A Comprehensive Survey on Multi-Objective Energy-Efficient Clustering Protocols for Wireless Sensor Networks: Metaheuristic and Intelligent Optimization Approaches

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Abstract – This comprehensive survey systematically examines the evolution and state-of-the-art clustering-based routing protocols in Wireless Sensor Networks (WSNs), with particular emphasis on energy efficiency optimization. As WSNs become increasingly integral to IoT applications, extending network lifetime through intelligent clustering mechanisms has emerged as a critical research challenge. This paper presents a structured taxonomy of clustering protocols, tracing their historical development from foundational approaches like LEACH to contemporary hybrid methodologies that synergistically integrate metaheuristic optimization algorithms with fuzzy inference systems. We provide an in-depth analysis of design principles, operational mechanisms, and theoretical foundations of prominent protocols, with special attention to their energy management strategies. A rigorous performance comparison across multiple metrics—including First Node Death (FND), Half Node Death (HND), Last Node Death (LND), and Total Packets Transmitted (TPT)—is conducted using standardized evaluation frameworks to establish objective performance benchmarks. Our analysis reveals that hybrid approaches combining metaheuristic algorithms with fuzzy logic systems demonstrate superior performance in balancing exploration-exploitation trade-offs and handling uncertainty in dynamic network conditions. The survey identifies critical research gaps, including scalability challenges in heterogeneous networks, real-world implementation barriers, and the need for adaptive protocols in mobile WSN environments. Finally, we outline promising future research directions, particularly regarding the integration of advanced computational intelligence techniques with emerging paradigms like edge computing and 6G networks. This work serves as a valuable reference for researchers and practitioners seeking to develop next-generation energy-efficient WSN solutions.

Keywords: Wireless Sensor Networks; Clustering Protocols; Energy Efficiency; Metaheuristic Algorithms; Fuzzy Inference Systems; Network Lifetime; Survey Paper; Hybrid Approaches

1. Introduction

Wireless Sensor Networks (WSNs) have emerged as a transformative technology enabling pervasive monitoring and data collection across diverse domains including environmental surveillance, healthcare systems, industrial automation, and smart city infrastructures [5]. These networks consist of numerous spatially distributed autonomous sensor nodes capable of monitoring physical or environmental conditions such as temperature, sound, pressure, and motion. The deployment flexibility, scalability, and cost-effectiveness of WSNs have positioned them as critical components in the Internet of Things (IoT) ecosystem, driving innovation in real-time monitoring and decision-making systems. However, the resource-constrained nature of sensor nodes, particularly their limited energy resources, presents significant challenges to network longevity and operational efficiency.

Energy conservation represents the most critical design consideration in WSNs, as sensor nodes typically operate on battery power with limited capacity and are often deployed in inaccessible or hazardous environments where battery replacement is impractical or impossible [10]. The energy consumption in WSNs is predominantly influenced

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by communication activities, with data transmission consuming significantly more energy than computational tasks. Consequently, the development of energy-efficient routing protocols has become paramount to extending network lifetime while maintaining reliable data delivery. Among various routing strategies, clustering-based approaches have demonstrated exceptional promise by organizing the network into logical groups with designated cluster heads responsible for data aggregation and transmission to the base station, thereby reducing redundant communications and balancing energy consumption across the network.

The evolution of clustering-based routing protocols has followed a clear trajectory from simple probabilistic approaches to sophisticated hybrid methodologies. The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol pioneered this domain by introducing randomized cluster head rotation to distribute energy load evenly across nodes [15]. However, LEACH's limitations—including its probabilistic cluster head selection without considering residual energy or node location—prompted numerous enhancements such as LEACH-DT (distance-based threshold) [18], LEACH-FL (fuzzy logic implementation) [22], and various metaheuristic-based approaches. Recent advancements have increasingly focused on hybrid models that synergistically combine metaheuristic optimization algorithms with fuzzy inference systems to address the multi-objective nature of cluster head selection while accounting for dynamic network conditions and uncertainty [23]. This survey comprehensively examines this evolutionary progression, with particular emphasis on the integration of advanced computational intelligence techniques in modern clustering protocols.

