# Multi-hop routing in IoT/WSN: Critical review and proposal of a conceptual framework for hybrid, multi-objective, and explainable protocols

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***Abstract*—Energy remains the most critical and limiting resource in Wireless Sensor Networks (WSNs) and Internet of Things (IoT) systems, directly constraining network lifetime, scalability, and real-world deployability. Although multi-hop routing is widely adopted to reduce transmission energy and balance traffic load, recent solutions increasingly rely on metaheuristic optimization and machine learning techniques whose computational, control, and learning overhead is rarely accounted for. This leads to a fundamental energy–intelligence trade-off that challenges the sustainability of intelligent routing in resource-constrained environments. This paper presents a critical, energy-centric review of multi-hop routing approaches for IoT and WSNs proposed between 2018 and 2025. Heuristic, metaheuristic, dynamic and Heterogeneous routing, reinforcement learning, deep reinforcement learning, and explainable AI-based protocols are systematically analyzed with an emphasis on net energy efficiency, scalability, feasibility on constrained devices, and model realism, rather than reported performance gains alone. The analysis reveals that energy is predominantly treated as a secondary optimization objective rather than as a governing system constraint. To address this limitation, we propose a hybrid and explainable routing framework governed by energy awareness, in which intelligence activation is explicitly conditioned on its net energy benefit. This perspective provides a principled foundation for sustainable and trustworthy intelligent routing in next-generation IoT and WSN systems.**

***Index Terms*—Multi-hop routing, Internet of Things, Wireless Sensor Networks, Energy efficiency, Reinforcement learning, Energy-governed routing.**

## I. Introduction

Wireless Sensor Networks (WSNs) and Internet of Things (IoT) systems play a central role in modern and industrial applications, including smart cities, industrial monitoring, precision agriculture, and critical infrastructure monitoring. Despite advances in low-power communication technologies and embedded systems enabling large-scale deployments of hundreds or thousands of sensor nodes, energy availability remains the most critical constraint, directly impacting network lifetime, scalability, and deployability [1], [2].

In energy-constrained IoT/WSN environments, wireless communication is the dominant source of power consumption. As network size increases, direct communication with a sink becomes inefficient, leading to premature battery depletion, unbalanced energy consumption, and instability [3]. Consequently, multi-hop routing remains a key mechanism for reducing transmission energy, balancing traffic load, and extending network lifetime in large-scale deployments [3], [4].

However, designing energy-efficient multi-hop routing protocols has become increasingly complex due to multiple conflicting requirements. Routing decisions must balance energy consumption, delay, packet delivery ratio, reliability, and scalability in heterogeneous and dynamic environments [4]. To address this complexity, recent research has shifted toward advanced optimization and learning-based techniques, including metaheuristic routing strategies aimed at improving energy balance and network lifetime [5].

More recently, machine learning (ML) and reinforcement learning (RL) approaches have emerged for adaptive routing in dynamic IoT/WSN environments. Techniques such as Q-learning, Deep Q-Networks (DQN), and multi-agent reinforcement learning (MARL) enable nodes or cluster heads to learn routing policies from feedback, improving energy efficiency and robustness [6], [7]. However, the energy cost of learning, inference, and control signaling remains largely underestimated. Training phases, policy updates, and information exchange may introduce overheads that partially or fully offset routing gains [6].

Furthermore, many studies still treat energy as one optimization objective among others, rather than a governing design constraint. Fixed-weight multi-objective models and simplified energy assumptions limit adaptability under changing conditions [5]. The increasing use of deep reinforcement learning also introduces black-box decisions, raising concerns about transparency, trust, and maintainability in critical IoT applications [8].

Motivated by these observations, this paper presents an energy-centric critical review of multi-hop routing approaches for IoT and WSN networks published between 2018 and 2025. The main contributions are summarized as follows: i. We provide a structured analysis of heuristic, metaheuristic, dynamic and heterogeneous routing, reinforcement learning, deep reinforcement learning, and explainable AI-based routing approaches. ii. We critically analyze these solutions with a focus on real energy efficiency, hidden overhead, scalability, and feasibility on constrained devices, rather than reported gains alone. iii. We propose a conceptual framework for a hybrid, multi-objective, explainable routing protocol in which energy is a primary design constraint governing optimization, learning, and decision explainability.

