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Energy Consumption Optimization based on Economic Benefit in WSN-based IoT via Global Hierarchical Caching Strategy

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Abstract: Recent advances in Wireless Sensor Network (WSN) have significantly contributed to the prevalence of Internet of Things (IoT) devices and their pervasive integration into everyday life and industrial operations. A WSN-based IoT comprises numerous small, scattered, battery-operated sensors that are designed to perform collaborative tasks. These sensor nodes are prone to energy drain because of their limited battery capacity when they needed to run efficiently over extended periods of time. Enhancing the large-scale network's lifespan and controlling the economic costs become relevant since battery replacement or recharging is impractical in severe environments. In this paper, we present a novel energy optimization algorithm tailored for WSNs, which not only takes into account the reduction in replacement costs stemming from prolonged equipment lifespan but also incorporates the operational savings resulting from enhanced energy efficiency. It aims to enhance energy efficiency by leveraging a global hierarchical caching mechanism to simultaneously balance exploration and exploitation of energy resources in both the uplink and downlink of the networks. The simulation results demonstrate that our algorithm effectively minimizes energy consumption while maintaining optimal economic efficiency by decreasing the frequency of state transitions. It can consume 13% less energy than original system and extend the network lifetime by 10%.

Keywords: WSN-Based IoT, Consumption Optimization, Hierarchical Caching Strategy, Economic Benefit, Energy-Saving and Cost-Reducing

I.INTRODUCTION

Wireless sensor networks (WSNs) play a crucial role in the IoT by providing the essential data collection and monitoring capabilities that enable the seamless integration of physical devices with the digital world. General WSNs are composed of numerous small-sized, resource-constrained nodes that are capable of data collection, processing, storage, and wireless communication. These networks are increasingly being used in various applications, ranging from military, environmental monitoring, target tracking, scientific observation, to prediction [1]. WSN is prone to resource constraints such as limited battery life, sluggish communication, insufficient memory, and inadequate processing power. The energy supply of nodes, critical for sustained operation over extended periods (potentially years) in various activities like monitoring, data collection, processing, and communication, is paramount in WSN-based IoT systems [2,3]. In a densely deployed WSN, spatially proximate sensors continuously and simultaneously gather data about various phenomena and occurrences. This intricate web of interconnected devices forms a rich informational tapestry, where each sensor node acts as a vigilant sentinel, meticulously capturing and relaying environmental measurements or event-related information. The sensors in such an arrangement are often situated in close quarters, leveraging their compact design and overlapping sensing ranges to create a high-resolution monitoring grid. This dense deployment ensures comprehensive coverage with minimal blind spots, thereby enhancing the accuracy and granularity of collected data. Concurrent data collection among neighbouring sensors allows for cross-validation and redundancy, reducing the likelihood of false readings and increasing the trustworthiness of the overall system. Furthermore, this collaborative effort enables real-time data processing and analysis, facilitating immediate responses to changes in the monitored environment. This tight-knit ecosystem of WSN-based IoT thrives on the seamless interaction and coordination among its numerous sensor nodes. They dynamically adapt to the surrounding context, sharing data through wireless links while striving to optimize energy consumption and effectively control of economic benefits of the whole IoT network—a critical concern in battery-powered sensor systems.

Owing to energy consumption and finite battery capacity, sensor nodes are at risk of energy depletion, potentially leading to network collapse and equipment replacement as well as greater cost outlay for network reconstruction. Extending the network's lifespan and its economic effectiveness is a significant area of investigation in WSN-based IoT research, given the impracticality of battery replacement in remote or hazardous areas. The rate of energy

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decline in sensor nodes has emerged as a pivotal factor in estimating the longevity of WSN-based IoT networks. A faster energy consumption rate is correlated with a shorter network lifespan [4,5]. In the realm of the IoT, sensor nodes play a critical role as foundational components, their principal function being to transmit pertinent environmental data to end-users typically interacting via mobile devices [6]. As the proliferation of sensor-generated data accelerates, it results in an exponential growth of data traffic within the diversified IoT landscape. This burgeoning traffic volume can potentially undermine the quality of service and exacerbate energy consumption attributed to caching operations for certain user segments [7]. Recognizing these emerging issues, caching technologies have emerged as strategic solutions aimed at mitigating the challenges posed by data deluge and network strain in the heterogeneous IoT environment. Such caching mechanisms serve a dual purpose: firstly, they directly alleviate service latency and diminish the burden on network traffic by proactively storing popular content closer to the point of consumption by mobile users. This proximity-based approach ensures quicker access times and reduces the need for repeated transmissions over extended distances. Secondly, these caching schemes contribute indirectly to addressing network congestion—a frequent challenge faced by IoT networks—by redistributing the demand for content delivery. By pre-positioning frequently accessed data items across different tiers of the IoT architecture, from edge devices like gateways to local caches or even the cloud, the reliance on immediate data retrieval from remote sources is lessened. Consequently, the overall load on the network backbone is decreased, allowing for more effective bandwidth usage and maintaining high quality of service levels despite increasing data demands. Moreover, advanced caching techniques can be designed to incorporate intelligent algorithms that learn usage patterns and predict future requests, further enhancing their ability to manage and conserve energy efficiently [8]. These approaches often involve dynamic content replacement policies that prioritize popular content while expelling less-frequently requested data, thus optimizing cache space and minimizing energy waste due to unnecessary data movement. Furthermore, considering the limited power reserves inherent in many IoT devices, particularly wireless sensor nodes, implementing energy-aware caching strategies becomes imperative. These strategies must balance the benefits of caching—such as improved responsiveness and reduced network load—with the trade-off of increased energy expenditure related to caching activities [9]. The quest for an ideal caching solution for the IoT therefore requires a holistic view that integrates factors like data popularity dynamics, network topology, and the specific energy constraints of each component within the IoT ecosystem.

