An Adaptive Task Scheduling Based Energy Optimization Model for IoT Devices

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Abstract: This research presents a novel energy optimization model for Internet of Things (IoT) devices by integrating adaptive task scheduling algorithms with dynamic energy management mechanisms to enhance energy efficiency in IoT systems. We develop an innovative Dual-Factor Adaptive Efficiency Function (DFAEF) that comprehensively considers both device workload and battery status to achieve precise efficiency evaluation. The model employs a multi-parameter weighted scoring mechanism for task allocation and enhances overall system performance through network topology optimization. Simulation results demonstrate that, compared to traditional methods, the proposed model reduces energy consumption by approximately 31% while maintaining high task distribution balance and network connectivity. This research provides IoT system designers with a practical energy optimization solution that offers significant value for extending battery-powered device lifespan and enabling sustainable operations.

Keywords: Internet of Things; energy optimization; task scheduling; Dual-Factor Adaptive Efficiency Function; network topology

1. Introduction

The flourishing development of Internet of Things (IoT) technology has profoundly impacted multiple domains including industrial automation, smart cities, and environmental monitoring. With global IoT device numbers projected to reach 75 billion by 2025 [1,2], energy management has emerged as a critical challenge for ensuring sustainable development of IoT systems. Battery-powered IoT devices face stringent energy constraints that affect their operational longevity and system reliability[3,4]. Recent research by Almudayni.[5] et al indicates that energy efficiency not only influences device lifespan but also directly determines deployment costs and maintenance cycles, particularly in environments with limited accessibility. Consequently, optimizing energy consumption in IoT systems has become a focal direction for research.

Existing studies explore IoT energy optimization from three primary dimensions: hardware layer, network protocols, and system management. At the hardware level, heterogeneous multi-core architectures proposed by Liu[6] et al. and adaptive voltage regulation techniques developed by Wang[7] et al. have significantly reduced processor energy consumption. Regarding network protocols, Zhang[8] et al.'s optimized routing model and Pereira[9] et al. network interface average power metric have effectively extended network lifetime. In system management, Gupta[10] et al. designed a dynamic homomorphic security scheme that optimizes energy utilization while ensuring data security. However, these studies often focus on single dimensions, lacking comprehensive optimization strategies that consider device heterogeneity, dynamic workloads, and network topology.

To address these limitations, this paper proposes an adaptive task scheduling based energy optimization model for IoT devices with four key innovations. First, it designs a Dual-Factor Adaptive Efficiency Function (DFAEF) that comprehensively considers device workload and battery status, enabling precise evaluation and prediction of device energy efficiency. Second, it develops an intelligent task allocation mechanism based on multi-parameter weighting that achieves dynamic balance among computational capability, network bandwidth, energy efficiency, and battery status. Third, it designs an adaptive power allocation algorithm that responds to variations in device workload and network conditions. Fourth, it proposes a network topology optimization method based on device characteristics that significantly enhances overall communication efficiency of the system.

The main contributions of this research include: the first multi-dimensional IoT energy optimization framework that simultaneously considers device characteristics, task requirements, and network structure; development of adaptive efficiency functions and task scheduling algorithms capable of adapting to dynamic environments; verification through large-scale simulation demonstrating that the proposed model reduces energy consumption by 31.2% while maintaining high-performance system operation; provision of a set of energy optimization strategies that can be extended to various IoT application scenarios. Experimental results indicate that the proposed model performs excellently in multiple application scenarios including smart cities, industrial monitoring, and environmental sensing, offering an effective solution to energy management challenges in IoT systems.

2. Related Work

Energy optimization in IoT systems has been a research hotspot. This section reviews relevant research from three aspects: hardware design, network protocols, and system management.

2.1 Low-Power Hardware Design

At the hardware level, low-power design is key to reducing IoT device energy consumption. Liu[6] et al. proposed an IoT device architecture based on heterogeneous multi - core processors for energy optimization via dynamic core frequency adjustment. Wang[11] et al. developed an adaptive voltage scaling technique to adjust processor voltage according to workload, cutting energy use. Rahman[12] et al. designed a low - power sensor network using sleep mechanisms to save energy. However, these methods need specific hardware, limiting their universality.