## II. Literature Selection Methodology

This review adopts a structured literature selection methodology. The primary databases consulted are IEEE Xplore, Scopus, Web of Science, and ScienceDirect, which collectively cover the majority of peer-reviewed research in IoT and wireless sensor networks. The search relied on a combination of keywords including “multi-hop routing”, “WSN”, “IoT”, “energy efficiency”, “reinforcement learning”, “deep reinforcement learning”, and “explainable AI”. Only publications between 2018 and 2025 were considered, except for a limited number of foundational works cited for historical context. Studies were included if they explicitly addressed multi-hop routing in IoT or WSN environments and incorporated energy-related metrics such as energy consumption, network lifetime, or load balancing. Although WSNs and IoT networks share similar sensing and communication principles, IoT systems are generally more heterogeneous, scalable, and service-oriented. In this paper, WSNs are considered as a sensing-oriented subset of IoT architectures. Articles focusing on single-hop communication, physical-layer optimization, or non-energy-aware routing were excluded. The initial search returned approximately 80 publications, from which about 50 articles were retained after abstract screening and relevance filtering.

## III. State of the Art of Multi-Hop Routing Approaches

Recent multi-hop routing solutions for IoT and Wireless Sensor Networks (WSNs) are analyzed in this work from a comparative perspective rather than through a strict taxonomic classification. Existing approaches often present overlapping characteristics, combining multiple decision-making mechanisms and contextual inputs. Therefore, we categorize the literature according to the dominant routing mechanism and the primary contextual parameters exploited, with particular emphasis on energy-related assumptions and overheads. This perspective captures the gradual transition from lightweight heuristic routing to optimization and learning-assisted solutions, while explicitly highlighting the trade-offs between energy efficiency, adaptability, computational overhead, and practical feasibility.

### A. Heuristic-Based Routing Approaches

Classical heuristic-based routing protocols constitute the earliest and most lightweight solutions for multi-hop communication in IoT/WSN networks. They rely on simple deterministic or probabilistic rules using local information such as residual energy, hop count, distance to the sink, or link quality [9], [10]. Representative protocols include hierarchical clustering schemes such as LEACH and its extensions [11], as well as HEED, which incorporates residual energy and communication cost into cluster-head selection [12]. Chain-based routing protocols like PEGASIS aim to minimize transmission distances through linear node organization [13], while threshold-based protocols such as TEEN and APTEEN reduce unnecessary transmissions in event-driven scenarios [14]. Gradient-based approaches (e.g., Directed Diffusion) and ad hoc–derived routing protocols (AODV, DSR) have also been adapted to WSN/IoT contexts to support multi-hop routing [15]. Although these protocols exhibit low computational complexity and minimal control overhead, their reliance on static rules and simplified energy models limits adaptability to dynamic topologies, heterogeneous devices, and evolving application requirements [9], [10].

### B. Metaheuristic-Based Routing and Clustering

To overcome the limited adaptability of classical heuristics, metaheuristic approaches have been introduced for global optimization of routing and clustering. Inspired by swarm intelligence and evolutionary principles, algorithms such as Particle Swarm Optimization (PSO), Ant Colony Optimization (ACO), and Genetic Algorithms (GA) are widely used for cluster formation, cluster-head selection, and multi-hop routing [16], [17]. More recent works explore Grey Wolf Optimizer (GWO) [18], Whale Optimization Algorithm (WOA) [19], Firefly Algorithm (FA) [20], and Glowworm Swarm Optimization (GSO) [21] to enhance convergence stability, reduce stagnation, and improve routing robustness in large-scale IoT/WSN systems. Although these methods often improve network lifetime and energy balance in simulations, they introduce higher computational cost, parameter sensitivity, and control overhead, raising scalability concerns for resource-constrained nodes [24]. In addition, local-search metaheuristics such as Simulated Annealing (SA), Tabu Search (TS), and Variable Neighborhood Search (VNS) have been applied; they are less complex than population-based methods but may still fall into local optima in dynamic environments.