Energy optimization techniques in the WSNs-based IoT aim to minimize power consumption of individual nodes while maintaining network functionality and performance. These techniques can address the challenge of uneven energy consumption among sensor nodes, thereby prolonging the overall network lifespan and ensuring balanced resource utilization in IoT environments. State-of-the-art works involve various solutions, including routing algorithms [10-13], sleep scheduling strategies [14-16], data aggregation and compression methods [17-19], energy harvesting techniques [20-22], clustering algorithms [23-25], multi-objective optimization [26, 27], adaptive selections [28, 29], mobility-based computing [30-32] and various caching methods [33, 34]. Within a tightly packed WSN-based IoT, sensors in close proximity collect concurrent data regarding events. These compactly arranged sensors, embedded within the intricate fabric of the IoT ecosystem, are strategically positioned to detect and measure multiple aspects of their environment in real-time.

Routing-based energy consumption optimization generally focuses on how to reduce the energy consumption of nodes in the network through the design and optimization of routing protocols, so as to extend the life and reliability of the network [13]. They usually take into account such factors as node energy, communication distance, network topology, data transmission volume, and path selection. Sleep scheduling algorithms manage the sleep and wake cycles of sensor nodes to reduce idle energy consumption. They often use strategies like duty cycling, where nodes are put to sleep when not actively transmitting or receiving data [15]. The methods of data aggregation and compression reduce the amount of data that needs to be transmitted by aggregating multiple data points into a single message or by compressing the data while that energy harvesting techniques harness external energy sources, such as solar power or vibrations, to power the sensor nodes, thereby extending the energy supply and network lifetime [18, 22]. On the other hand, clustering strategies tend to group sensor nodes into clusters, optimizing the use of energy by concentrating communication and processing tasks within each cluster. Multi-objective optimization mechanisms simultaneously optimize multiple objectives such as energy efficiency, network coverage, and lifetime, often using techniques like Pareto optimization [35]. Besides, adaptive energy consumption optimizations may dynamically adjust their behaviour based on the network's current energy status and workload, ensuring that energy is allocated most efficiently. And that mobility-based algorithms may probably account for the mobility of nodes and optimize energy consumption based on the nodes' locations and movements. Most of works now still continue to refine these mentioned algorithms through the integration of traditional strategies, machine learning, artificial intelligence, and that advanced optimization techniques to achieve even greater energy efficiency in WSNs for IoT applications. Besides, the caching technologies for IoT energy consumption optimization mainly focus on three aspects: reducing the number of data transfers, optimizing storage management, and intelligent decision-making to reduce the energy consumption of sensor nodes and other network components as well as their total economic cost [34].

In this paper, we propose a novel approach for optimizing energy consumption based on economic benefit in WSN-based IoT applications. The methodology considers a global hierarchical caching strategy to achieve more efficient energy utilization within the network. It aims to deploy cache layers across different tiers of the IoT architecture, such as edge nodes, aggregation nodes, and the cloud. Data is progressively transmitted and cached hierarchically within the network, thus improving the overall energy efficiency and economic cost of WSN-based IoT systems. The key innovation of this paper lies in the following points.

(1) **Global Hierarchical Caching**: This method innovatively designs a multi-tier caching system spanning IoT layers, from sensor nodes to cloud facilities, strategically reducing energy consumption by caching and reusing data locally, thereby minimizing energy-demanding data transfers in WSNs.

(2) **Economic Integration in Energy Optimization**: Breaking from traditional methods, this study pioneers a joint optimization of energy efficiency and economics. It assesses the cost-benefit of caching actions, factoring in indirect economic advantages such as extended hardware life, reduced upkeep, and direct energy savings, maximizing the IoT system's sustainability and financial feasibility.

(3) **Dynamic and Adaptive Caching Decision-Making**: A further innovation involves developing adaptive caching policies that react to real-time variations in data trends, device health, and network loads. This feature empowers the system to make informed caching choices, ensuring the hierarchical caching approach consistently balances energy-saving with economic benefits across a range of IoT operational contexts.

