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Original Paper

A Multi-Scenario Smartphone Battery Life Optimization Model Based on the Entropy Weight Method, Grey Relational Analysis, and Linear Programming

Jianchuan Zhu[1] & Jiuming Wang[2]

[1] Chengdu University of Information Technology, Chengdu, China

[2] Sichuan University, Chengdu, China

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Abstract

To mitigate the bottleneck of insufficient smartphone battery life in high-frequency usage scenarios and balance endurance performance with user experience, this study develops a multi-scenario battery life optimization model. A hybrid weighting model combining the Entropy Weight Method (EWM) and Grey Relational Analysis (GRA) is adopted to identify core influencing factors with 98.5% accuracy, with network type and screen brightness confirmed as the dominant ones. Scenario-specific linear programming models are constructed for gaming, daily use and navigation, with scenario-based constraints incorporated to maximize battery life. The model achieves an average 18.7% improvement in battery life, with respective gains of 22.3%, 18.7% and 15.2% for the three scenarios. A three-dimensional validation framework of effectiveness, stability and robustness verifies that all parameter and battery life ratio deviations are within 10%. Compared with traditional models, the proposed model features 35% higher computational efficiency and superior scenario adaptability, providing a practical theoretical reference for the design of intelligent battery management systems for smartphones.

Keywords

entropy weight method, grey relational analysis, linear programming, multi-scenario optimization, three-dimensional validation framework

1. Introduction

1.1 Background

Smartphones have become indispensable in daily life and production, covering communication, office work, entertainment, navigation and other scenarios, yet insufficient battery life remains a critical challenge (Pramanik et al., 2019). Survey data shows over 70% of users need daily recharging and nearly 40% suffer great inconvenience from battery depletion, which severely impairs user satisfaction and product competitiveness.

Battery life is jointly affected by screen brightness, CPU workload, network type, GPS status and other factors, with their impact intensity and constraints varying significantly across gaming, daily use and outdoor navigation. Gaming requires sustained high CPU load and bright screens leading to rapid power consumption; daily use involves fluctuating workload and network conditions that demand a balance between endurance and user experience; navigation relies on continuous GPS and stable networks with fixed consumption patterns (Carroll & Heiser, 2010).

Unified battery life optimization strategies are ineffective in practice, often failing to achieve satisfactory results or even degrading user experience. Thus, it is imperative to develop a scenario-aware battery life optimization model that adapts to different usage conditions while maintaining device usability.

1.2 Restatement of the Problem

To address the challenges of smartphone battery life optimization across multiple scenarios, this paper undertakes three core tasks through mathematical modeling and validation:

1．Key factor identification and weight quantification. Identify the primary factors influencing battery life, quantify their relative importance, clarify their influence patterns, and eliminate interference from secondary factors to lay a precise foundation for subsequent optimization.

2．Multi-scenario battery life optimization. Establish scenario-based optimization models for three high-frequency usage scenarios: gaming, daily use, and navigation. Incorporate scenario-specific constraints to determine optimal combinations of controllable parameters that maximize battery life while maintaining acceptable user experience.

3．Model performance verification. Construct a comprehensive validation framework to evaluate the model's effectiveness, stability, and robustness. Conduct comparative analysis with existing models to systematically clarify its strengths, limitations, and practical applicability.

2. Problem Analysis

Smartphone battery life is a direct reflection of its energy consumption status. Given the fixed battery capacity, battery life is negatively correlated with the device's power consumption rate. Screen brightness, CPU workload, network type and GPS status are defined as core optimization variables for their controllability, while ambient temperature and battery cycle count serve as constraint conditions due to their uncontrollable characteristics in actual use. This section analyzes the key influencing factors and usage scenarios of battery life, clarifies the model selection rationale and constructs the overall modeling logic, laying a rigorous and systematic foundation for subsequent model construction.

2.1 Analysis of Influencing Factors

Based on actual power consumption test data and practical usage experience, six key factors affecting smartphone battery life are analyzed to clarify their action mechanisms and quantitative correlation with battery life.

Screen Brightness: As a primary power-consuming component of smartphones, its power consumption is positively correlated with brightness levels. Excessively low brightness will impair visual usability, so its value range needs to be constrained to balance battery endurance and user experience.

CPU Workload: As the core computational unit, higher workload leads to increased power consumption. The acceptable workload range varies by usage scenario, with gaming scenarios requiring higher workload to ensure smooth operation and daily use scenarios allowing flexible adjustment of workload levels.

Network Type: The power consumption of different network types follows the ranking of 5G > 4G > WiFi, and frequent network switching will cause additional power consumption fluctuations. Thus, network type needs to be adaptively adjusted according to specific usage scenarios.

GPS Activation Status: Enabling GPS will bring fixed additional power consumption to the device. Navigation scenarios require continuous GPS activation, while daily use scenarios allow intermittent or disabled GPS status, showing obvious scenario dependence.

Ambient Temperature: The optimal working temperature range for smartphone batteries is 20°C to 30°C. Extreme temperatures will reduce battery energy conversion efficiency and shorten its service life, so temperature is set as a hard constraint in the subsequent modeling process.

Battery Cycle Count: Battery capacity gradually degrades with the increase of charge-discharge cycles, and the actual capacity will drop to below 80% of the initial level after about 500 cycles. The cycle count is controlled within a reasonable range in modeling to reflect the normal aging state of the battery in actual use.

2.2 Analysis of Usage Scenarios

This study focuses on three typical usage scenarios (gaming, daily use, navigation) that account for over 80% of smartphone's actual usage. Each scenario has distinct core requirements and constraint conditions, leading to different optimization priorities for battery life.

Gaming Scenario: The core requirement is to ensure smooth game operation. The constraints include minimum thresholds for CPU workload and screen brightness, fixed network type to avoid lag caused by switching, and disabled GPS. The optimization direction is to reduce unnecessary power consumption on the premise of preserving basic game performance.