### C. Dynamic and Heterogeneous Routing

With the diversification of IoT applications and devices, routing protocols increasingly incorporate context awareness to adapt routing decisions according to environmental and operational conditions [31]. dynamic and Heterogeneous routing exploits information such as residual energy, link quality indicators (ETX, RSSI), traffic priority, node mobility, and interference levels [32], [33]. In parallel, routing protocols designed for heterogeneous IoT networks explicitly account for differences in node capabilities, battery capacity, and communication technologies, aiming to balance load and extend network lifetime [34], [35]. Dynamic routing mechanisms, often, combined with fuzzy logic or probabilistic models have been proposed to cope with frequent topology changes and variable traffic patterns [36]. While these approaches enhance flexibility and robustness, they introduce additional complexity related to context acquisition, processing, and dissemination, which can significantly impact energy consumption if not carefully controlled [30].

### *D. Reinforcement Learning and Deep Reinforcement Learning-Based Routing*

Reinforcement Learning (RL) has emerged as a powerful paradigm for adaptive multi-hop routing, enabling nodes or cluster heads to learn routing policies through interaction with the environment rather than relying on predefined rules [22]. Early RL-based routing protocols based on Q-learning and SARSA have demonstrated effectiveness in small-scale or moderately dynamic networks [23], [24], but suffer from scalability limitations due to growing state–action spaces [25]. To address these issues, Deep Reinforcement Learning (DRL) techniques such as Deep Q-Networks (DQN) and Double DQN (DDQN) have been adopted to enable richer state representations and improved decision-making in dense IoT/WSN environments [26], [27]. Furthermore, Multi-Agent Reinforcement Learning (MARL) has been proposed to support decentralized and cooperative routing among nodes, enhancing scalability and robustness in large-scale deployments [28], [29]. Despite their improved adaptability and long-term optimization capabilities, RL and DRL-based routing approaches introduce significant computational, training, and communication overhead, leading to a critical and often underestimated energy–intelligence trade-off [30].

Although advanced optimization and DRL approaches demonstrate strong adaptability in simulation environments, their scalability and deployability remain constrained in highly dynamic IoT scenarios involving dense node populations, mobility, and strict hardware limitations. Consequently, selective and context-aware activation of intelligence becomes essential to maintain practical energy efficiency.

### *E. Explainable AI-Based Routing*

The increasing adoption of ML and DRL for routing decisions has raised concerns regarding transparency, trust, and maintainability, particularly in industrial and safety-critical IoT applications [37], [38]. To address these issues, recent works explore the integration of Explainable Artificial Intelligence (XAI) into intelligent routing protocols [39]. Post-hoc explanation techniques such as SHAP and LIME provide feature-level attribution for routing decisions [40], [41], while intrinsic interpretability approaches based on Grad-CAM and attention mechanisms offer insights into deep routing models' internal behavior [42], [43]. Beyond interpretability, XAI has been proposed for debugging, anomaly detection, and feedback-driven learning refinement [44]. Although still at an early stage, XAI-enabled routing represents a promising direction toward trustworthy, auditable, and energy-aware intelligent IoT/WSN deployments.

Table.I consolidates the dominant decision mechanisms, contextual parameters, and energy-related assumptions of existing multi-hop routing approaches, providing a unified view of their operational trade-offs.

TABLE I
COMPARATIVE ANALYSIS OF MULTI-HOP ROUTING APPROACHES IN IOT/WSN NETWORKS

| **Approach** | **Decision mechanism** | **Contextual parameters** | **Energy-related assumptions and limitations** |
|---|---|---|---|
| Heuristic-based routing | Static or rule-based decisions | Residual energy, hop count, distance to sink | Radio-centric energy models; control overhead, idle listening, and re-clustering costs often ignored |
| Metaheuristic-based routing | Iterative global or semi-global optimization | Residual energy distribution, node position, cluster size | Computational and coordination overhead rarely included; net energy gain often assumed |
| Reinforcement learning (RL) | Online policy learning via environmental feedback | Energy state, link quality, traffic load, historical rewards | Training and inference costs frequently neglected; scalability issues on constrained nodes |
| Deep / Multi-agent RL | Decentralized learning with function approximation | High-dimensional state features, neighbor states, traffic dynamics | Severe energy–intelligence trade-off; synchronization and memory overhead often unmodeled |
| Dynamic and heterogeneous routing | Adaptive decision rules using network context | Residual energy, ETX/RSSI, node role, traffic priority | Frequent context acquisition increases signaling and processing energy |
| Explainable AI-based routing | Interpretable learning and post-hoc explanation | Routing policy features, decision attribution scores | Additional computation and memory overhead; energy cost of explainability rarely evaluated |

To complement the overview provided in Table I, Table II and Table III further detail the contextual information and explainability mechanisms employed by dynamic and Heterogeneous routing and XAI-based routing approaches, respectively.