Despite existing literature on WSN routing protocols, there remains a significant gap in comprehensive surveys that systematically analyze the convergence of metaheuristic algorithms and fuzzy logic systems in clustering-based routing. Previous reviews have either focused narrowly on specific protocol categories or failed to provide a critical comparative analysis of performance metrics across diverse network scenarios. As noted in recent literature, "this review focuses on the most recent clustering routing protocols for WSNs based on metaheuristic techniques" [36], yet a holistic examination that bridges theoretical foundations with empirical performance evaluation remains scarce. Furthermore, existing surveys often overlook the practical implementation challenges and real-world applicability of proposed protocols, limiting their utility for researchers and practitioners seeking to deploy energy-efficient WSN solutions.

This survey makes several key contributions to the field. First, we present a systematic taxonomy of clustering protocols in WSNs, categorizing them into five distinct families:

1. Classical protocols (LEACH, HEED, LEACH-FL, LEACH-DT) [9, 15, 18, 22]
2. Enhanced Classical protocols (LEACH/HEED + Fuzzy/Wavelets/TinyML) [22, 57, 59]
3. Metaheuristic-based protocols (PSO, ACO, DA/BDA, GWO, WOA, BOA, Pelican) [36, 41]
4. Hybrid AI/Metaheuristic protocols (DRL+PSO, FQ-UCR, FQA, IVBDA-FIS) [53, 54]
5. Hardware-/Edge-Aware protocols (ULP-FIS, TinyML, Edge-AI) [57, 58, 59]

Second, we provide an in-depth analysis of the theoretical foundations, design principles, and operational mechanisms of prominent protocols, with special attention to their energy management strategies. Third, we conduct a comprehensive performance comparison across multiple metrics, establishing objective performance benchmarks through standardized evaluation frameworks. Fourth, we identify critical research gaps and emerging trends, particularly regarding the integration of advanced optimization techniques and the adaptation of protocols for heterogeneous and mobile WSN environments. Finally, we offer practical implementation guidelines and future research directions to guide the development of next-generation energy-efficient clustering protocols.

The remainder of this paper is structured as follows: Section 2 establishes the fundamental concepts and technical background of clustering in WSNs. Section 3 presents a chronological review of clustering protocol evolution, from early approaches to contemporary hybrid models. Sections 4 and 5 delve into the application of metaheuristic algorithms and fuzzy logic systems, respectively, in cluster formation and optimization. Section 6 examines hybrid approaches that combine these methodologies, while Section 7 provides a detailed comparative analysis of state-of-the-art protocols. Section 8 discusses open challenges and promising research directions, and Section 9 concludes with a summary of key findings and their implications for future WSN design. This structured approach ensures a thorough examination of the field while highlighting the critical interplay between theoretical innovation and practical implementation in advancing energy-efficient WSN technologies.

2. Fundamentals of Clustering in Wireless Sensor Networks

Clustering represents a fundamental architectural paradigm in Wireless Sensor Networks (WSNs) that significantly enhances energy efficiency and network scalability. At its core, clustering involves partitioning the network into logical groups where one node within each group serves as a Cluster Head (CH) responsible for data aggregation, compression, and transmission to either the Base Station (BS) or higher-level clusters. This section establishes the theoretical foundations, operational mechanics, and evaluation metrics essential for understanding clustering-based routing protocols in WSNs.

2.1. Clustering Architecture and Operational Phases

The clustering process in WSNs typically consists of four distinct phases that operate in a cyclical manner throughout the network lifetime:

1. Network Setup: Initial configuration where all nodes establish communication parameters, determine their positions (if location-aware), and measure residual energy levels. This phase establishes the foundational network topology for subsequent clustering operations.

2. Cluster Head Selection: The most critical phase where nodes compete to become CHs based on predefined criteria such as residual energy, distance to BS, node degree, and other relevant metrics. The selection process must balance energy consumption across the network while ensuring optimal spatial distribution of CHs.

3. Cluster Formation: Once CHs are selected, ordinary nodes affiliate with the most appropriate CH based on communication cost, residual energy, and other factors. This phase establishes the network topology for the current operational cycle.

