remain inactive for most of the discharge period.

In the Light scenario, display power increased to 0.270 W and accounted for 35.8% of the total, while system overhead and CPU/GPU activity contributed 39.3% and 18.3%,

respectively. Display power became the largest individual contribution in Medium, reaching 0.757 W or 40.9% of the total. CPU/GPU activity contributed a further 0.514 W, corresponding to 27.7%. Network activity and GPS/camera operation contributed 6.5% and 6.1%, respectively.

The Heavy workload was dominated by CPU/GPU and display activity. Their mean powers reached 1.685 and 1.420 W, corresponding to 44.8% and 37.7% of the total device power. Together, these two categories accounted for 82.5% of the Heavy power demand. The increase from Medium to Heavy was therefore driven primarily by processor and display activity, which together accounted for approximately 96% of the increase in total mean power. Network power was lower in Heavy than in Medium because the Heavy reference workload was defined as computation-dominant rather than network-dominant.

For every scenario, the sum of the integrated component energies agreed with the independently accumulated total device energy to numerical round-off precision. This agreement confirms the internal consistency of the component-power aggregation and shows that conversion losses were not counted within the device-side categories; they were applied separately through the DC-DC efficiency in the battery-power coupling.

3.4. Global Sensitivity Analysis

Global sensitivity was evaluated for the Heavy workload class, which produces the highest discharge power and temperature rise among the four reference scenarios. Fourteen factors were varied using six grid levels, 20 Morris trajectories, and a normalized step size of 0.60, resulting in 300 design points. Each design point was evaluated using 20 Heavy-workload realizations generated with common random numbers. The mean TTE normalized by the Heavy reference TTE of 4.316517 h was used as the model output. Consequently, 6000 FM-CDM trajectories were simulated using the same master seed. All simulations reached the voltage cutoff without an infeasible current solution or numerical failure.

Figure 5 presents the mean absolute elementary effect (μ^*) and the standard deviation of the elementary effects (σ). Ambient temperature showed the highest overall influence, with $\mu^* = 0.13905$ and $\sigma = 0.13744$. CPU/GPU power, SOH, display power, capacity factor, and DC-DC efficiency followed, with μ^* values of 0.12097, 0.11098, 0.10989, 0.10434, and 0.09641, respectively. Their comparatively smaller σ values indicate predominantly monotonic effects over the prescribed parameter ranges.

Thermal resistance exhibited a moderate μ^* of 0.04919 but a relatively large σ of 0.07038. This result indicates that its effect on TTE changes substantially with the ambient thermal condition and the resulting electro-thermal feedback. Cutoff voltage, OCV offset, and resistance factors produced intermediate sensitivities, with μ^* values of 0.02365, 0.02126, and 0.01926, respectively. Network power and wake-lock activity had lower effects, with μ^* values of 0.00819 and 0.00575. Thermal capacitance and electrical capacitance factors were the least influential factors for the TTE output within the investigated ranges, with μ^* values of 0.00100 and 0.00022. Their low TTE sensitivities do not imply that they have no effect on short-time voltage or temperature transients.

Overall, the Morris analysis identifies ambient temperature, CPU/GPU power, SOH, display power, effective capacity, and DC-DC efficiency as the dominant contributors to TTE variation under the Heavy workload. Thermal resistance also requires attention because its effect exhibits strong dependence on the coupled operating condition.

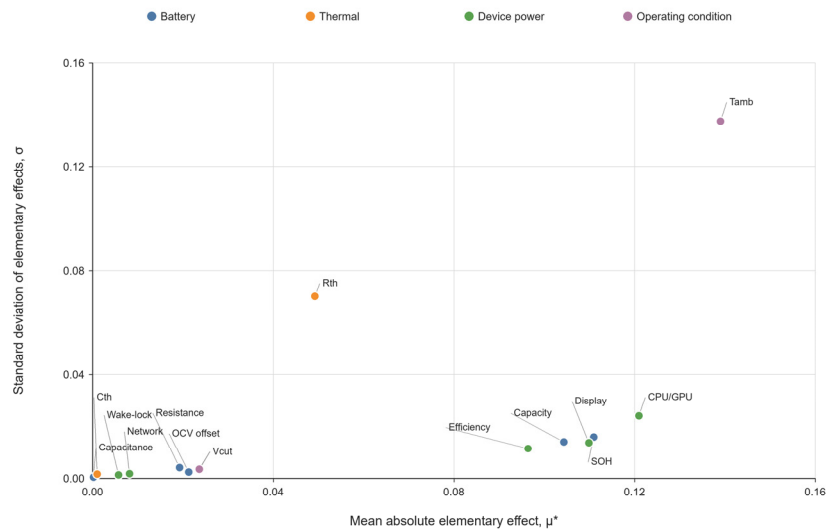


Figure 5. Morris sensitivity indices for TTE under the Heavy reference workload.