TABLE II
CONTEXTUAL INFORMATION EXPLOITED BY DYNAMIC AND HETEROGENEOUS ROUTING APPROACHES

| **Contextual information** | **Purpose in routing decisions** | **Refs.** |
|---|---|---|
| Residual energy | Load balancing and lifetime extension | [31], [32], [34] |
| Link quality (RSSI, ETX) | Reliable path selection and packet delivery improvement | [31], [33] |
| Traffic load / queue state | Congestion avoidance and delay reduction | [32], [35] |
| Node role / heterogeneity | Capability-aware routing and role assignment | [34], [35] |

TABLE III
EXPLAINABILITY MECHANISMS AND OBJECTIVES IN XAI-BASED ROUTING

| **XAI technique** | **Objective in routing framework** | **Refs.** |
|---|---|---|
| Feature attribution (SHAP, LIME) | Interpretation of routing decisions and energy drivers | [36], [37], [40] |
| Attention mechanisms | Identification of dominant state variables | [38], [41] |
| Rule extraction / policy explanation | Debugging and validation of learned routing policies | [39], [42] |
| Human-in-the-loop explanation | Trust enhancement and selective intelligence activation | [43], [44] |

## IV. CRITICAL ANALYSIS OF MULTI-HOP ROUTING APPROACHES

Recent multi-hop routing protocols for IoT and Wireless Sensor Networks (WSNs) demonstrate that routing intelligence can effectively improve network lifetime, energy efficiency, and quality-of-service. Across all categories, reported gains mainly stem from improved traffic distribution and avoidance of early node depletion. However, post-2018 studies consistently rely on simplified energy models that primarily account for radio transmission costs, while computation, control signaling, learning, and protocol maintenance overheads remain largely ignored [3]–[5]. As a result, energy optimization is often partial and relative, rather than enforced as a strict system-level constraint.

Heuristic-based routing protocols offer very low computational complexity, deterministic behavior, and bounded overhead, making them well suited for severely energy-constrained IoT/WSN deployments. Extensions of LEACH, HEED, PEGASIS, and TEEN integrate residual energy awareness and adaptive cluster-head rotation, yielding stable lifetime improvements under static or moderately dynamic conditions [11]–[14]. Their main limitation lies in poor adaptability to dynamic topologies, heterogeneous traffic, and dense networks, as well as reliance on radio-only energy models that ignore control traffic, idle listening, and re-clustering costs, often leading to optimistic lifetime estimates [1], [3], [9], [10], [15].

Metaheuristic-based routing approaches, including PSO, GA, ACO, GWO, and WOA, improve energy distribution and load balancing by enabling global or semi-global optimization of clustering and routing decisions. Simulation-based evaluations frequently report prolonged network lifetime and better fairness among nodes [16]–[21]. Nevertheless, iterative optimization, coordination overhead, parameter sensitivity, and convergence delay introduce non-negligible energy costs that are rarely modeled explicitly, raising concerns about their net energy benefit in realistic, large-scale, and time-varying IoT/WSN deployments [5], [18], [30].

Reinforcement learning–based routing enhances adaptability by allowing nodes or cluster heads to learn energy-aware routing policies through interaction with the environment. Q-learning and SARSA-based schemes perform well in dynamic scenarios with limited state spaces [22]–[24]. However, training and inference overhead, scalability issues, and memory requirements are frequently overlooked, limiting their practicality on low-power hardware [25], [30], [45].

Deep reinforcement learning and multi-agent RL approaches extend learning-based routing to high-dimensional, decentralized, and highly dynamic environments using DQN, DDQN, and MARL frameworks [26]–[29]. While these methods provide superior adaptability and cooperative decision-making, they introduce a severe energy–intelligence trade-off due to frequent retraining, model synchronization, and substantial computation and memory demands, which are rarely reflected in reported lifetime gains [30], [45], [49].

Dynamic and heterogeneous routing protocols exploit real-time network context such as residual energy, link quality, traffic priority, and node capability to improve robustness, QoS, and energy balance in heterogeneous deployments [31]–[35]. These benefits come at the cost of increased signaling, sensing, and processing overhead, making overall energy efficiency highly sensitive to context update frequency and network density [30], [47].