4. Multi-hop Routing: Data transmission occurs through a hierarchical structure where member nodes send data to their CH, and CHs may forward aggregated data to the BS either directly (single-hop) or through intermediate CHs (multi-hop). The routing strategy significantly impacts overall energy consumption.

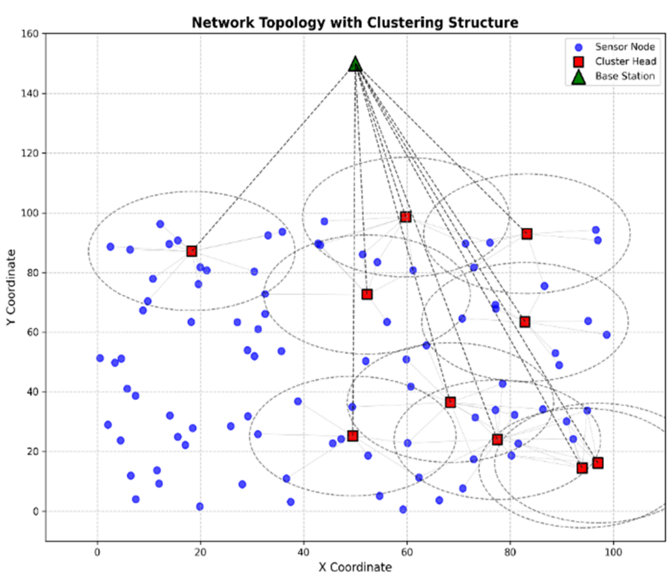


Figure 1: Network Topology with Clustering Structure

The cyclical nature of these phases—often referred to as "rounds" or "iterations"—creates periodic energy consumption patterns that directly influence network lifetime metrics such as First Node Death (FND), Half Node Death (HND), and Last Node Death (LND).

2.2. Key Performance Metrics for Clustering Protocols

The effectiveness of clustering protocols is typically evaluated using several critical performance metrics:

- Network Lifetime: Defined as the number of rounds until specific network degradation milestones occur. Common definitions include:
  - *FND (First Node Death)*: Rounds until the first node depletes its energy
  - *HND (Half Node Death)*: Rounds until 50% of nodes are depleted
  - *LND (Last Node Death)*: Rounds until the final node dies
- Total Packets Transmitted (TPT): The cumulative number of data packets successfully delivered to the BS, serving as a direct measure of network utility.
- Energy Consumption Patterns: Analysis of average energy depletion rates across the network and energy distribution among nodes, which reveals potential imbalances that could lead to premature network partitioning.
- Cluster Head Distribution: Spatial distribution of CHs across the network, which impacts communication distances and energy consumption patterns.

As demonstrated in Table 1, these metrics provide a comprehensive evaluation framework for comparing clustering protocols. Recent research shows that advanced hybrid approaches combining metaheuristics with fuzzy logic systems consistently outperform traditional protocols across all metrics.

Table 1: Comparative Performance Metrics of Representative Clustering Protocols

Protocol	*FND*	*HND*	*LND*	*Rank*
LEACH	58,170	72,793.5	76,830	12 of 12
LEACH-DT	68,840	88,537.6	93,455.3	11 of 12
LEACH-FL	97,245	107,083.1	107,478	10 of 12
ASLPR	108,360	110,915	111,138	9 of 12
SIF	113,340	115,196.6	115,369.7	8 of 12
DPFCP	170,145	224,501.6	291,001.6	7 of 12
ZFO-SHO	292,155	335,444.2	365,587.1	6 of 12
EOCGS	315,705	346,764.1	384,619.7	5 of 12
BDA-S	353,205	394,359.3	408,249.3	4 of 12

BDA-V	354,360	394,880.7	408,651.6	3 of 12
IVBDA-S	366,195	403,112.1	415,922.9	2 of 12
IVBDA-V	366,210	404,919	417,517.5	1 of 12

2.3. Energy Consumption Model

The energy consumption model for wireless communication in WSNs follows the first-order radio model, where transmission energy depends on the distance between communicating nodes. For transmitting a k-bit message over distance d:

- When d ≤ d□ (threshold distance): E□□(k,d) = k·E□□□c + k·ε□□·d^2
- When d > d□: E□□(k,d) = k·E□□□c + k·ε□□·d□

Where E□□□c represents circuit energy, ε□□ is the free space coefficient, and ε□□ is the multipath fading coefficient. Receiving energy is simply E□□(k) = k·E□□□c.