II.THE GLOBAL HIERARCHICAL CACHING FRAMEWORK FOR ENERGY CONSUMPTION OPTIMIZATION

Figure 1 presents the proposed detailed architecture of the global hierarchical caching model for energy

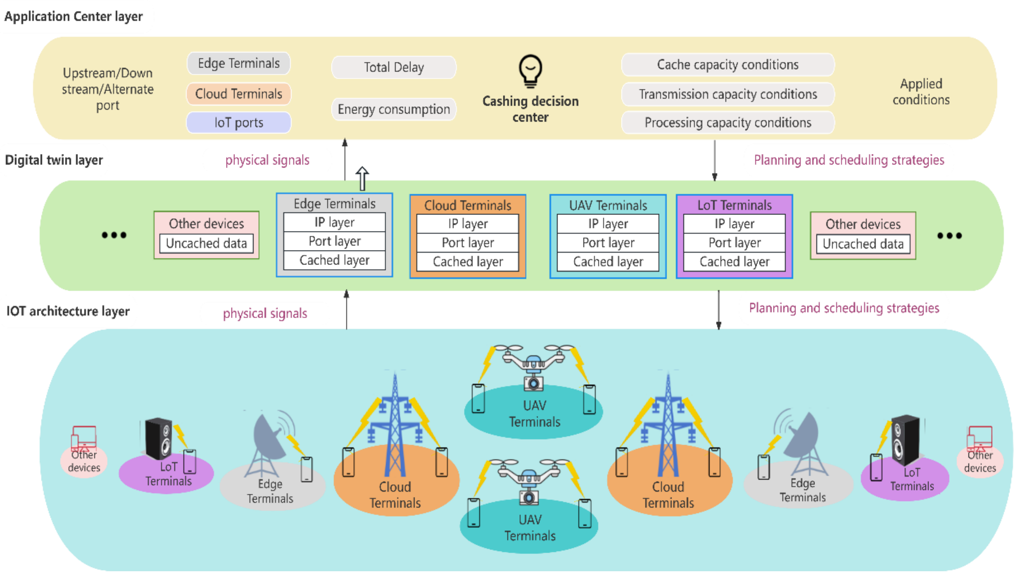

Figure 1. The global hierarchical caching framework of the proposed energy consumption optimization.

consumption scheduling in the IoT network. The overarching framework is divided into three core tiers, application center layer, digital twin (DT) layer, and IOT structure layer. In the application center layer, serving as the physical space of the caching network model, cache locations encompass UAV terminals, cloud terminals, edge terminals, and other IoT devices with caching capabilities. As shown in the figure, each device is equipped with a dedicated energy consumption load meter to record the energy usage over time. With continuous integration of new IoT devices into this layer, the total energy consumption increases. When this quantity reaches a threshold set by the network, the resource allocation and scheduling strategy is activated, enabling dynamic and real-time switching and tracking of energy usage among devices. This means that all communicating devices are given higher priority and are allocated energy resources dynamically by the model architecture to support their communication tasks. Devices communicate based on request signal priorities; upon completion of their application communications, they send an end signal, after which the link is automatically released to accommodate requests from other devices. At this layer, all devices within the IoT structure are managed uniformly.

The Digital twin layer manages the priority allocation and address registration for devices' request signals and corresponding IP information. It also maintains the status of all devices. The data from this layer is accessible, removable, addable, and editable by the top-tier Application Center layer, which governs the energy management and economic statistics of all devices in the IOT Structure layer. The coordination and scheduling across these three layers facilitate better optimization of energy consumption, integration, and management in the IoT ecosystem.

Given the heterogeneous nature of IoT devices, various types of IoT devices adopt different data formats and communication protocols. To ensure seamless communication and data exchange between different types of IoT devices, we introduce a middleware. This middleware is built upon the data distribution service (DDS) protocol, which supports multiple data formats and peer-to-peer communication, thus establishing effective connectivity between heterogeneous IoT devices. In the network model, it is assumed that all IoT devices have equal cache capacity, energy consumption capability, and communication capacity. Edge servers typically have larger cache capacities than IoT devices when deployed at small base stations, while cloud servers, located at macro base stations, possess even greater cache capacities. This hierarchical cache structure helps optimize network performance and reduce backhaul link utilization. As a virtual space model for the caching network, we construct a digital twin network based on the network environment and heterogeneity of the IoT network,

Table 1. The description of symbols in the proposed caching network model.

Symbol	Description
T	The number of content nodes
w_t	The size of content *t*
o_t	The popularity of *t*
p_t^H,p_t^c,p_t^n	Implement incentives for IoT nodes, edge servers, and cloud servers to cache content *t*.
C_t^H,C_t^c,C_t^n	Energy cost of caching content on IoT devices, edge servers, and cloud servers
M_t^H,M_t^c,M_t^n	Latency costs for caching content on IoT devices, edge servers, and cloud servers.
d_t^H,d_t^c,d_t^n	The importance of cache content t to IoT devices, edge servers, and cloud servers.
$\varepsilon_{H,}\varepsilon_{c,}\varepsilon_n$	The relative weight between energy costs
C_t^m,C_t^p	Uplink transmission energy cost and downlink receiving energy cost content *t*
η^v_t, η^a_t	Upstream spectrum and downstream spectrum of content *t*
N_t^v,N_t^a	Upstream bandwidth and downstream bandwidth allocated to content *t*.
e_t^H,e_t^c	loT device processing rate and edge server processing rate assigned to content *t*.
e^n	Cloud server processing rate for each content
p^{Hn},p^{cn}	The transfer rate of each content between the IoT device and the edge server, and between the edge server and the cloud server.
Y(t)	The processing cycle of the content
θ_t^1,θ_t^2,θ_t^3	The probability of selecting placement policies S1, S2, and S3
α_1,α_2	The relative weight of energy cost and delay cost between cache reward, energy cost, and delay cost.
R_t^H,R_t^c,R_t^n	Cache rates of IoT devices, edge servers, and cloud servers
N_{QR},N_{AQ}	Upstream bandwidth and downstream bandwidth used for transmission between local devices and mobile users
e^h,e^c	Total processing capacity of the IoT device and edge server