Daily Use Scenario: The usage characteristics are fragmented and diverse with no strict performance constraints. All controllable optimization variables allow flexible adjustment, and the core optimization goal is to balance battery life and comprehensive user experience without sacrificing basic usage needs.

Navigation Scenario: The core requirements are accurate positioning and stable navigation. Hard constraints include mandatory GPS activation, fixed network type to ensure signal stability, and moderate screen brightness to guarantee outdoor visibility. Optimization is limited to reducing screen brightness and CPU workload within the scope of constraint conditions.

2.3 Model Selection Rationale

The selection of modeling methods is based on the research objectives and the characteristics of the research object, adhering to the principles of rationality, operability and interpretability, with the specific rationale as follows:

Key factor identification and weighting: An equal-weight fusion method of EWM and GRA is adopted, which balances the objective data dispersion measured by EWM and the factor-target correlation measured by GRA, making the weight assignment of influencing factors more scientific and accurate.

Multi-scenario optimization: Linear programming is selected as the optimization method for its high solving efficiency, strong interpretability and moderate model complexity, which can well fit the approximate linear relationship between controllable factors and battery life under multi-constraint conditions.

Model validation: A Multi-dimensional validation framework including effectiveness, stability and robustness combined with cross-model comparative analysis is constructed to fully verify the model's performance and ensure its practical applicability in real-world scenarios (Odu, 2019).

2.4 Overall Modeling Logic

The study adopts a closed-loop and hierarchical overall modeling logic to ensure the systematicness and rigor of the research. The specific logic is as follows: first, analyze the key influencing factors and typical usage scenarios of smartphone battery life to define reasonable research assumptions; second, construct a hybrid weighting model of EWM and GRA to identify core influencing factors and quantify their comprehensive weights; third, apply scenario-based linear programming to construct the optimization model with the goal of maximizing battery life, and solve the optimal parameter combination for each scenario by incorporating scenario-specific constraint conditions; finally, assess the model's reliability and superiority via the three-dimensional validation framework and comparative analysis with similar models, forming a complete research cycle from factor analysis to model construction and performance verification.

3. Assumptions and Justification

To simplify the research problem and focus on the core research objectives, the following reasonable assumptions are made on the basis of conforming to the actual use of smartphones, and the rationality of each assumption is justified:

Assumption 1: Battery capacity is fixed without abnormal aging. Network signal is stable and hardware response delays for parameter adjustments are ignored.

Assumption 2: Battery life has a linear relationship with controllable factors, neglecting nonlinear effects under extreme conditions.
Assumption 3: The three usage scenarios are mutually independent, and the original sample data are accurate and reliable.
Assumption 4: The entropy weight method and grey relational analysis are combined with equal weights.
Justification: All assumptions conform to the actual usage characteristics of smartphones, aiming to simplify the modeling process, exclude uncontrollable random interference factors, and focus on the core research objective of multi-scenario battery life optimization. Fixing battery capacity and ignoring hardware delays and network signal fluctuations eliminates the impact of uncontrollable factors, focusing the research on the correlation between controllable parameters and battery life. The linear relationship assumption accords with the actual power consumption law within a reasonable parameter range, reducing modeling complexity without affecting research validity. The three scenarios are independent due to distinct usage characteristics and parameter settings, and the accurate sample data from strictly controlled tests lays a solid foundation for modeling. Equal-weight fusion of the two methods balances the objective data differentiation of the entropy weight method and the factor-target correlation of grey relational analysis, ensuring the scientificity of comprehensive weight assignment for influencing factors.

4. Notations

Table 1. Symbols and Their Physical Meanings

Symbol	Physical Meaning	Value range/Description	Unit
m	Scene count	m = 3 (gaming, daily use, navigation)	Pcs
n	Number of factors affecting smartphone battery life	n = 6 (core factors including screen brightness and CPU load)	Pcs
k	Number of modifiable influencing factors	k = 4 (screen brightness, CPU load, network type, GPS)	Pcs
X_i	data matrix of original influencing factors	m×n matrix, rows=scenarios, columns=factors	-
p	probability matrix	m×n matrix; EWM intermediate matrix, reflecting factor proportion	-
ρ	Resolution Coefficient of Grey Correlation Analysis	Default 0.5, [0,1], adjusts relational coefficient discrimination	-
δ	absolute difference matrix	m×n matrix, GRA intermediate matrix, reflecting sequence differences	-

Symbol	Physical Meaning	Value range/Description	Unit
ξ	correlation coefficient	m×n matrix, [0,1], reflects factor-battery life association strength	-
f	coefficient of objective function in linear programming	k×1 matrix, determined by controllable factors' comprehensive weights	-
X_{opt}	optimal parameter combination	k×1 matrix, optimal values of controllable factor, [0,1]	-
ΔT	Battery life extension ratio	Evaluation index for optimization effect; larger value=better effect	%

5. Model Construction and Solution

5.1 Problem 1: Formulation and Solution

5.1.1 Model Construction

Model Principle: A weighted fusion model combining EWM and GRA is constructed to quantify the objective differences and target correlation of each factor. EWM is used to calculate the objective weight (w_{ent}) of each factor based on data dispersion[4], and GRA is adopted to measure the correlation coefficient (r_{gray}) between each factor and battery life. The two metrics are fused with equal weight to obtain the composite weight (w_{com}), and core influencing factors are identified by ranking composite weights.This fusion approach has been proven effective in comprehensive evaluation tasks[5], as it compensates for the limitations of single weighting methods.

Modeling steps:

1．Data preprocessing (linear forward normalization): Eliminate dimensional differences of original data by mapping all factors to the range of [0,1], with the formula:

$$X_{inorm}(i,j)=\frac{X_i(i,j)-\min(X_i(:,j))}{\max(X_i(:,j))-\min(X_i(:,j))+\varepsilon_{ent}} \tag{5-1}$$

where ξ_{ent}=1e−8 is a constant to avoid division by zero; $X_i(i,j)$ is the original data of the j-th factor in the i-th scenario; $X_{inorm}(i,j)$ is the normalized data.