3.5. Electro-Thermal Coupling and Ambient-Temperature Effects

The effect of electro-thermal coupling was examined under the Heavy workload using the same initial state, workload realization, cutoff voltage, and 1 s time step as the reference case. An uncoupled isothermal reference was constructed by suppressing the temperature dependence of the electrical resistances and evaluating the device-power model at the prescribed ambient temperature while keeping the workload trace and all other model parameters unchanged. The resulting dependence of TTE on ambient temperature is shown in Figure 6.

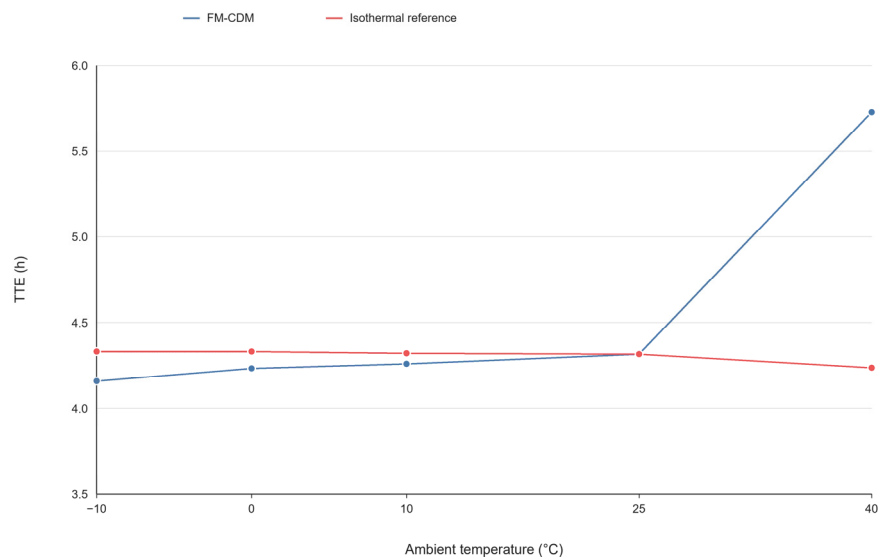


Figure 6. TTE response to ambient temperature under the Heavy workload.

At $-10\text{ }^{\circ}\text{C}$, the FM-CDM predicted a TTE of 4.1593 h, compared with 4.3319 h for the isothermal reference. The corresponding difference was -3.98% , and the cutoff SOC increased from 4.47% in the isothermal reference to 6.56% in the coupled model. At $0\text{ }^{\circ}\text{C}$, the coupled and isothermal TTE values were 4.2333 h and 4.3317 h, respectively, corresponding to a difference of -2.27% . These results indicate that the temperature-dependent

resistance increase at low ambient temperature causes the terminal voltage to reach the cutoff threshold, while a larger fraction of the stored charge remains available.

At 25 °C, the two TTE values were nearly identical, with 4.3165 h for the FM-CDM and 4.3164 h for the isothermal reference. At 40 °C, however, the FM-CDM predicted a TTE of 5.7275 h, whereas the isothermal reference predicted 4.2371 h. In the coupled simulation, the device temperature reached 48.92 °C at the cutoff and exceeded the processor-throttling onset of 42 °C. The resulting reduction in CPU/GPU activity partially offset the increased temperature-dependent leakage and produced a longer TTE. This high-temperature response demonstrates that thermal coupling affects both the battery-side voltage dynamics and the device-side power-demand path.

The comparison confirms that the influence of temperature is not represented by a single resistance correction alone. Ambient temperature, self-heating, temperature-dependent resistance, leakage power, and processor throttling jointly determine the cutoff event. The magnitude and direction of the TTE change therefore depend on the operating regime and on whether thermal feedback crosses a device-level control threshold.