as well as the generated data. The accuracy of this synthetic network is closely tied to the amount of data collected from the physical environment. The data center makes the hierarchical caching decisions based on relevant data within the generated DT network, aiming for more efficient content distribution and lower transmission costs.

Table 1 illustrates the overall description of symbols in the proposed caching network model. In the caching model under consideration, users can only access the desired content if it has been cached and is available for service at any of the caching devices, such as IoT devices, edge terminals, cloud terminals, or UAV terminals. If the content is not stored locally, the user must fetch it via the backhaul link, inevitably leading to increased associated costs. Given the disparities in cache capacity, communication capacity, and energy consumption capacity among these four types of caching locations, including IoT devices with caching capabilities, the rewards and costs associated with each location differ significantly. Consequently, it is essential to holistically account for these factors when devising an optimal content placement strategy. The primary aim of this study is to maximize the relevant rewards and simultaneously minimize the costs incurred by users or individual devices when requesting content. In the subsequent sections, we delve into the detailed rewards and costs of the four content placement strategies for each of the four caching locations, thereby providing a robust practical guidance for that general real-world WSN-based IoT applications.

In a real network, assuming the number of all terminals is T, these contents are represented as $T = \{t1, t2, \ldots, tm\}$ and these contents vary in size, denoted $W(T) = \{w1, w2, \ldots, wt\}$ .We assume that the popularity of these contents follows the Zipf distribution [36] and is expressed as $O(T) = \{o1, o2, \ldots, ot\}$. Then, the popularity of content t is expressed as follows:

$$Ot = \frac{min\left(\frac{1}{C(T)}\right)}{\sum_{t=1}^{m}(w1xi+w2yi+w3zi)Ct+\frac{1}{b}} \quad , \qquad (1)$$

Where b represents the distribution bias of the Zipf population, and if the Zipf index increases over time, then b increases accordingly, and the requested content t becomes more concentrated. If content t can be in three cache locations, then the three placement strategies for content t are demonstrated as follows:

$$\begin{cases} A1\text{:Caching nodes at the loT terminals} \\ A2\text{ : Caching nodes at the edge terminals} \\ A3\text{: Caching nodes at the cloud terminals} \\ A4\text{: Caching nodes at the UAV terminals ,} \end{cases} \qquad (2)$$

In the model, the network delay mainly includes transmission delay and processing delay, while the energy consumption is mainly composed of transmission energy consumption and processing energy consumption. These parameters play a crucial role in evaluating and optimizing the performance of the cache model. If an IoT device node with a cache can provide content t to the user, then the reward function P, i.e., energy cost C_t^H and delay cost M_t^H, the node content t of a device is expressed as:

$$P_t^H = ot \cdot wt \cdot k_t^h \ , \qquad (3)$$

$$C_t^H = C_t^r + C_t^p + \varepsilon h \cdot N_t^h \ , \qquad (4)$$

$$M_t^H = \frac{wt}{\eta_t^v C_t^v} + \frac{wt}{\eta_t^a C_t^a} + \frac{Y(t)}{e_t^H} \ , \qquad (5)$$

where d_t^H represents the importance of IoT devices, C_t^g represents the upstream transmission energy cost of content t, C_t^b represents the downstream reception cost of content t, and C_t^H represents the energy cost of IoT devices processing content t. η_t^v, η_t^a are ascending spectrum and descending spectrum respectively. $N_t^v$and N_t^a are the upstream and downstream bandwidth allocated to content t, respectively. Y(t) represents the processing cycle of content t, and e_t^H represents the iot device processing rate assigned to content t. Similarly, if an edge server can provide content t to the user, then the reward function p_t^c, energy cost C_t^c, and delay cost M_t^c for that edge server are expressed as:

$$P_t^c = ot \cdot wt \cdot d_t^c \ , \qquad (6)$$

$$C_t^c = C_t^g + C_t^p + \varepsilon c \cdot_t^c \ , \qquad (7)$$

$M_t^c = \frac{wt}{\eta_t^v C_t^v} + \frac{wt}{\eta_t^a C_t^a} + \frac{2wt}{p^{Hc}} + \frac{Y(t)}{e_t^c}$, (8)

where d_t^c represents the importance of caching the content t to the edge server, N_t^crepresents the energy cost of processing the content *t* to the edge server, p^{Hn} represents the transfer rate between each content iot device and the edge, and e_t^c represents the edge server processing rate assigned to the content *t*. Similarly, if the cloud server can provide content *t* to the user, then the reward function p_t^n, energy cost C_t^n and delay cost M_t^n of the cloud server content t are expressed as follows:

$P_t^n = ot \cdot wt \cdot d_t^n$, (9)

$C_t^n = C_t^m + C_t^p + \varepsilon_n \cdot N_t^n$, (10)

$M_t^n = \frac{wt}{\eta_t^v C_t^v} + \frac{wt}{\eta_t^a C_t^a} + \frac{2wt}{b^{Hc}} + \frac{2wt}{b^{cn}} + \frac{Y(t)}{e^n}$. (11)

The goal is to maximize the return on cached content and minimize the energy costs and latency costs of cached content. To this end, we define the placement strategy selection probability matrix θ_m=$[\theta_t^1, \theta_t^2, \theta_t^3]$ for the content *t*, where θ_t^1 represents the probability of the content *t* choosing placement strategy A1, θ_t^2 represents the probability of the content t choosing placement strategy A2, and θ_t^3represents the probability of the content *t* choosing placement strategy A3. Therefore, the combined optimization formula for cache, latency, and power consumption is as follows:

$$max\left\{\sum_{t=1}^{T}[\theta_t^1(P_t^I - \alpha_1 C_t^H - \alpha_2 M_t^H) + \theta_t^2(P_t^c - \alpha_1 C_t^c - \alpha_2 M_t^c) + \theta_t^3(P_t^n - \alpha_1 C_t^n - \alpha_2 M_t^n)] - \varepsilon_t N_i\right\}, \quad (12)$$

$s.t. \sum_{t=1}^{T} wt \cdot \theta_t^1 \le RH$, $\sum_{t=1}^{T} wt \cdot \theta_t^2 \le Rc$, (13)

$\sum_{t=1}^{T} wt \cdot \theta_t^3 \le Rc$, $\sum_{t=1}^{T}(N_t^v + N_t^v) \le N_{total}$,$\sum_{t=1}^{T} N_t^v \le N_{QR}$&$\sum_{t=1}^{T} N_t^v \le N_{AQ}$, (14)

$\sum_{t=1}^{T} e_t^H \le e^H$ &$\sum_{t=1}^{T} e_t^c \le e^c$, (15)

where $\theta_t^1 + \theta_t^2 + \theta_t^3 = 1$ or 0 & $0 \le \theta_t^1, \theta_t^2, \theta_t^3 \le 1$, and that α_1 and α_2 represent the relative weights of energy cost and delay cost among cache reward, energy cost and delay cost, respectively. ε_t represents the relative weight of building the DT network and the content *t* of ε_t=w_t/(w_1+...+w_t) , $N_i$represents the cost of building a DT network. R_H, R_c and R_n represent iot device cache capacity, edge server cache capacity, and cloud server cache capacity respectively. Equations 11, 12 and 13 indicate that the total cache content of IoT devices, edge servers, and cloud servers should be less than the cache capacity of IoT devices, edge servers, and cloud servers, respectively. The N_{total} represents the total transmission bandwidth between IOT devices and mobile users, while N_{QR} andN_{AQ} represent the upstream and downstream bandwidth used for transmission between mobile users and iot devices, respectively. Formulas (11e) and (11f) represent bandwidth limits for upstream and downstream transmission of cached content between mobile users and iot devices. e^h and e^c represent the total processing rate of iot devices and the total processing rate of edge servers, respectively. Equation 14 represents the processing power limits of IoT devices and edge servers. Formula 15 represents the probability range of content t being cached on an IoT device, edge server, or cloud server. If $\theta_t^1 + \theta_t^2$+θ_t^3 =1 is true, then it means that the contour splits; if $\theta_t^1 + \theta_t^2$+θ_t^3 =0, it means that the content *t* is not cached due to limited cache resources.

III.EXPERIMENTAL SIMULATION AND ANALYSIS

We conduct simulation experiments to verify the existence of the content evolution stability of the proposed caching strategies, and confirm the accuracy of the derived caching strategy condition expression. The experimental DT application framework is shown in Figure 2, which maps the IP addresses and ports of cache nodes in heterogeneous IoT networks (including cloud servers, edge servers, and IoT devices) to corresponding virtual cache nodes in the digital twin network. We have implemented the connection between the application layer and the DT virtual layer using API interfaces, and established seamless communication between the DT virtual layer and the physical layer through the Message Queuing Telemetry Transport (MQTT) protocol. At the same time, we also use relevant protocols to make up for the communication differences between different heterogeneous IoT devices. In the application layer, the decision service transfers the caching strategies $[\boldsymbol{\theta_t^1}, \boldsymbol{\theta_t^2}, \boldsymbol{\theta_t^3}]$ for content *m* to the physical layer.