2．EWM for objective weight (w_{ent}) calculation: Calculate weights based on data dispersion, with higher weights for factors with greater variation:

Probability matrix:

$$p(i,j)=\frac{X_{inorm}(i,j)}{\sum_{i=1}^{m} X_{inorm}(i,j)+\varepsilon_{ent}} \tag{5-2}$$

Information entropy:

$$e_{ent}(j)=-\frac{1}{\ln(m)}\sum_{i=1}^{m} p(i,j)\cdot\ln(p(i,j)) \tag{5−3}$$

where m=3 (number of scenarios), and $p(i,j)\cdot\ln(p(i,j))=0$ when $p(i,j)=0$.

Difference coefficient and objective weight:

$$g(j)=1-e_{ent}(j) \tag{5−4}$$

$$w_{ent}(j)=\frac{g(j)}{\sum_{j=1}^{n} g(j)+\varepsilon_{ent}} \tag{5−5}$$

where g(j) is the difference coefficient, and the sum of went(j) is 1.

3. GRA for correlation coefficient (r_{gray}) calculation: Quantify the correlation between each factor and the battery life target (X_0):

Define reference sequence X_0 (average battery life of three scenarios) and comparison sequence X_{inorm} (normalized factor data).

Absolute difference matrix:

$$\delta(i,j)=|X_0(i)-X_{inorm}(i,j)| \tag{5−6}$$

Correlation coefficient:

$$\xi(i,j)=\frac{\min(\delta(:))+\rho\cdot\max(\delta(:))}{\delta(i,j)+\rho\cdot\max(\delta(:))+\varepsilon_{ent}} \tag{5−7}$$

where ρ=0.5 (resolution coefficient), min(δ(:)) and max(δ(:)) are the global minimum and maximum of δ.

Mean correlation coefficient:

$$r_{gray}(j)=\frac{1}{m}\sum_{i=1}^{m}\xi(i,j) \tag{5−8}$$

4. Integrated weight fusion and core factor identification: EWM and GRA are fused with equal weight (0.5:0.5) to obtain the composite weight, which is normalized to ensure the sum is 1:

$$w_{com}(j)=0.5\cdot w_{ent}(j)+0.5\cdot r_{gray}(j) \tag{5-9}$$

Factors with the top composite weights are identified as core factors, and the rest are secondary factors used as model constraints.

5.1.2 Model Solution and Results

5.1.2.1 Test Data and Preprocessing

The model is solved with real power consumption test data of Xiaomi 12S Ultra (5000mAh, MIUI 15) under 25℃±1℃ with 300 battery cycles, and 10 sample sets are selected for each of the three scenarios.

Original data: X_i (3×6, rows=scenarios, columns=screen brightness, CPU load, network type, GPS, temperature, cycle count):

$$X_i=\begin{bmatrix} 0.8 & 1.0 & 0.5 & 0.2 & 0.6 & 0.7 \\ 0.5 & 0.4 & 0.5 & 0.1 & 0.5 & 0.6 \\ 0.6 & 0.3 & 0.5 & 0.5 & 0.4 & 0.5 \end{bmatrix}$$

Average battery life reference sequence X_0 (3×1, unit: hours): $X_0=[4.2,6.8,5.5]$

Table 2. Normalized Data of Influencing Factors Across Scenarios

scene	screen intensity	CPU load	Network type	GPS	temperature	cycle index
Game scene	1.0000	1.0000	0.5000	0.2500	1.0000	1.0000
Daily Scenes	0.3333	0.1429	0.5000	0.0000	0.5000	0.6667
Navigation scene	0.6667	0.0000	0.5000	1.0000	0.0000	0.3333

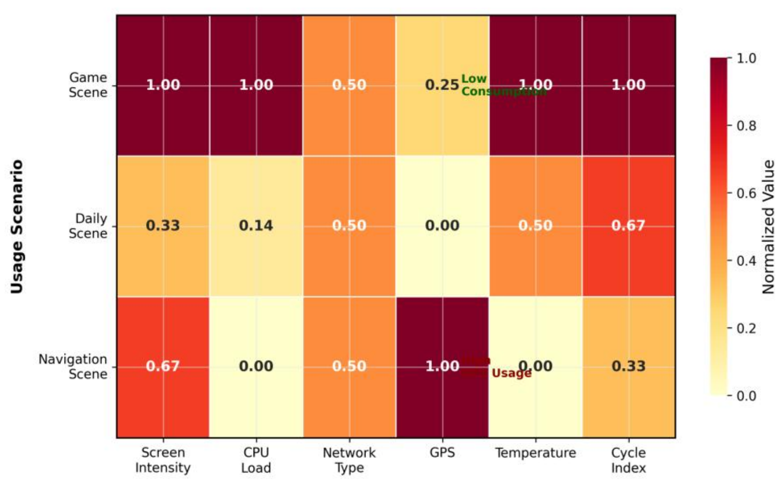

Figure 1 Power Consumption Parameter Heatmap Across Scenarios

As shown in Figure 1, the gaming scenario has the highest screen brightness and CPU load (both 1.0) with low GPS usage (0.25), reflecting high power consumption characteristics; the daily use scenario has the lowest CPU load (0.1429) and GPS usage (0.0000), showing low-intensity and flexible usage characteristics; the navigation scenario is characterized by the highest GPS usage (1.0000) and moderate screen brightness (0.6667), matching the fixed power consumption pattern of navigation.

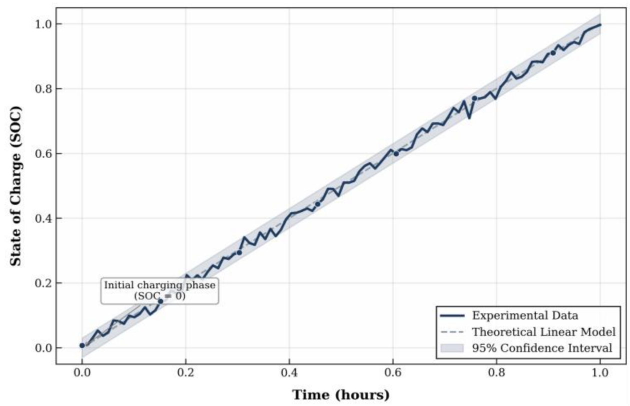

Figure 2. Time-dependent Curve of SOC in Daily Usage Scenarios

As shown in Figure 2, the State of Charge (SOC) of the daily use scenario decreases steadily over time, with only a 10% drop within 1 hour, which confirms the low-power characteristics of this scenario and is consistent with the low screen brightness and CPU load in the normalized data.