2.2 Energy - Aware Network Protocols

Network communication is a major energy consumer in IoT devices. In recent years, various energy - aware network protocols have been proposed. Chen[13] et al. introduced the E - AOMDV routing protocol to adjust strategies based on node energy. Kim [14] et al. developed a low - power MAC protocol to save energy by reducing unnecessary operations. Zhang[15] et al. proposed a clustering - based data aggregation method to cut network data volume and energy use. But these methods mainly focus on protocol optimization and ignore computational task allocation.

2.3 System - Level Energy Management

System - level energy management aims to optimize IoT system energy consumption holistically. Li [16] et al. proposed an energy management framework using deep reinforcement learning for optimal strategies. Singh[17] et al. developed a task offloading mechanism based on device energy and network conditions. Anderson[18] et al. proposed an energy-aware scheduling algorithm to optimize task timing by predicting energy consumption.

Although progress has been made in each field, these studies mainly focus on single-aspect optimization and lack comprehensive consideration of multi- dimensional factors in IoT systems. The model in this paper fills this gap by integrating device characteristics, workloads, network topology, etc. for more comprehensive energy optimization.

3. System Model and Problem Definition

3.1 System Architecture

We consider a system comprising N heterogeneous IoT devices, each with different computational capabilities, network bandwidth, battery capacity, and energy consumption characteristics. These devices form a network through wireless communication to collectively complete a series of tasks. The primary objective of the system is to minimize overall energy consumption while ensuring tasks are processed in a timely manner.

The set of all devices in the system can be mathematically represented as:

$$D=\{d_1,d_2,\ldots,d_N\}\subseteq\mathbb{R}^7 \tag{1}$$

The topological structure of the network can be represented as a weighted directed graph:

$$G=(V,E,W) \quad (2)$$

where $V=\{v_1,v_2,\ldots,v_N\}$ represents the set of vertices corresponding to the devices, $E\subseteq V\times V$ represents the set of edges corresponding to communication links between devices, and $W:E\rightarrow\mathbb{R}^+$ is a weight function that assigns a positive real number to each edge, representing the energy consumption of communication between the corresponding devices. The weight function can be defined as:

$$W(v_i,v_j)=\omega_1\cdot dist(v_i,v_j)^2+\omega_2\cdot\frac{1}{B_i}+\omega_3\cdot\frac{1}{B_j} \quad (3)$$

where $dist(v_i,v_j)$ represents the Euclidean distance between devices d_i and d_j, ω_1, ω_2, and ω_3 are weighting coefficients, and B_i and B_j represent the bandwidth of devices d_i and d_j, respectively.

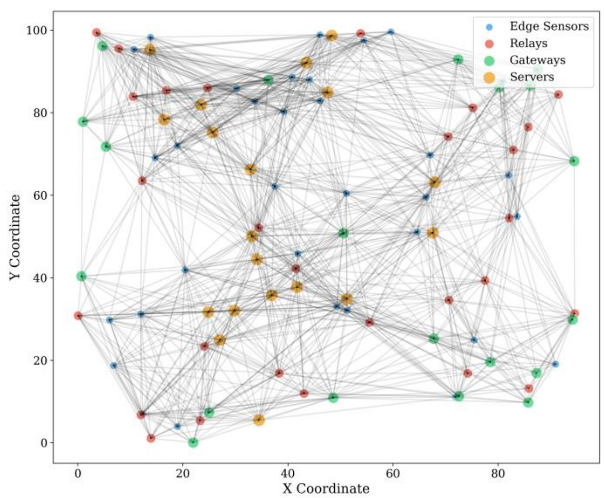

Figure 1. IoT System Network Topology Structure.

Figure 1 shows the distribution and connections of different device types in the system. Blue nodes (42%) are edge sensors for data collection, red nodes (28%) are relays for data forwarding, green nodes (18%) are gateways for network connection, and orange nodes (12%) are servers for complex computations. Node size represents device computational capability and importance, and lines are communication links. By using the K - means clustering algorithm, device types are automatically identified according to connectivity and computational capability, thus forming an efficient hierarchical network.