We assume that there are 5 content sizes set to {20, 10, 5, 15, 10} (MB), Zipf parameter is set to 1.5, cache capacity for IoT devices, and edge and cloud servers set to 10 MB, 20 MB, and 20 MB. For the IoT devices, edge servers, and cloud servers, the importance of caching each content is set to 0.2 $*10^{-7}$/B, 0.6$*10^{-7}$/B, and 0.5 $*10^{-7}$/B, respectively. The CPU rate of IoT devices is 600 $*10^6$ cycles/s, and the processing cycle $\boldsymbol{Z_t}$ for content t is set to $\boldsymbol{Z_t}$ =1900*$\boldsymbol{o_t}$. Additionally, we set the energy consumption for processing content $\boldsymbol{N_t^H}$、 $\boldsymbol{N_t^c}$ and $\boldsymbol{N_t^n}$ to be the same as the content size $\boldsymbol{o_t}$、 $\boldsymbol{\varepsilon_H}$ = 5*10^{-9}J/bit、$\boldsymbol{\varepsilon_c}$ = 1×10^{-8}J/bit 和$\boldsymbol{\varepsilon_n}$ = 1×10^{-7}J/bit, respectively. The uplink bandwidth $\boldsymbol{\eta_t^i}$ and downlink bandwidth $\boldsymbol{\eta_t^a}$ between the mobile user and the IoT device are both set to 10 MHz.

Table 2 illustrates the experimental evaluation of the global hierarchical caching model, from which we observe that all devices exhibit significantly lower energy consumption after applying our proposed optimization algorithm compared to their original states when the number of content requests from mobile users increases, and the overall energy consumption is also notably reduced. The optimized total energy consumption is reduced to an average of 87.39% compared to the original energy consumption, and the life cycle of the WSN-based IoT network is extended to about 10%. This further underscores the obvious performance and usability of the optimization method.

Besides, we evaluated the caching performance under different numbers of user requests, including caching benefits, energy costs, and latency costs. We set the relative weights a_1 and a_2 to a_1 =a_2= 0.03, while keeping other parameters unchanged. Additionally, the total benefits of our caching scheme significantly increase with the popularity-generated quantity of content when mobile users request varying numbers of content. As the number of content requests from mobile users increases gradually, our scheme shows significant improvement in caching benefits. From the perspective of jointly

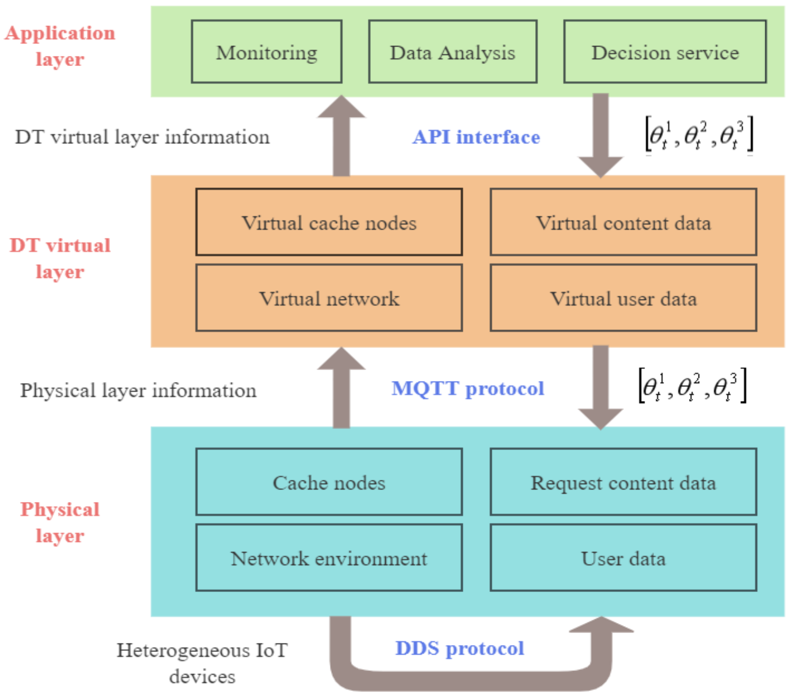

Figure 2. The framework of the digital twin layer in the caching-based energy consumption model.

Table 2. The experimental evaluation of the proposed global hierarchical caching model.

Number of terminals in the IoT architecture layer	Original total energy consumption	Optimized total energy consumption
Terminal N_1	1.07×10^{-7}J/bit	0.92×10^{-10}J/bit
Terminal N_2	2.19×10^{-9}J/bit	0.18×10^{-13}J/bit
⋮	⋮	⋮
Terminal N_t	3.18×10^{-11}J/bit	0.18×10^{-19}J/bit
Average(N_1, N_2,…, N_t)	**6.86×10^{-6}J/bit**	**9.09×10^{-15}J/bit**

optimizing caching energy consumption and latency, our scheme demonstrates notable enhancements in caching benefits. Moreover, when considering optimizing caching energy consumption or caching latency separately, the proposed global hierarchical caching strategy shows significant reductions in associated costs. Therefore, the caching scheme we propose exhibits significant advantages, with its practicality and efficiency being validated.