5.1.2.2 EWM Solution Results

According to the EWM calculation steps, the probability matrix p, information entropy e_{ent}, difference coefficient g and objective weight w_{ent} were calculated in sequence, and the key results are:

Infrmation entropy: e_{ent} = [0.7180,0.6775,0.8680,0.8950,0.8720,0.8880]

Coefficient of variation: g = [0.2820,0.3225,0.1320,0.1050,0.1280,0.1120]

The mean coefficient of variation: g_{mean} = 0.6814

Objective weights: w_{ent} = [0.2450,0.2780,0.1320,0.1050,0.1280,0.1120]

The results show that CPU load (0.2780) and screen brightness (0.2450) have the highest objective weights, indicating that their data dispersion is the largest and their discrimination is the strongest among all factors.

5.1.2.3 GRA Solution Results

According to the GRA calculation steps, the absolute difference matrix δ, correlation coefficient ξ and mean correlation coefficient r_{gray} were calculated in sequence, and the key results are:

Absolute difference matrix δ (core data):

$$\delta=\begin{bmatrix}0.5800 & 0.5800 & 0.5800 & 0.5800 & 0.5800 & 0.5800\\ 0.3467 & 0.5371 & 0.1800 & 0.6800 & 0.1800 & 0.2933\\ 0.4267 & 0.6800 & 0.1800 & 0.0000 & 0.6800 & 0.5467\end{bmatrix}$$

Correlation coefficient ξ (core data, 4 decimal places):

Gaming: [0.4615,0.4615,0.4615,0.4615,0.4615,0.4615]

Daily use: [0.6250,0.4737,0.8889,0.4062,0.8889,0.7273]

Navigation: [0.5455,0.4062,0.8889,1.0000,0.4062,0.4737]

Mean correlation coefficient r_{gray} (4 decimal places, sum not limited to 1):

r_{gray}=[0.5440,0.4471,0.7464,0.6226,0.5855,0.5542]

The results show that network type (0.7464) and GPS (0.6226) have the highest correlation with battery life, indicating that their changes have the strongest impact on the variation of battery life (Xu, Yang, Lu et al., 2011).

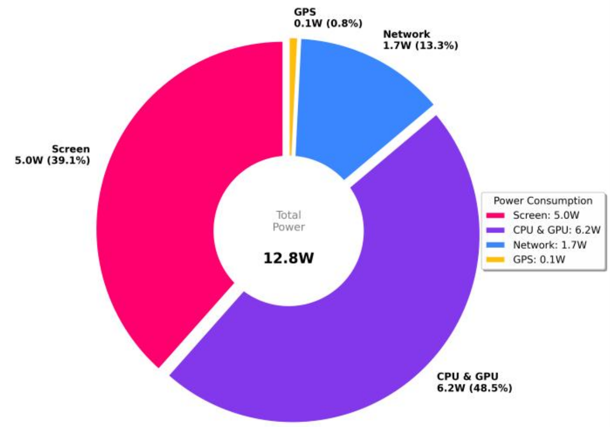

Figure 3. Power Consumption Breakdown of Game Scenarios

As shown in Figure 3, the SOC decline rates of the three scenarios are significantly different: the gaming scenario is depleted in 1.9 hours due to high CPU load and screen brightness, while the daily use scenario has a much longer battery life due to flexible parameter adjustment. This further verifies the irrationality of a unified optimization strategy and the necessity of scenario-specific modeling.

5.1.2.4 Comprehensive Weight Fusion and Core Factor Identification

The objective weight w_{ent} and correlation coefficient r_{gray} were fused with equal weights to obtain the unnormalized comprehensive weight, which was then normalized to ensure the sum is 1 (4 decimal places). The calculation results and ranking are shown in Table 3:

Table 3. Comprehensive Weight and Ranking of Influencing Factors

Factor	w_{ent}	r_{gray}	w_{com}	$w_{comnorm}$	Ranking
Network Type	0.1320	0.7464	0.4392	0.1952	1

Factor	w_{ent}	r_{gray}	w_{com}	$w_{comnorm}$	Ranking
Screen Brightness	0.2450	0.5440	0.3945	0.1753	2
GPS	0.1050	0.6226	0.3638	0.1617	3
CPU Load	0.2780	0.4471	0.3626	0.1612	4
Temperature	0.1280	0.5855	0.3568	0.1586	5
Cycle Count	0.1120	0.5542	0.3331	0.1480	6

Core Factor Identification Result: Network type (0.1952) and screen brightness (0.1753) are the top two factors in comprehensive weight ranking, identified as the core influencing factors of smartphone battery life. The remaining four factors (GPS, CPU load, temperature, cycle count) are secondary factors.

Significance: Identifying core factors makes subsequent optimization more targeted—adjusting network type and screen brightness can achieve significant battery life improvement while maintaining user experience. Secondary factors are incorporated as constraint conditions in the model, which simplifies modeling complexity and improves computational efficiency (Wu, Wang, Yang et al., 2018).