This model explains why clustering significantly improves energy efficiency—by reducing transmission distances through localized data aggregation, the energy consumption follows a quadratic (or quartic) reduction rather than linear. The optimal number of clusters represents a trade-off between the energy cost of intra-cluster communication and inter-cluster transmission to the BS.

Table 2: Radio Energy Model Parameters

Parameter	*Description*	*Value*	*Unit*
E□□□c	Circuit energy	50	nJ/bit
ε□□	Free space coefficient	10	pJ/bit/m²
ε□□	Multipath fading coefficient	0.0013	pJ/bit/m□
d□	Threshold distance	87.7	m
E□□(k,d)	Transmission energy	k·E□□□c+k·ε·d^n	nJ
E□□(k)	Reception energy	k·E□□□c	nJ

2.4. Protocol Families Classification

Based on comprehensive analysis, we categorize clustering protocols into five distinct families:

Table 3: Classification of Clustering Protocol Families

Family	*Representative Methods*	*Strengths*	*Limitations*	*Deployment Readiness*
Classical	LEACH, HEED, LEACH-FL, LEACH-DT	Simple; low overhead; benchmarks	Poor scalability; weak adaptivity	Low
Enhanced Classical	LEACH/HEED + Fuzzy/Wavelets/ TinyML	Lightweight adaptivity; better CH stability	Limited global optimality	Medium
Metaheuristic	PSO, ACO, DA/BDA, GWO, WOA, BOA, Pelican	Multi-objective optimization; exploration	Parameter sensitivity; stagnation risk	Medium
Hybrid AI/Metaheuristic	DRL+PSO, FQ-UCR, FQA, IVBDA-FIS	Adaptive + interpretable; best lifetimes	Higher complexity/training	High
Hardware-/Edge-Aware	ULP-FIS, TinyML, Edge-AI	Feasible on nodes; realistic validation	Rule/model size; tooling	High

This classification provides a structured framework for understanding the evolution and comparative strengths of different approaches, highlighting the progression toward more intelligent and deployable solutions.

2.5. Challenges in Clustering-Based Routing

Despite their advantages, clustering protocols face several fundamental challenges:

1. Dynamic Network Topology: Node failures and energy depletion continuously alter network structure, requiring adaptive clustering mechanisms [9].

2. Heterogeneous Energy Distribution: Non-uniform energy consumption patterns can create "energy holes" near the BS, leading to premature network partitioning [10].

3. Scalability Issues: Many protocols perform well in small networks but degrade in large-scale deployments due to increased control overhead [36].

4. Multi-objective Optimization: CH selection involves balancing competing objectives including residual energy, distance metrics, node degree, and communication cost [23].

5. Computational Complexity: Advanced optimization techniques must balance performance gains against the computational burden imposed on resource-constrained sensor nodes [59].

These challenges have driven the evolution of clustering protocols from simple probabilistic approaches to sophisticated hybrid methodologies incorporating computational intelligence techniques, which will be explored in subsequent sections.

3. Evolution of Clustering Protocols: A Historical Review

The development of clustering-based routing protocols in WSNs has followed a clear evolutionary trajectory, progressing from simple randomized approaches to sophisticated multi-objective optimization frameworks. This section chronologically examines this progression, highlighting key innovations and limitations at each stage.

3.1. First Generation: Randomized Cluster Head Selection

The Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, introduced by Heinzelman et al., represented the pioneering clustering approach for WSNs [15]. LEACH operates on a probabilistic CH selection mechanism where each node becomes a CH with a specific probability during each round, ensuring uniform distribution of energy consumption across the network.