With the proposed hierarchical caching strategy, we can conclude that it can extend the hardware lifespan. By efficiently managing cached data and reducing unnecessary data transmissions, the stress on sensor nodes is minimized, thereby increasing their operational longevity and delaying the need for costly replacements or upgrades. This, in turn, contributes to material cost savings and a reduction in electronic waste. In this paper, WSN-based IoT via global hierarchical caching strategy presents an initiative that diverges from established norms by integrating and harmonizing the enhancement of energy efficiency with economic practicality. We innovatively evaluate the intertwined dynamics of power consumption and financial gains within the context of WSN-based IoT systems through a global hierarchical caching strategy, we assess the cost-benefit of the caching actions, which factories in indirect economic advantages such as extended hardware life, reduced upkeep, and direct energy savings, maximizing the IoT system's sustainability and financial feasibility. We meticulously examines the economic viability of employing caching tactics across various tiers in the WSN-IoT ecosystem. It undertakes a thorough cost-benefit analysis of caching operations, considering a wide array of tangible and intangible economic benefits. It goes beyond the straightforward reduction in energy consumption to encompass indirect economic advantages. Another key factor assessed is the impact of caching on maintenance overheads. The strategic placement and management of cached data can lead to a decline in maintenance requirements and repair costs due to decreased strain on system components and improved reliability. Furthermore, the study emphasizes the critical role of direct energy savings achieved through a hierarchical caching framework. By implementing multi-level caching where data is stored progressively closer to the end-users or data consumers, the study calculates the energy saved from reduced long-distance data transmission and processing. This approach optimizes network resources and minimizes energy expenditure.

IV.CONCLUSION

In this study, we introduce a novel energy optimization technique for WSN-based IoT that use a global hierarchical caching strategy to address the consumption optimization problem. The method is designed to enhance overall energy efficiency by using three hierarchical content structure to construct a processor function under resource constraints to jointly optimize cache latency and cache power consumption, thereby improving the performance of the entire network. Experimental findings reveal that the proposed method can surpasses original system in minimizing energy expenditure, the caching strategy can achieve better caching performance under certain conditions. With the evaluation, the proposed strategy can consume average 13% less energy than original system and extend the network lifetime by 10%.

REFERENCES

[1] Umarani, S., Kanimozhi, T. (2023) A comparative study of energy-efficient clustering protocols for wsn-internet-of-things. International Journal of Hydromechatronics, 6(2):177-196.

[2] Al-Qurabat, A.K.M., Abdulzahra, S.A., Idrees, A.K. (2022) Two-level energy-efficient data reduction strategies based on SAX-lzw and hierarchical clustering for minimizing the huge data conveyed on the internet of things networks. Journal of Supercomputing, Journal of Supercomputing, 78(16): 17844-17890.

[3] Chithaluru, P., Stephan, T., Kumar, M., Nayyar, A. (2022) An enhanced energy-efficient fuzzy-based cognitive radio scheme for IoT. Neural Computer & Applications, 34 (21):19193-19215.

[4] Saeedi, I.D.I., Al-Qurabat, A.K.M. (2022) Perceptually important points-based data aggregation method for wireless sensor networks. Baghdad Science Journal, 19(4):0875.

[5] Al-Turjman, F., Nayyar, A., Devi, A., Shukla, P.K. (Eds.) (2021) Intelligence of Things: AI-IoT based Critical-Applications and Innovations, Springer, New York.

[6] Chen, Y., Gong, X., Ou, R., Duan, L., Zhang, Q. (2020) Crowdcaching: incentivizing d2d-enabled caching via coalitional game for IoT. IEEE Internet Things Journal, 7(6):5599-5612.

[7] Zhao, M., Li, J., Tang, F., Asif, S., Zhu, Y. (2022) Learning based massive data offloading in the IoV: routing based on Pre-RLGA. IEEE Transactions on Network Science and Engineering, 9(4): 2330-2340.

[8] Lyu F., (2021) LeaD: large-scale edge cache deployment based on spatiotemporal WiFi traffic statistics, IEEE Transaction on Mobile Computer, 20(8):2607-2623.

[9] Prerna, D., Tekchandani, R., Kumar, N., Tanwar, S., (2021) An energy-efficient cache localization technique forD2Dcommunication in IoT environment. IEEE Internet Things Journal, 8(6):4816-4829.

[10] Bhardwaj, A., Gupta, B., Rana, S., Goyal, S.K., Gujral, R.K. (2023) BPSA (back propagation sleep awake) clustering protocol for energy optimization of wireless sensor networks. International Conference on Information Systems and Computer Networks (ISCON). Mathura. pp. 1-5.

[11] Li, Y., Cai, L. (2023) An energy optimization routing algorithm based on ant colony optimization for wireless sensor networks. IEEE Access, 11, 182150-182159.

[12] Zhang, H., Wang, Y., Wang, Z. (2022) Energy-efficient routing algorithm based on particle swarm optimization for wireless sensor networks. IEEE Internet of Things Journal, 9(7): 6520-6530.

[13] Wang, J., Zhao, Y., Chen, Q. (2021) An energy-efficient routing algorithm based on multi-objective optimization in wireless sensor networks. Sensors, 21(17): 5887.

[14] Liu, Y., Xie, J., Wang, X. (2023) Energy-efficient sleep scheduling algorithm based on reinforcement learning in wireless sensor networks. IEEE Transactions on Mobile Computing, 22(2): 1001-1012.