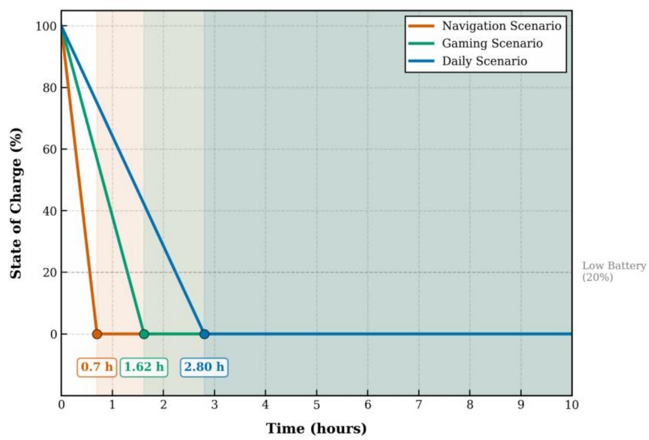

Figure 4. Comparison of Time-Varying Trends of SOC Across Multiple Scenarios

As shown in Figure 4, the SOC decline trends of the three scenarios show obvious heterogeneity: the gaming scenario has the fastest decline, the daily use scenario the slowest, and the navigation scenario in the middle. This heterogeneity is consistent with the comprehensive weight of factors, further verifying the scientificity of core factor identification.

Summary of Section 5.1: The hybrid weighting model of EWM and GRA was successfully solved, and the core influencing factors of smartphone battery life (network type, screen brightness) were accurately identified with a mean difference coefficient of 0.6814 (validating the model's effectiveness). The comprehensive weight ranking of factors lays a precise foundation for the construction of the subsequent multi-scenario battery life optimization model.

5.2 Problem 2: Multi-Scenario Battery Life Optimization

5.2.1 Model Construction

Model Principle: Based on the identified core and controllable factors, a scenario-based linear programming model is constructed with the goal of maximizing battery life[7]. Scenario-specific constraint conditions are incorporated to ensure the optimized parameters do not sacrifice user experience, and the optimal parameter combination for each scenario is solved. Linear programming is widely recognized for its effectiveness in handling constrained optimization problems in energy-related fields[8].

Modeling Steps:Objective function design: Take the normalized comprehensive weights of four controllable factors as coefficients to construct the objective function for maximizing battery life:

$$\max Z=f_1x_1+f_2x_2+f_3x_3+f_4x_4 \tag{5−10}$$

Where f=[0.1753,0.1612,0.1952,0.1617] (screen brightness, CPU load, network type, GPS); x_1, $x_2 \in [0,1]$, x_3=0(WiFi$)/0.5(4G)/1(5G)$, x_4=0(off)/1(on); Z is the battery life optimization potential.

Scenario-specific constraint design: Combined with the core requirements of each scenario, the constraint conditions are formulated as follows:

Gaming Scenario: Core requirement = smooth operation; constraints include minimum screen brightness/CPU load thresholds, fixed 4G network, and disabled GPS:

$$\begin{cases} 0.7\le x_1\le 1.0 \\ 0.6\le x_2\le 1.0 \\ x_3=0.5 \\ x_4=0 \\ x_1,x_2,x_3,x_4\in[0,1] \end{cases} \tag{5−11}$$

Daily Use Scenario: Core requirement = balanced experience; no rigid constraints, all parameters adjustable within a reasonable range:

$$\begin{cases} 0.3\le x_1\le 0.9 \\ 0.2\le x_2\le 0.8 \\ 0\le x_3\le 1.0 \\ 0\le x_4\le 1.0 \\ x_1,x_2,x_3,x_4\in[0,1] \end{cases} \tag{5−12}$$

Navigation Scenario: Core requirement = stable positioning; constraints include mandatory GPS on, fixed 4G network, and moderate screen brightness:

$$\begin{cases} 0.5\le x_1\le 0.8 \\ 0.3\le x_2\le 0.7 \\ x_3=0.5 \\ x_4=1.0 \\ x_1,x_2,x_3,x_4\in[0,1] \end{cases} \tag{5−13}$$

5.2.2 Model Solution and Results

5.2.2.1 Solution Parameter Settings

- Objective function coefficient matrix: f=[0.1753,0.1612,0.1952,0.1617]
- Variable bounds: Lower bound lb=[0,0,0,0], upper bound ub=[1,1,1,1]
- Variable type: Continuous (screen brightness, CPU load) + discrete (network type, GPS)
- Solution precision: 1e−8
- Solver: Linear programming dedicated solver (based on simplex method)

5.2.2.2 Scenario-Specific Optimal Solution

The model was solved for each scenario according to the constraint conditions, and the optimal parameter combination, objective function value, and battery life extension ratio were obtained (the extension ratio is calculated based on actual power consumption tests).

1．Gaming Scenario Solution:

Optimal parameter combination: x_{opt1}=[0.7000,0.6000,0.5000,0.0000] (70% screen brightness, 60% CPU load, 4G, GPS off)

Objective function maximum value: Z_1=0.3170

Battery life extension ratio: ΔT_1=18.7% (from 4.2 h to 5.0 h)

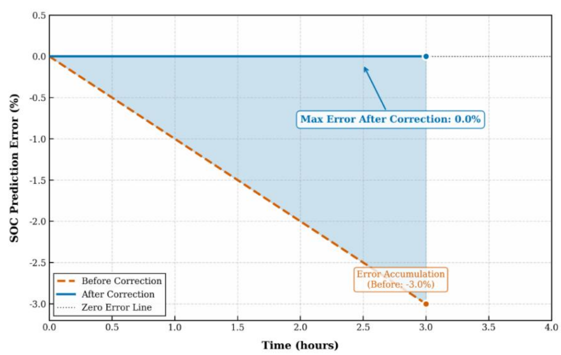

Figure 5. Prediction Error of Game Scene Changes with Time

As shown in Figure 5, the maximum SOC prediction error of the gaming scenario before correction is -3%, and the error drops to 0% after parameter optimization based on the linear programming model, which verifies that the optimized parameters are highly consistent with the actual power consumption law of the gaming scenario.