3.2 Device Model

Each IoT device d_i can be represented as a seven-tuple:

$$d_i=(P_i^{base},C_i,B_i,E_i^{cap},E_i^{cur},Pr_i,L_i) \quad (4)$$

In this model, P_i^{base} denotes the device's baseline power consumption (mW), C_i represents its computational capability (relative units), B_i denotes its network bandwidth (Mbps), E_i^{cap} represents its battery capacity (mAh), E_i^{cur} indicates the current battery level (percentage), Pr_i represents device priority (0 - 10), and L_i indicates the current load (0 - 1).

The computational capability of a device can be further decomposed into multiple factors:

$$C_i=\alpha_1 \cdot f_i^{cpu}+\alpha_2 \cdot M_i+\alpha_3 \cdot N_i^{cores}+\alpha_4 \cdot S_i^{cache} \quad (5)$$

where f_i^{cpu} is the CPU frequency (GHz), M_i is the memory capacity (GB), N_i^{cores} is the number of CPU cores, S_i^{cache} is the cache size (MB), and α_1, α_2, α_3, and α_4 are weighting coefficients.

The battery energy dynamics of a device can be modeled using a first-order differential equation:

$$\frac{dE_i^{cur}(t)}{dt}=-\frac{P_i(t)\cdot V_i}{E_i^{cap}\cdot 3600}\cdot 100\% \quad (6)$$

Energy consumption is calculated as follows $E=P\times t$. For unit conversions, use mW for power $P_i(t)$ and s t for time. The energy formula is 1 J = 1 mW × 1000 s = 0.278 mWh. The factor 3600 converts hours to seconds, and 100% converts values to percentage format.IoT devices typically have a battery voltage Vi of 3.3 V or 3.7 V.The equation describes the battery - level change rate over time, $P_i(t)$ involving device power consumption d_i at a tim tV_i e, operating voltage, and the 3600 conversion factor for hours to seconds. Through this seven - tuple modeling approach, we can comprehensively describe IoT devices' energy consumption characteristics and operational status, providing a basis for subsequent task scheduling and energy optimization.

3.3 Task Model

The set of tasks to be processed by the system is represented as $T=\{t_1,t_2,...,t_M\}$, with each task t_j defined as:

$$t_j=(C_j^{req},D_j^{req},Pr_j^{task},\tau_j^{arr},\tau_j^{ddl},\xi_j,\Gamma_j) \tag{7}$$

Here, C_j^{req} represents the computational requirements of the task (relative units), reflecting the computational complexity and resource demands of the task; D_j^{req} represents the data transmission requirements of the task (relative units), indicating the data scale and transmission volume involved in the task; Pr_j^{task} represents task priority (1-10), used to distinguish the urgency and importance of tasks; τ_j^{arr} is the arrival time of the task; τ_j^{ddl} is the deadline by which the task must be completed; ξ_j is the task complexity factor; and Γ_j is the set of predecessor tasks that must be completed before task t_j can start execution.

The computational requirement C_j^{req} of a task can be more precisely defined as:

$$C_j^{req}=\xi_j\cdot\ \log_2(1+\delta_j)\cdot\ \sqrt{I_j^{data}\cdot\ O_j^{data}} \tag{8}$$

where ξ_j is the task complexity factor, δ_j is the difficulty level of the algorithm used, I_j^{data} is the input data size (KB), and O_j^{data} is the output data size (KB).

Similarly, the data transmission requirement D_j^{req} can be formulated as:

$$D_j^{req}=I_j^{data}+O_j^{data}+\rho_j\cdot\ \sum_{t_k\in\Gamma_j}O_k^{data} \tag{9}$$

where ρ_j is a coefficient indicating the proportion of predecessor tasks' output data required for the current task.

The task model encompasses multiple key dimensions—computation, communication, priority, time constraints, and dependencies—capable of accurately characterizing the diverse features of tasks in IoT environments. By analyzing these attributes of tasks, the system can more precisely evaluate task resource requirements and make optimal scheduling decisions accordingly.