3.6. Implications and Model Scope

The combined power-attribution, uncertainty, and sensitivity results provide a mechanism-based interpretation of TTE variation. Display power and CPU/GPU activity are the main controllable contributors under active workloads, whereas ambient temperature and thermal resistance determine how strongly electrical and device-level states interact. Consequently, display brightness and average pixel level can be reduced to limit direct power demand, while workload-aware CPU/GPU scheduling can reduce both computation power and temperature-driven feedback. The stochastic workload model also indicates that batching background tasks and reducing unnecessary network-state transitions can decrease repeated high-power activation events.

The FM-CDM is intended as a scenario-conditional numerical framework. Its TTE predictions depend on the specified battery parameters, device-power coefficients, thermal parameters, SOH value, and workload probability distributions. Application to a particular smartphone therefore requires re-identification or independent confirmation of these quantities. The present results quantify the response of the defined model and reference scenarios; they do not constitute a universal accuracy ranking against measurement-based or data-driven predictors. Independent smartphone measurements, held-out workload traces, and common dataset comparisons with explicit error metrics are appropriate next steps for external validation.

4. Conclusions

This study developed the Fusion Mechanism-Coordinated Dynamic Model (FM-CDM) for mechanism-based analysis of smartphone battery depletion under time-varying device-level power demands. The framework combines a second-order Thevenin battery model, voltage-based cutoff-event detection, component-level power models, electro-thermal feedback, SOH representation, stochastic workload generation, and numerical uncertainty analysis.

Under the reference configuration, the predicted TTE decreased from 58.6371 h in Standby to 22.5271 h in Light, 8.9888 h in Medium, and 4.3165 h in Heavy. All reference cases reached the 3.20 V cutoff before the modeled SOC state reached zero, with cutoff SOC values ranging from 0.91% to 3.38%. Monte Carlo analysis with 500 realizations per workload class produced load-dependent TTE variability, with coefficients of variation from 4.56% to 6.51%.

Component-level attribution showed that active workloads were dominated by display and CPU/GPU power, whereas fixed overhead accounted for most of the Standby

demand. Morris screening under the Heavy workload identified ambient temperature, CPU/GPU power, SOH, display power, capacity, and DC-DC efficiency as the most influential factors. Thermal resistance exhibited a moderate mean effect but a comparatively large standard deviation of elementary effects, indicating strong dependence on the coupled operating condition.

The ambient temperature comparison further showed that electro-thermal feedback changes the cutoff event in a regime-dependent manner. Relative to the uncoupled isothermal reference, the coupled model reduced TTE by 3.98% at $-10\text{ }^{\circ}\text{C}$ and increased TTE by 35.18% at $40\text{ }^{\circ}\text{C}$ because the simulated device temperature crossed the processor-throttling threshold. These results support the inclusion of thermal feedback and device-level control logic in a theoretical TTE model.

The present FM-CDM should be interpreted as a reproducible theoretical and numerical framework whose outputs are conditional on the stated parameterization and workload assumptions. Future work should identify device-specific parameters, evaluate the model against independent smartphone measurements, and perform common-dataset benchmarking using explicit TTE error metrics.

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Abbreviations

The following abbreviations are used in this manuscript:

FM-CDM Fusion Mechanism-Coordinated Dynamic Model	
SOC	State of Charge
TTE	Time-to-Empty
OCV	Open-Circuit Voltage
ECM	Equivalent Circuit Model
APL	Average Pixel Level
RRC	Radio Resource Control
SOH	State of Health
BMU	Battery Management Unit
MCS	Monte Carlo Simulation
EE	Elementary Effect
NLS	Non-linear Least Squares

Appendix A

This appendix provides the component-level device-power parameters and uncertainty-factor definitions used in the numerical analyses. The core battery electrical, thermal, and state-of-health parameters are reported in Table 1, whereas the scenario-dependent workload definitions are provided in Table 2. Tables A1 and A2 therefore contain only the additional parameters required to reproduce the component-power, Monte Carlo, and Morris analyses.

Table A1. Component-level device-power and thermal-control parameters used in the reference configuration.