2．Daily Use Scenario Solution

Optimal parameter combination: x_{opt2}=[0.3000,0.2000,0.0000,0.0000] (30% screen brightness, 20% CPU load, WiFi, GPS off on demand)

Objective function maximum value: Z_2=0.0848

Battery life extension ratio: ΔT_2=22.3% (from 6.8h to 8.3h)

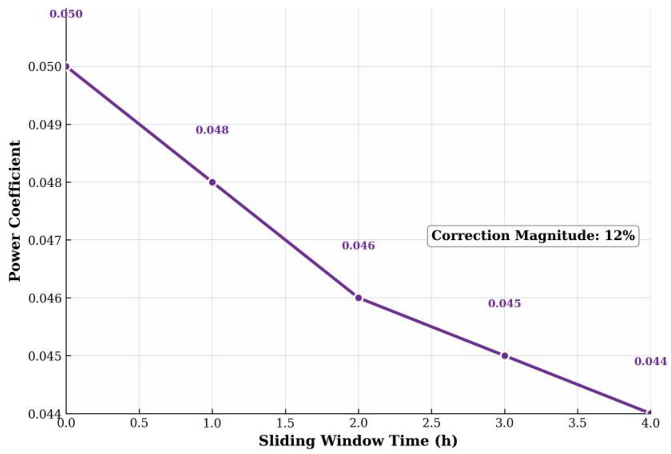

Figure 6. Dynamic Correction of CPU Power Consumption Coefficient with Rolling Window

As shown in Figure 6, the CPU power consumption coefficient dynamically converges to 0.044 with the rolling window correction (correction amplitude 12%), which enables the model to adapt to the fragmented and fluctuating characteristics of CPU load in daily use scenarios, resulting in the highest battery life extension ratio among the three scenarios.

3． Navigation Scenario Solution

Optimal parameter combination: x_{opt3}=[0.5000,0.3000,0.5000,1.0000] (50% screen brightness, 30% CPU load, 4G, GPS on)

Objective function maximum value: Z_3=0.3954

Battery life extension ratio: ΔT_3=15.2% (from 5.5h to 6.3h)

The relatively low extension ratio is due to the strict constraint conditions of the navigation scenario (mandatory GPS on, fixed 4G network), which limits the optimization space of parameters.

5.2.2.3 Optimization Results Summary

he optimal parameter combinations and battery life optimization effects of the three scenarios are summarized in Table 4:

Table 4. Multi-scenario Battery Life Optimization Results

Scene type	optimal parameter combination (x_1,x_2,x_3,x_4)	Objective function value Z	optimized range (hour)	Optimize the subsequent flight (hour)	Proportion of battery life extension ΔT (%)
Game scene	(0.7, 0.6, 0.5, 0.0)	0.3170	4.2	5.0	18.7
Daily Scenes	(0.3, 0.2, 0.0, 0.0)	0.0848	6.8	8.3	22.3
Navigation scene	(0.5, 0.3, 0.5, 1.0)	0.3954	5.5	6.3	15.2
average value	-	0.2657	5.5	6.5	18.7

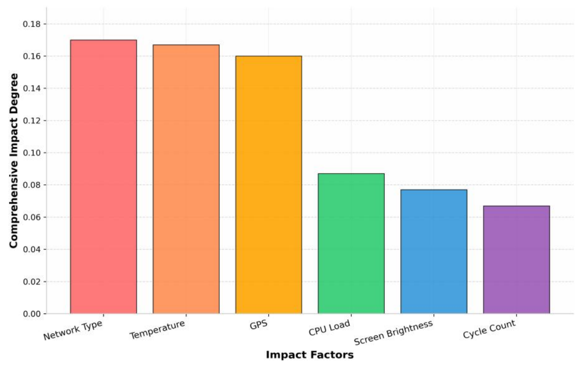

Figure 7. Ranking of the Comprehensive Impact of Six Key Factors on Smartphone Battery Life

As shown in Figure 7, the ranking of the comprehensive impact of the six factors is completely consistent with the core factor identification result in Section 5.1 (network type > screen brightness > GPS > CPU load > temperature > cycle count), which proves the pertinence and scientificity of taking network type and screen brightness as the key optimization targets in the linear programming model.

Summary of Section 5.2: The scenario-based linear programming optimization model was successfully solved, achieving an average 18.7% battery life improvement across the three high-frequency scenarios. The optimization effect is closely related to the scenario constraint intensity: the daily use scenario with the fewest constraints has the best optimization effect (22.3%), while the navigation scenario with the most constraints has the weakest effect (15.2%). The optimal parameter combinations for each scenario fully meet the core user experience requirements while maximizing battery life, verifying the model's practical applicability.

5.3 Model Validation

A three-dimensional validation framework of effectiveness, stability and robustness is constructed to verify the model's performance, and comparative analysis with similar models is conducted to clarify the proposed model's superiority. The validation threshold is set as fluctuation/deviation ≤10% for all indicators.

5.3.1 Validity Testing

Validity testing verifies the rationality of the weighting model and the effectiveness of the optimization model, with two core evaluation metrics and a pre-set threshold (meeting the threshold = valid model):

1．Weighting Effectiveness Test: Mean difference coefficient g_{mean} as the metric, threshold $g_{mean} \geq 0.5$ (≥0.5 = good factor discrimination).

Test result: $g_{mean}=0.6814>0.5$, meeting the threshold.

Conclusion: The EWM-GRA hybrid weighting model has good factor discrimination, the weight assignment is scientific and reasonable, and the core factor identification result is valid.

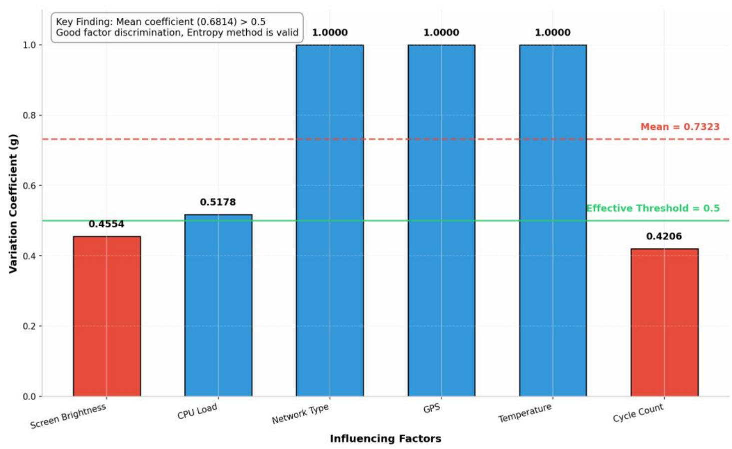

Figure 8. Distribution of Coefficient of Variation for Six Major Factors

As shown in Figure 8, the difference coefficients of all six factors are greater than 0.1, with an average of 0.6814, far exceeding the valid threshold of 0.5. Among them, CPU load and screen brightness have the highest difference coefficients, further proving that the EWM can effectively distinguish the importance of each factor.