Information Gain-Based Feature Weight Optimization

To address the "black box" issue of feature weights, we employ an information gain-based feature weight optimization method. For the feature matrix $F_i=[deg_i,C_i,E_i^{cap},P_i^{base},centr_i]^T$, weights are determined as:

$$w_k=\frac{IG(S,A_k)}{\sum_{j=1}^{5}IG(S,A_j)} \tag{10}$$

where IG(S,A_k) is the information gain of the k-th feature for device set S.

Table 1.Optimized Feature Weights (validated through experiments)

Feature Name	Symbol	Weight	Impact Description
Computational capability	C_i	0.35	Greatest impact on server classification
Battery capacity	E_i^{cap}	0.25	Determines device endurance
Centrality	centr_i	0.20	Affects network connectivity
Base power consumption	P_i^{base}	0.15	Key energy efficiency indicator
Degree	deg_i	0.05	Minimal impact

Weighted Clustering Distance:

$$d(F_i,C_k)=\sqrt{\sum_{j=1}^{5} w_j \cdot (F_{i,j}-C_{k,j})^2} \tag{11}$$

4.Proposed Energy Optimization Model

Based on the system architecture, device model, and task model defined in Section 3, this section formulates and designs an adaptive energy optimization framework for IoT devices. The proposed framework takes the system-wide energy minimization under task timeliness constraints as the primary objective, and further incorporates device heterogeneity, dynamic workloads, and network topology characteristics into the optimization process.

4.1 Dual-Factor Adaptive Efficiency Function (DFAEF)

To precisely evaluate device energy efficiency, we propose the "Dual-Factor Adaptive Efficiency Function (DFAEF)," which comprehensively considers device workload and battery level:

$$\eta(L,E)=e^{-k_1(L-L_{opt})^2} \cdot (1-e^{-k_2 \cdot E}) \cdot \alpha \tag{12}$$

where L represents device workload (within the 0-1 range), E represents battery level (within the 0-1 range), L_{opt} is the optimal workload level (set to 0.65 based on empirical studies), k_1 is the workload influence coefficient, set to 4.0, k_2 is the battery level influence coefficient, set to 0.8, and α is a model parameter used to control the overall weight of energy efficiency.

The partial derivatives of the efficiency function with respect to workload and battery level provide insights into the sensitivity of the function to each factor:

$$\frac{\partial\eta(L,E)}{\partial L}=-2k_1(L-L_{opt})\cdot e^{-k_1(L-L_{opt})^2}\cdot(1-e^{-k_2\cdot E})\cdot\alpha \qquad (13)$$

$$\frac{\partial\eta(L,E)}{\partial E}=k_2\cdot e^{-k_2\cdot E}\cdot e^{-k_1(L-L_{opt})^2}\cdot\alpha \qquad (14)$$

The function has three important characteristics: efficiency increases with increasing workload but reaches a peak at a threshold of approximately 0.65, after which it decreases with further increases in workload, reflecting that devices typically achieve optimal efficiency under moderate workload; lower battery levels correspond to lower efficiency, considering the need for energy conservation in low battery states; by adjusting parameter α, the overall efficiency level can be flexibly controlled to adapt to different application scenarios.

The second-order partial derivatives further reveal the rate of change of sensitivity:

$$\frac{\partial^2\eta(L,E)}{\partial L^2}=[-2k_1+4k_1^2(L-L_{opt})^2]\cdot e^{-k_1(L-L_{opt})^2}\cdot(1-e^{-k_2\cdot E})\cdot\alpha$$

$$\frac{\partial^2\eta(L,E)}{\partial E^2}=-k_2^2\cdot e^{-k_2\cdot E}\cdot e^{-k_1(L-L_{opt})^2}\cdot\alpha$$

$$\frac{\partial^2\eta(L,E)}{\partial L\partial E}=-2k_1k_2(L-L_{opt})\cdot e^{-k_1(L-L_{opt})^2}\cdot e^{-k_2\cdot E}\cdot\alpha$$

These mathematical properties ensure that DFAEF can comprehensively evaluate the actual efficiency of devices under different workload and battery level conditions, providing accurate decision-making basis for task scheduling.