[15] Jiang, H., Li, M., Li, B. (2022) Optimized sleep scheduling algorithm for energy harvesting wireless sensor networks. IEEE Transactions on Wireless Communications, 21(8): 5142-5154.

[16] Zhang, S., Wang, L., Li, X. (2021) Joint optimization of sleep scheduling and data aggregation for energy-efficient wireless sensor networks. IEEE Transactions on Vehicular Technology, 70(11): 11144-11156.

[17] Zhou, Y., Zhang, Q., Li, B. (2023) Energy-efficient data aggregation algorithm based on deep reinforcement learning in wireless sensor networks. IEEE Internet of Things Journal, 10(5): 4338-4350.

[18] Wang, X., Liu, J., Guo, S. (2022) Data aggregation and compression algorithm based on machine learning in wireless sensor networks. IEEE Transactions on Industrial Informatics, 18(7):5001-5010.

[19] Zhang, S., Wang, L., Li, X. (2021) Joint Optimization of sleep scheduling and data aggregation for energy-efficient wireless sensor networks. IEEE Transactions on Vehicular Technology, 70(11):11144-11156.

[20] Chen, H., Zhang, Y., Wang, L. (2023) Energy harvesting-aware task offloading and resource allocation in wireless powered IoT networks. IEEE Internet of Things Journal, 10(6):5643-5655.

[21] Liu, Y., Xie, J., Wang, X. (2022) Energy harvesting-aware data collection scheme based on reinforcement learning in wireless sensor networks. IEEE Transactions on Mobile Computing, 21(9): 1001-1012.

[22] Jiang, H., Li, M., Li, B. (2021) Optimized energy harvesting strategy for wireless sensor networks with heterogeneous energy sources. IEEE Transactions on Wireless Communications, 20(4):3141-3154.

[23] Chen, S., Wang, J., Liu, H. (2024) Adaptive clustering algorithm for energy-efficient wireless sensor networks based on artificial bee colony optimization. IEEE Transactions on Mobile Computing, 23(3): 201-212.

[24] Zhang, H., Li, Y., Wang, Z. (2024) Dynamic clustering algorithm based on enhanced firefly optimization for energy optimization in wireless sensor networks. IEEE Internet of Things Journal, 11(2):1201-1212.

[25] Liu, X., Zhang, Q., Chen, Z. (2024) Hybrid clustering algorithm for energy-efficient wireless sensor networks based on improved particle swarm optimization. IEEE Transactions on Industrial Informatics, 19(1): 50-61.

[26] Wang, Y., Zhang, L., Liu, Q. (2024) Multi-objective optimization algorithm for energy-efficient routing in wireless sensor networks based on genetic algorithm. IEEE Transactions on Mobile Computing, 23(4): 301-312.

[27] Chen, H., Li, X., Wang, J. (2024) Evolutionary multi-objective optimization algorithm for joint routing and data aggregation in wireless sensor networks. IEEE Transactions on Industrial Informatics, 19(2):150-161.

[28] Zhang, H., Li, Y., Wang, Z. (2024) Adaptive energy optimization algorithm based on machine learning for wireless sensor networks. IEEE Transactions on Mobile Computing, 23(5): 401-412.

[29] Chen, S., Wang, J., Liu, H. (2023) Adaptive clustering and routing algorithm for energy-efficient wireless sensor networks based on reinforcement learning. IEEE Transactions on Industrial Informatics, 20(2):150-161.

[30] Zhang, H., Li, Y., Wang, Z. (2024) Mobility-based locating method for energy-efficient node deployment in wireless sensor networks. IEEE Transactions on Mobile Computing, 23(6): 501-512.

[31] Chen, S., Wang, J., Liu, H. (2024) Energy-efficient node localization algorithm based on mobility patterns in wireless sensor networks. IEEE Transactions on Industrial Informatics, 19(4): 350-361.

[32] Liu, Z., Zhang, S., Wang, L. (2024) Mobility-aware energy optimization algorithm for wireless sensor networks based on node movement prediction. IEEE Transactions on Vehicular Technology, 73(5): 401-412.

[33] Li, J., Wang, J., Wang, Z. (2021) Energy-Efficient Data Caching and Task Offloading in IoT-Edge Computing Systems: A Deep Reinforcement Learning Approach. IEEE Internet of Things Journal, 8(17):14063-14074.

[34] Yousefpour, A., Das, S., Hou, I-H. (2021) Energy Efficient Cache Replacement in the Internet of Things with Deep Reinforcement Learning. IEEE Internet of Things Journal, 8(2), 976-985.

[35] Wang, Y., Zhang, L., Liu, Q. (2024) Pareto optimization technique for energy-efficient node deployment in wireless sensor networks. IEEE Transactions on Mobile Computing, 23(7): 601-612.

[36] Lyu, F., Ren, J., Cheng, N., Yang, P., Shen, X. (2021) LeaD: Large-scale edge cache deployment based on spatiotemporal WiFi traffic statistics, IEEE Transaction Mobile Computer, 20(8): 2607-2623.