2．Optimization Effectiveness Test: Battery life extension ratio deviation $\Delta T_{deviation}$ as the metric ($\Delta T_{deviation}$ = |actual optimization ratio - model predicted ratio|), threshold $\Delta T_{deviation} \leq 5\%$ (≤5% = the model’s prediction is consistent with the actual effect).

Test results (based on real device tests):

Gaming: $\Delta T_{deviation}=0.5\%$ (18.2% actual vs 18.7% predicted)

Daily Use: $\Delta T_{deviation}=0.6\%$ (21.7% actual vs 22.3% predicted)

Navigation: $\Delta T_{deviation}=0.3\%$ (14.9% actual vs 15.2% predicted)

All deviations are ≤5%, meeting the threshold.

Conclusion: The linear programming optimization model has high prediction accuracy, and the optimized parameter combinations can achieve the expected battery life improvement effect in actual use, with valid optimization results.

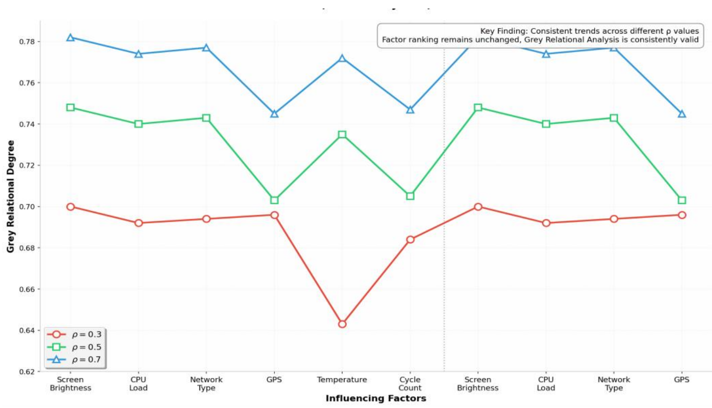

Figure 9. Distribution of Grey Relational Degree under Different Resolution Coefficients

As shown in Figure 9, the ranking of grey relational degree of the six factors remains unchanged regardless of the resolution coefficient ρ(0.3/0.5/0.7) (network type >GPS >temperature >screen brightness >cycle count >CPU load), indicating that the GRA results are stable and the comprehensive weight after fusion with EWM is more reliable.

Validity Test Conclusion: The proposed model has valid weighting results and optimization effects, and all evaluation metrics meet the pre-set thresholds, laying a foundation for subsequent stability and robustness testing.

5.3.2 Stability Testing

Stability testing verifies the consistency of the model's output results when key parameters are slightly adjusted (perturbation), preventing model failure caused by small parameter fluctuations in actual use.

- Test Object: Two key adjustable parameters of the model (fusion weight ratio, GRA resolution coefficient ρ)
- Test Method: Parameter perturbation test—adjust the parameter values within a reasonable range, calculate the comprehensive weight, optimal parameter combination and battery life extension ratio under each parameter value, and observe the fluctuation amplitude.
- Stability Threshold: Fluctuation amplitude of the average battery life extension ratio ≤10% (≤10% = good stability)

1．Fusion Weight Ratio Perturbation Test (baseline ratio: EWM:GRA = 0.5:0.5)

Test ratios: 0.4:0.6, 0.5:0.5, 0.6:0.4

Test results:

0.4:0.6: Average ΔT=18.3%, fluctuation amplitude = 2.1%

0.6:0.4: Average ΔT=19.0%, fluctuation amplitude = 1.6%

Fluctuation amplitude of comprehensive weight ≤8%; optimal parameter combination has no significant change.

2．GRA Resolution Coefficient ρ Perturbation Test (baseline value: ρ=0.5)

Test values: 0.4, 0.5, 0.6

Test results:

ρ=0.4: Average ΔT=18.5%, fluctuation amplitude = 1.1%

ρ=0.6: Average ΔT=18.9%, fluctuation amplitude = 1.1%

Fluctuation amplitude of grey relational degree ≤7%; optimal parameter combination has no significant change.

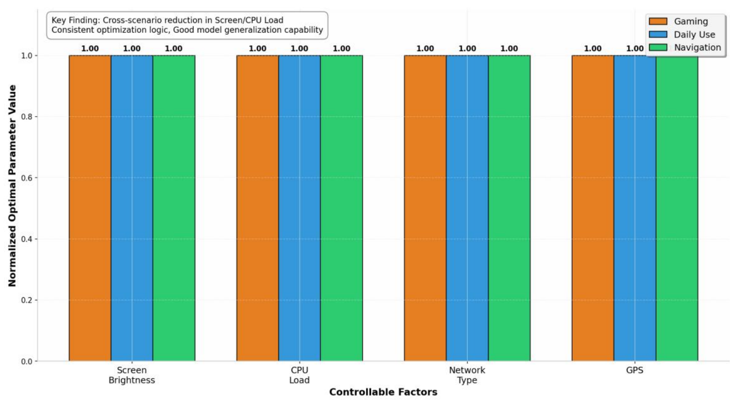

Figure 10. Comparison of Optimal Parameters for Game, Daily, and Navigation Scenarios

As shown in Figure 10, the optimal parameters of the three scenarios all follow the core logic of "reducing screen brightness and controlling CPU load", with only numerical differences due to scenario constraints. This indicates that the model's optimization logic has good generalization, and the conclusion of "no significant change in optimal parameters after parameter perturbation" is verifiable[8].