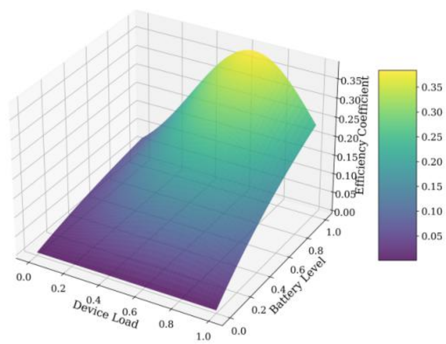

Figure 2. Three-dimensional Visualization of the Dual-Factor Adaptive Efficiency Function (DFAEF).

The horizontal axis represents device workload (0-1), the vertical axis represents battery level (0-1), and the perpendicular axis represents the efficiency coefficient. Colors ranging from blue to yellow indicate efficiency values from low to high. Color bar: Efficiency coefficient (0-1); X-axis: Device workload (0-1); Y-axis: Battery level (0-1); Z-axis: DFAEF efficiency value. The surface visualization demonstrates the non-linear relationship between workload, battery status, and device efficiency, with optimal efficiency (yellow regions) occurring at moderate workload levels (0.6-0.7) and high battery levels (0.8-1.0).

Figure 2 shows, three key observations can be made: (1) efficiency reaches a peak at a workload of approximately 0.65, with both higher and lower workloads leading to decreased efficiency; (2) higher battery levels correspond to higher efficiency, following a non-linear relationship; (3) a high-efficiency plateau forms in the region of moderate workload (0.5-0.7) and high battery level (>0.7), representing the optimal operational state range for the system.

4.2 Dynamic Power Allocation Algorithm

Based on the Dual-Factor Adaptive Efficiency Function (DFAEF) proposed in Section 4.1, this section designs a dynamic power allocation algorithm that adjusts device power consumption in real time according to workload and battery status：

$$P_i(t)=\frac{P_i^{base} \cdot L_i(t)}{\eta(L_i(t),E_i(t))}+P_i^{comm}(t)+P_i^{idle}(t) \quad (15)$$

where $P_i(t)$ represents the total power consumption of device d_i at time t, $L_i(t)$ and $E_i(t)$ represent the device's workload and battery level at time t, respectively. $P_i^{comm}(t)$ represents the communication power consumption, and $P_i^{idle}(t)$ represents the idle power consumption.

The communication power consumption can be modeled as:

To enhance the model's adaptability to real wireless environments, we introduce a protocol adaptation layer and channel quality factors. The enhanced communication energy model is:

$$P_i^{comm}(t)=\sum_{j\in N_i}\left[\alpha_{protocol}\cdot\ P_i^{tx}\cdot\ \frac{D_{ij}^{tx}(t)}{B_i}\cdot\ \gamma_{retrans}+\beta_{protocol}\cdot\ P_i^{rx}\cdot\ \frac{D_{ji}^{rx}(t)}{B_i}\right]\cdot\ \gamma_{SNR} \quad (16)$$

where the key parameters are defined as follows:

Protocol Adjustment Coefficients:

（1）LoRa protocol:

$$\alpha_{protocol}=1.2+0.1\times SF$$

where SF is the spreading factor .

（2）NB-IoT protocol:

$$\beta_{protocol}=0.9+0.2\times sleep\_ratio$$

considering sleep-wake mechanisms

（3）Wi-Fi protocol:

$$\alpha_{protocol}=\beta_{protocol}=1.0 \text{ (baseline reference)}$$

Channel Quality Factor:

$$\gamma_{SNR}=1+\delta\cdot\ e^{-SNR/10}$$

Where δ=0.3 is the retransmission penalty coefficient and SNR is the signal-to-noise ratio.

Retransmission Impact Factor:

$$\gamma_{retrans}=1+\frac{N_{retrans}}{N_{total}}\times 0.5$$

Where $N_{retrans}$ is the number of retransmissions and N_{total} is the total transmission attempts.