Explainable AI–based routing approaches improve transparency, trust, and debugging capabilities in learning-based routing by providing post-hoc or intrinsic explanations of routing decisions [36]–[44]. While this enhances system maintainability and supports human in the loop control, the additional computation, memory usage, and explanation generation overhead remain largely unexplored from an energy perspective, leaving their feasibility on severely constrained IoT/WSN nodes an open issue [46], [50].

Across all categories, a recurring limitation is the systematic underestimation of non-communication energy costs, including computation, learning, control signaling, and context management. Recent surveys converge on the conclusion that sustainable routing solutions must move toward hybrid and adaptive frameworks, where intelligence is activated only when its expected energy benefit outweighs its cost [3], [30], [45]. These observations directly motivate the energy-governed hybrid and explainable routing framework proposed in the next section.

## V. Energy-Governed Hybrid and Explainable Routing Framework for IoT/WSN

### A. Motivation and Design Rationale

The analysis in section III highlights a common limitation of current multi-hop routing solutions: energy is rarely treated as a primary design constraint. Heuristic approaches offer simplicity but low adaptability, metaheuristics improve global optimization at the cost of higher computation, and RL/DRL provides adaptability but incurs substantial learning-related energy consumption. Consequently, reported performance gains often do not translate into sustainable energy savings in real deployments. To address this, a hybrid routing framework governed by energy-awareness can be proposed, where optimization and learning mechanisms are activated only if their expected net energy benefit justifies the cost. Routing strategy selection is dynamic, considering current network conditions, residual energy, and intelligence cost.

### B. Architectural Overview

The framework follows a layered, modular architecture suitable for resource-constrained IoT/WSN nodes while maintaining adaptability. It comprises three layers (see Fig.1). The proposed framework adopts a layered architecture in which a lightweight heuristic routing layer ensures continuous connectivity with minimal and predictable energy consumption, while an adaptive intelligence layer provides corrective optimization only when it is energetically justified. The baseline heuristic remains permanently active and executes routing decisions in real time, guaranteeing robustness under strict resource constraints. Network operation is continuously monitored through low-cost metrics, including residual energy trends, per-packet energy expenditure, route stability, and load imbalance. Observed energy degradation is interpreted as a symptom of potential routing inefficiency rather than

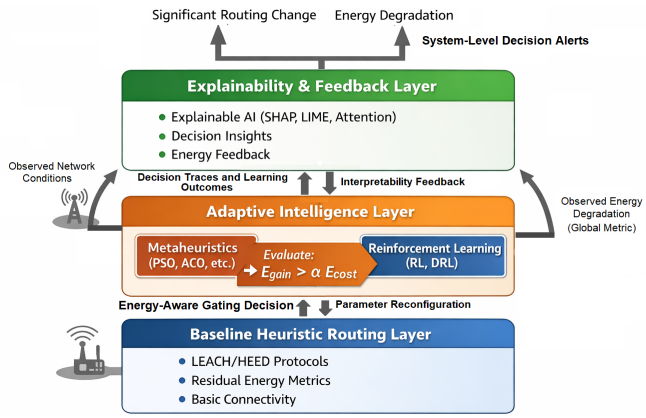


Fig. 1. Energy-Governed Hybrid and Explainable Routing Framework for IoT/WSN.

as a direct trigger for intelligence activation. Upon detecting persistent inefficiency patterns, the framework performs a cost–benefit evaluation to estimate the potential energy savings achievable through optimization. Learning-based mechanisms, including metaheuristics or reinforcement learning, are activated only if the expected energy savings exceed the additional computation and control overhead they induce. Importantly, reinforcement learning is never fully disabled; instead, its level of engagement is regulated. Under stable conditions, the RL agent operates in a passive monitoring mode, collecting state information with negligible overhead. Active learning, exploration, and policy updates are enabled only when routing inefficiency is sufficiently severe to justify their energy cost. Once an improved routing policy or parameter configuration is obtained, it is transferred to the baseline heuristic layer through lightweight policy reconfiguration. The baseline then resumes sole execution, while the adaptive layer returns to a low-overhead monitoring state. This selective and energy-aware regulation of intelligence is intended to enhance to enhance routing performance without compromising network lifetime, thereby resolving the inherent energy–intelligence trade-off in resource-constrained IoT and WSN environments.