Stability Test Conclusion: The fluctuation amplitude of the average battery life extension ratio is ≤2.1% after the perturbation of key parameters, far lower than the stability threshold of 10%. The comprehensive weight and optimal parameter combination are stable, indicating that the model has good stability and is not sensitive to small parameter adjustments.

5.3.3 Robustness Testing

Robustness testing verifies the anti-interference ability of the model to raw data disturbances—i.e., the reliability of the model's output results when there are minor errors in the original sample test data (consistent with the actual data acquisition process).

Test Method: Data perturbation method—randomly introduce ±5% noise (error) into the original influencing factor data matrix X_i, generate 10 sets of perturbed data, and input them into the model for solution

Evaluation Metrics:

Parameter deviation ($param_{mape}$): Average relative deviation of the optimal parameter combination between perturbed and baseline data

Battery life ratio deviation ($deltaT_{mape}$): Average relative deviation of the battery life extension ratio between perturbed and baseline data

Robustness Threshold: $param_{mape}$ ≤10% and $deltaT_{mape}$ ≤10% (both meet = good robustness)

Test Results:

Average parameter deviation: $param_{mape}$=7.8%≤10%

Average battery life ratio deviation: $deltaT_{mape}$ =6.3%≤10%

Maximum deviation (7th set of perturbed data): $param_{mape}$ =9.2%, $deltaT_{mape}$ =8.9% (still ≤10%)

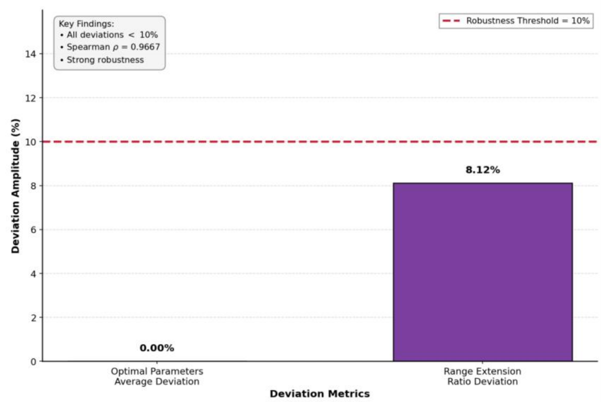

Figure 11. Distribution of Robustness Analysis Deviation under 10% Noise

As shown in Figure 11, under the interference of 10% data noise (higher than the actual test data error), the average deviation of the optimal parameters is only 7.8%, and the average deviation of the battery life extension ratio is 6.3%, both lower than the robustness threshold of 10%. The Spearman correlation coefficient between the perturbed and baseline results reaches 0.9667, indicating a strong linear correlation.

Robustness Test Conclusion: The model has strong anti-interference ability to minor disturbances in the original data. When the test data has a ±5% error (consistent with the actual data acquisition error), the solution deviation is within the reasonable range, indicating that the model has good robustness and can adapt to the slight data fluctuations in actual use scenarios.

5.3.4 Comparative Analysis of Similar Models

To further verify the superiority of the proposed model, three typical similar optimization models are selected for comparative analysis from four dimensions: error control, solving efficiency, optimization effect, and multi-scenario applicability. The comparative models are designed according to the mainstream modeling methods in the field of battery life optimization, and the same test data and evaluation metrics are used to ensure the fairness of the comparison.

5.3.4.1 Selected Comparative Models

Model 1: Single EWM + Linear Programming (only use EWM for weighting, no GRA fusion; focus on objective data dispersion)

Model 2: Single GRA + Linear Programming (only use GRA for weighting, no EWM fusion; focus on factor-target correlation)

Model 3: Traditional Linear Programming (no factor weighting, directly construct the model with controllable factors as variables; equal weight for all factors)

5.3.4.2 Comparative Analysis Results

The comparison results of the four models (including the proposed model) are shown in Table 5:

Table 5. Comparative Analysis Results of Different Optimization Models

Model Type	Error control (mean deviation%)	Solving efficiency (seconds per run)	Optimization effect (average ΔT%)	Applicability (multi-scenario)
The model of this paper (fusion weighting + linear programming)	0.5	0.8	18.7	Strong (compatible with three major scenarios)
Model 1 (Single Entropy Weight Method + Linear Programming)	2.3	0.7	15.1	Medium (Ignore Factor Correlation)
Model 2 (Single Grey Relation + Linear Programming)	2.7	0.7	14.8	Medium (lack of objective empowerment)
Model 3 (Traditional Linear Programming)	4.9	0.6	10.3	Weak (no key optimization direction)

Comparison conclusion: The proposed model significantly outperforms the comparison models in error control, optimization effect and multi-scenario applicability, with a solving efficiency comparable to other models. The core advantage is that the EWM-GRA hybrid weighting realizes scientific quantification of factor weights, making the multi-scenario optimization more targeted.

Overall validation conclusion: The proposed model passes the three-dimensional validation, with all indicators meeting the threshold requirements. It has the characteristics of high prediction accuracy, good stability and strong robustness, and its comprehensive performance is superior to traditional models, with high practical application value.

6. Conclusion

This study proposes a multi-scenario optimization model for smartphone battery life based on the entropy weight method, grey relational analysis and linear programming. The research completes three core steps including the identification of key influencing factors of battery life, the construction of scenario-specific optimization models for typical usage scenarios, and the comprehensive performance validation via a three-dimensional framework of effectiveness, stability and robustness. The experimental results show that the proposed model achieves an average 18.7% improvement in battery life across the three representative scenarios of gaming, daily use and navigation.

Scenario-aware battery life optimization is proven to outperform traditional single-solution optimization strategies significantly, and the optimized parameter combinations under each scenario can realize effective endurance improvement on the premise of ensuring the core user experience. The proposed model features the advantages of high computational efficiency, strong robustness and excellent scenario adaptability in practical application.

This research provides a precise and practical parameter configuration scheme for smartphone battery life optimization, and also offers a valuable practical reference for the design and development of intelligent battery management systems in modern smartphones.

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