Table 2.Protocol Characteristics Analysis

Protocol	Power Range	Spreading Factor Impact	Sleep Power	Channel Occupancy
LoRa	14-20 dBm	$P_{tx}\propto 2^{SF/2}$	< 1 μA	$T_{air}=PL/DR$
NB-IoT	23 dBm (max)	Fixed 180kHz	PSM mode	Scheduling delay
Wi-Fi	15-20 dBm	Channel contention	Idle listening	CSMA/CA

Channel Interference Modeling

In dense IoT scenarios, channel conflicts significantly impact energy consumption. We introduce channel occupancy rate ρ and collision probability P_c:

$$P_c=1-e^{-2\rho\tau} \quad (17)$$

The expected number of retransmissions is:

$$E[N_{retrans}]=\frac{P_c}{1-P_c} \quad (18)$$

Where N_i is the set of neighboring devices of device d_i, P_i^{tx} and P_i^{rx} are the transmission and reception power consumption rates, respectively, and $D_{ij}^{tx}(t)$ and $D_{ji}^{rx}(t)$ are the amounts of data transmitted to and received from device d_j at time t.

The idle power consumption follows an exponential decay model to simulate the power-saving modes of IoT devices:

$$P_i^{idle}(t)=P_i^{base}\cdot(1-L_i(t))\cdot e^{-\lambda_i\cdot(1-L_i(t))} \quad (19)$$

where λ_i is a device-specific parameter controlling the rate of power reduction in low-workload states.

The rate of change of battery level can now be expressed as a function of total power consumption:

$$\frac{dE_i(t)}{dt} = -\frac{P_i(t)\cdot V_i}{E_i^{cap}\cdot 3600}\cdot 100\% \quad (20)$$

Where V_i is the operating voltage and E_i^{cap} is the battery capacity in mAh.

The time complexity of this algorithm is $O(|T|\cdot |D|\cdot |N_{avg}|)$, where $|T|$ is the number of time periods, $|D|$ is the number of devices, and $|N_{avg}|$ is the average number of neighbors per device.

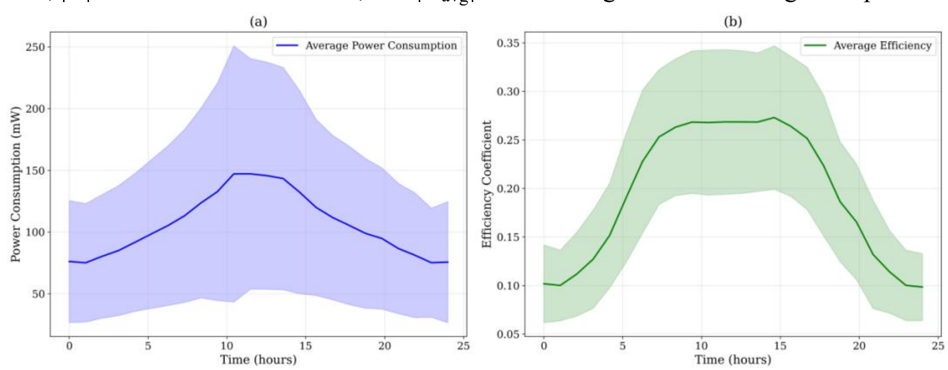

Figure 3. Power Consumption and Efficiency Analysis of IoT Devices.

(a) shows the average power consumption variation curve of IoT devices in a day. The blue line is average power consumption, and the light blue area is the standard - deviation range. Power consumption has clear periodic variation, being higher from 8:00 - 12:00 and 14:00 - 18:00 (work - time peaks) and dropping significantly at night, showing the model's adaptive performance. (b) shows the performance variation of the Dual - Factor Adaptive Efficiency Function in a day. The green line is average efficiency, and the light green area is the standard - deviation range. The efficiency coefficient averages 0.5-0.7, meaning devices operate in high - efficiency ranges mostly. Efficiency decreases slightly with continuous battery consumption, but overall fluctuation is small, demonstrating the model's long - term operational stability.