Subsystem	Parameter	Symbol	Value	Unit
Display	Active display-driver power	$P_{\text{disp},0}$	0.035	W
Display	Brightness-APL power coefficient	k_{disp}	2.20	W
Display	Brightness exponent	a_L	1.15	-
Display	Average-pixel-level exponent	b_{APL}	0.65	-
Processor	Maximum dynamic-power coefficients	P_{max}	[0.40, 0.70, 1.20, 1.40]	W
Processor	Reference leakage powers	$P_{\text{leak}}^{\text{ref}}$	[0.012, 0.016, 0.022, 0.024]	W
Processor	Minimum normalized frequency factor	ρ_{min}	0.25	-
Processor	Normalized voltage-frequency coefficients	$[c_{v,0}, c_{v,1}]$	[0.55, 0.45]	-
Processor	Leakage-temperature coefficient	β_{leak}	0.025	K ⁻¹
Processor	Leakage gate	$[g_0, g_1, \alpha_{\text{gate}}]$	[0.20, 0.80, 0.01]	-
Thermal control	Throttling-onset temperature	T_{on}	315.15	K
Thermal control	Full throttling temperature	T_{full}	320.15	K
Thermal control	Minimum throttling multiplier	ϑ_{min}	0.65	-
Network	Idle, Tail, and Active state powers	P_{net}	[0.018, 0.190, 0.680]	W
Auxiliary module	GPS active-state power	$P_{\text{GPS,act}}$	0.380	W
Auxiliary module	Camera active-state power	$P_{\text{cam,act}}$	0.850	W
Wake lock	Active wake-lock power	$P_{\text{wake,act}}$	0.220	W
Wake lock	Wake-lock pulse duration	d_{wake}	30	S
Overhead	Baseline device power	P_{base}	0.230	W
Overhead	Processor-activity coefficient	k_{α}	0.100	W
Overhead	Display-on coefficient	$k_{\text{disp,on}}$	0.050	W

Note: The processor-domain vectors are ordered as Little CPU, Medium CPU, Big CPU, and GPU. The values define the theoretical reference configuration used in the numerical analyses and are not presented as measurements from a specific commercial smartphone. Workload-dependent activity ranges and event-arrival parameters are reported separately in Table 2.

Table A2. Uncertain factors, Monte Carlo distributions, and physical bounds used in the uncertainty and Morris analyses.

Factor	Symbol	Reference	Monte Carlo Distribution	Bounds	Unit
Effective capacity factor	ξ_Q	1.00	Bounded lognormal, CV = 0.03	[0.95, 1.05]	-
Initial state of health	SOH ₀	1.00	Uniform	[0.90, 1.00]	-
Ambient temperature	T_{amb}	298.15	Truncated normal, $\sigma = 3.0$	[288.15, 308.15]	K
Cutoff voltage	V_{cut}	3.20	Truncated normal, $\sigma = 0.02$	[3.15, 3.25]	V
Electrical resistance factor	ξ_R	1.00	Bounded lognormal, CV = 0.10	[0.85, 1.15]	-
Polarization-capacitance factor	ξ_C	1.00	Bounded lognormal, CV = 0.05	[0.90, 1.10]	-
Thermal resistance factor	$\xi_{R_{\text{th}}}$	1.00	Bounded lognormal, CV = 0.10	[0.80, 1.20]	-
Thermal capacitance factor	$\xi_{C_{\text{th}}}$	1.00	Bounded lognormal, CV = 0.05	[0.90, 1.10]	-
DC conversion efficiency	η_{dc}	0.92	Truncated normal, $\sigma = 0.015$	[0.88, 0.96]	-
Display-power factor	ξ_{disp}	1.00	Bounded lognormal, CV = 0.10	[0.85, 1.15]	-
Processor-power factor	ξ_{proc}	1.00	Bounded lognormal, CV = 0.10	[0.85, 1.15]	-
Network-power factor	ξ_{net}	1.00	Bounded lognormal, CV = 0.10	[0.85, 1.15]	-
Wake-lock power factor	ξ_{wake}	1.00	Bounded lognormal, CV = 0.20	[0.50, 1.50]	-
OCV offset	ΔV_{OCV}	0	Truncated normal, $\sigma = 0.01$	[-0.02, 0.02]	V

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