- *Operational Energy-Aware Framework*

To operationalize the proposed framework, a minimal yet explicit energy model is introduced to account for both radio and non-radio overheads associated with routing intelligence. The total energy consumption of $node_i$ during a decision interval is defined as:

$$E_i = E_i^{Tx} + Ei^{Rx} + E_i^{Ctrl} + E_i^{Comp} \tag{1}$$

where:
$E_i^{Tx}$ and $Ei^{Rx}$ represent the transmission and reception energy, respectively, while $E_i^{Ctrl}$ and $E_i^{Comp}$ capture the energy overhead induced by control signaling and local computation. Based on this formulation, a lightweight decision rule is adopted to dynamically select the routing strategy. Let $E_i^{Res}$, denote the residual energy of $node_i$ and $\Delta_t$ represent a measure of network dynamics (e.g., topology changes or traffic variability). Heuristic-based routing is maintained when $E_i^{Res} < \theta_t$ or $\Delta_t < \theta_D$, where $\theta_t$ and $\theta_D$ are predefined thresholds. Conversely, learning-based routing is activated only when both conditions $E_i^{Res} >= \theta_t$ and $\Delta_t >= \theta_D$ are satisfied, ensuring that the additional non-radio energy cost remains acceptable. To formalize the activation of intelligent routing, a net energy benefit criterion is introduced. Learning-based routing (metaheuristic or RL/DRL) is activated only if:

$$\Delta E_{\text{save},i} > E_{\text{Ctrl},i} + E_{\text{Comp},i} + \varepsilon \tag{2}$$

where $\Delta E_{\text{save},i}$ denotes the expected energy saving compared to heuristic routing, $E_{\text{Ctrl},i}$ and $E_{\text{Comp},i}$ represent the control and computation energy overhead induced by intelligence, and $\varepsilon$ is a safety margin accounting for estimation uncertainty. The threshold-based conditions on residual energy and network dynamics ($E_{\text{Res},i}$ and $\Delta_t$) can be interpreted as practical estimators of $\Delta E_{\text{save},i}$ in constrained IoT/WSN environments. In practical terms, the framework relies on heuristic routing in quasi-static and homogeneous deployments to minimize computation and control overhead. In contrast, under dynamic or heterogeneous conditions characterized by frequent topology variations or traffic imbalance, deep reinforcement learning is selectively enabled to improve routing adaptability and long-term energy balancing.

- *Expected benefits*

By explicitly governing intelligence through energy-awareness, the proposed framework addresses the core limitations identified in existing routing approaches. It represents a promising research direction for long-term energy balance, more transparency through explainability, and scalable deployment. More broadly, this framework could shift the routing paradigm from performance-driven intelligence to energy-governed intelligence, providing a principled foundation for future research on sustainable and trustworthy IoT/WSN routing protocols.

- *Implementation Perspectives and Practical Limitations*

Although the proposed framework provides a conceptual foundation for energy-governed routing, several implementation challenges remain open. Estimating the expected energy gain $\Delta_{Esave,i}$ and selecting appropriate thresholds $(\theta_t, \theta_D)$ are highly scenario-dependent and subject to uncertainty. Moreover, the overhead induced by monitoring and explainability mechanisms must be experimentally evaluated on real platforms. Therefore, the framework should be viewed as a promising conceptual direction rather than a fully validated routing solution.

## VI. Conclusion and Research Perspectives

This paper presented an energy-centric review of multi-hop routing approaches for IoT and wireless sensor networks proposed between 2018 and 2025. The analysis showed that most existing approaches treat energy as a secondary optimization objective rather than as a governing system constraint. While heuristic protocols provide lightweight operation, their adaptability remains limited, whereas metaheuristic and learning-based approaches improve routing intelligence at the cost of additional computational and communication overhead. To address these limitations, this paper introduced an energy-governed, hybrid, and explainable routing framework in which intelligent mechanisms are activated only when their expected energy benefit exceeds their overhead. The proposed framework should be viewed as a conceptual foundation for future experimentally validated routing architectures rather than as a fully operational protocol solution. Future work should focus on realistic energy modeling, adaptive intelligence activation, and long-term validation on simulation and real IoT/WSN platforms.

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