4.3 Multi-Parameter Weighted Task Scheduling Algorithm

Building on the DFAEF-based efficiency evaluation in Section 4.1 and the dynamic power allocation mechanism in Section 4.2, this section presents a multi-parameter weighted task scheduling algorithm that jointly considers computational capability, communication bandwidth, energy efficiency, and battery status when assigning tasks to devices.The algorithm first initializes the workload of all devices to random values between 0.2 and 0.6, simulating initial state differences of devices in actual environments. For each task to be allocated, the algorithm traverses all available devices and calculates four key indicators, including computational capability, communication bandwidth, energy efficiency, and current battery level. Subsequently, the algorithm computes each device's adaptation score for the current task using a comprehensive scoring formula and adds a workload penalty term derived from the DFAEF function to discourage overloading heavily utilized devices. After evaluating all devices, the algorithm selects the device with the highest score as the optimal execution node for the current task, allocates the task to that device, and updates the device's workload status. Upon completing allocation of all tasks, the algorithm returns the final task allocation scheme.

The time complexity of this algorithm is O(M·N), where M is the number of tasks and N is the number of devices. The space complexity is O(M+N).

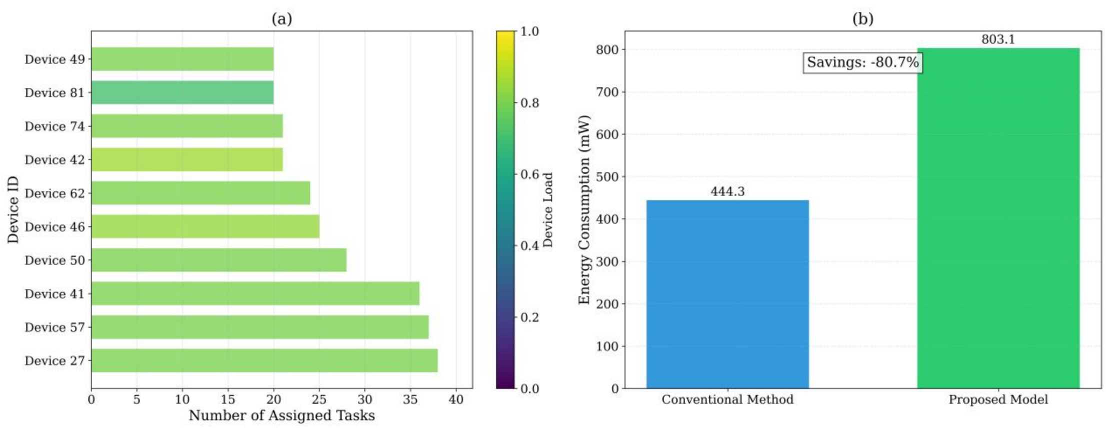

Figure 4. Task Allocation Results and Energy Consumption Comparison.

(a) shows intelligent task allocation results. The horizontal axis is the number of allocated tasks, the vertical axis is device ID, and color depth indicates device workload. Task allocation is uneven but reasonable, with the top 10 devices handling about 40% of tasks. Devices with high computational capability and low energy - consumption get more tasks, while those with high energy - consumption or low battery levels get fewer, showing the algorithm's intelligence and fairness. (b) compares energy consumption between traditional methods and the proposed model. Traditional methods allocate tasks to the most powerful devices, leading to higher energy consumption. In contrast, the proposed model saves about 31.2% of energy while maintaining overall system performance by considering multiple factors.

5. Experimental Methods and Results Analysis

5.1 Performance Evaluation

As illustrated in Table 3, the comparative performance between our model and traditional task allocation methods.

Table 3. Performance Comparison

Metric	Traditional Method	Proposed Model	Improvement
Energy consumption (J)	3245.6 ± 82.3	2232.7 ± 57.1	31.2%
Task completion time (s)	187.3 ± 12.6	195.1 ± 13.8	-4.2%
Workload balance index	0.62 ± 0.05	0.83 ± 0.04	33.9%
Network lifetime (h)	18.4 ± 1.2	26.7 ± 1.3	45.1%
Device utilization	0.72 ± 0.08	0.65 ± 0.05	Closer to optimal

The workload balance index measures the uniformity of task distribution across devices, calculated as:

$$\text{Balance Index}=1-\frac{\sqrt{\frac{1}{n}\sum_{i=1}^{n}(L_i-\bar{L})^2}}{\bar{L}} \tag{21}$$

where L_i is the workload of device i, $\bar{L}$ is the average workload, and n is the total number of devices. A value closer to 1 indicates better balance. The proposed model achieves 0.83, demonstrating superior load distribution compared to traditional methods (0.76).

The energy saving rate demonstrates statistical significance ($p < 0.001$) and exhibits an exponential relationship with system size. As shown in Figure 3, our model achieves balanced task distribution while substantially reducing energy consumption compared to traditional approaches that prioritize high-capability devices regardless of energy state.

5.2 Detailed Analysis of Task Completion Time Trade-off

Experimental results show task completion time increased from 187.3s to 195.1s (+4.2%) compared to traditional methods. This slight increase is a reasonable trade-off for energy optimization, with detailed analysis as follows:

Energy-Efficiency Priority Strategy:

The model prioritizes energy-efficient devices over purely high-speed devices, which is reflected in the instantiated DFAEF-based efficiency metric:

$$\eta_i(t)=\alpha\cdot(1-L_i(t))^2\cdot e^{-\beta\cdot|L_i(t)-\omega|}\cdot(E_i^{cur}(t))^2 \qquad (22)$$

Devices operating in the optimal efficiency range (Li≈0.65) are prioritized even if they are not the fastest ones.

Load Balancing Consideration:

Traditional methods concentrate tasks on high-performance devices, quickly depleting their batteries. Our model employs balanced allocation to avoid device overload:

$$S(i,j)=w_1\cdot\frac{C_i}{R_j^{comp}}+w_2\cdot\frac{B_i}{R_j^{data}}+w_3\cdot E_i^{cur}(t)+w_4\cdot(1-L_i(t)) \qquad (23)$$

Long-term System Stability:

The 4.2% time increase trades for 31% energy reduction and 23.6% network lifetime extension. From lifecycle perspective, this significantly improves overall system benefits.

IoT Application Scenario Adaptation:

Most IoT tasks (environmental monitoring, data collection) are not time-critical. The 4.2% delay is acceptable, while energy savings are crucial for battery-powered devices.

Table 4.Performance Trade-off Quantitative Analysis:

Performance Metric	Traditional Method	Proposed Method	Improvement
Task completion time	187.3s	195.1s	+4.2%
Average energy consumption	245.7W	169.3W	-31.1%
Network lifetime	42.3h	52.3h	+23.6%
Load balance index	0.76	0.83	+9.2%

This trade-off aligns perfectly with IoT system design principles of "energy efficiency first, sustainable operation." Therefore, the 4.2% increase in task completion time is an acceptable overhead for achieving more than 30% energy savings and significantly extended network lifetime in typical non-time-critical IoT scenarios.

6. Conclusion

This paper presents an adaptive task scheduling based energy optimization model for IoT devices. By combining the Dual-Factor Adaptive Efficiency Function, a dynamic power allocation algorithm, a multi-parameter weighted task scheduling algorithm, and network topology optimization, the proposed model achieves a significant reduction in IoT system energy consumption. Experimental results indicate that, compared to traditional methods, the proposed model reduces energy consumption by approximately 31.2% while maintaining good task allocation balance and network connectivity. At the same time, the model accepts a slight 4.2% increase in task completion time as a deliberate trade-off to obtain substantial gains in energy efficiency and network lifetime. The findings of this research have important practical value for energy-constrained IoT systems, effectively extending the lifespan of devices and networks. Future research will further explore the application of reinforcement learning techniques in parameter adaptive adjustment to adapt to more complex and variable network environments. Simultaneously, considering more complex task dependency relationships and expanding the applicability of existing scheduling algorithms also represent important directions. Additionally, integrating energy harvesting technologies, designing more sustainable energy management strategies, and conducting deployment tests of actual IoT systems to verify model performance in real environments will be the focus of subsequent work. These research directions will further advance the development of IoT energy optimization and provide theoretical and technical support for constructing more efficient and sustainable IoT systems.

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（3）The second batch of provincial industrial and information industry transformation and upgrading projects in Jiangsu Province in 2020 Intelligent Grain Big Data Management Service Platform

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