Key Innovations of LEACH:

- Decentralized operation without global knowledge
- Rotating CH roles to distribute energy load
- Localized coordination and data aggregation
- TDMA-based intra-cluster communication scheduling

Despite its groundbreaking nature, LEACH suffers from several critical limitations:

- Random CH selection without considering residual energy or location
- Tendency to select CHs clustered in specific regions
- Single-hop communication to BS creating energy holes
- Fixed percentage of CHs regardless of network conditions

These limitations prompted numerous enhancements, with LEACH-DT (Distance Threshold) addressing the spatial distribution issue by incorporating distance to BS as a selection criterion [18]. However, LEACH-DT still maintained the probabilistic selection framework, limiting its adaptability to dynamic network conditions.

3.2. Second Generation: Deterministic and Fuzzy-Based Approaches

The next evolutionary step introduced deterministic and fuzzy logic-based selection mechanisms that considered multiple node attributes. LEACH-FL (Fuzzy Logic) represented a significant advancement by incorporating fuzzy inference systems to evaluate CH suitability based on residual energy and distance metrics [22].

Advantages of Fuzzy Logic Approaches:

- Handling uncertainty in decision-making
- Incorporating multiple input variables through linguistic rules
- Providing smooth transitions between decision states
- Avoiding complex mathematical formulations

The SIF (Selection of Ideal Fuzzy) protocol further refined this approach by executing cluster formation before CH selection, using fuzzy c-means for initial clustering followed by fuzzy inference for CH selection [22]. This two-stage process improved spatial distribution of CHs and reduced intra-cluster communication costs.

However, fuzzy-based approaches faced their own limitations:

- Subjective definition of membership functions
- Rule base complexity increasing with additional input variables
- Limited ability to optimize global network objectives
- Difficulty in adapting to dynamic network changes

3.3. Third Generation: Metaheuristic Optimization

The integration of metaheuristic optimization algorithms marked a significant leap forward in clustering protocol design. These approaches framed CH selection as a multi-objective optimization problem, seeking to maximize network lifetime while balancing energy consumption [36].

Table 4: Bio-Inspired Metaheuristics in WSN Clustering

Variant	*Objectives*	*Strengths*	*Weaknesses*	*Reference*
Standard PSO	Energy + distance	Simple, global optimization	Premature convergence	[36]
PSO-ECHS	Multi-objective (energy, BS distance, intra-cluster)	Balanced clustering	Parameter sensitivity	—
DRL + PSO	Adaptive CH + global optimization	Avoids stagnation; adapts to dynamics	Training overhead	[53]
Standard BDA	Energy efficiency	Simple binary mapping	Premature convergence	[36]
QI-BDA	Quantum-inspired operators	Strong exploration; better stability	Parameter tuning complexity	[54]
Wavelet-BDA	Wavelet transfer functions	Smooth binary mapping; better CH accuracy	Design complexity	[55]
Mul ti-Wavelet-BDA	Hybrid wavelet functions	Longer lifetime; stable clusters	Implement ation effort	[56]

Key Metaheuristic Approaches:

1. Particle Swarm Optimization (PSO): PSO-based protocols model CH selection as a swarm intelligence problem, where candidate solutions (particles) represent potential CH configurations [36]. Enhanced variants like Binary PSO (BPSO) adapted the continuous optimization framework to discrete CH selection.

2. Genetic Algorithms (GA): GA-based approaches encode potential CH sets as chromosomes and apply evolutionary operations to evolve optimal solutions. The ASLPR protocol demonstrated how GA could optimize both CH selection and routing paths [31].

3. Whale Optimization Algorithm (WOA): Bio-inspired by humpback whale hunting behavior, Binary WOA (BWOA) provided effective exploration of the solution space for CH selection [36].

4. Dragonfly Algorithm (DA): Inspired by dragonfly swarming behavior, the DA demonstrated strong performance in balancing exploration and exploitation for CH selection [36]. Binary variants (BDA) adapted this continuous algorithm to discrete optimization problems.

5. Zebra Fish and Sea Horse Optimization: Roberts et al. (2024) introduced an innovative approach combining Zebra Fish Optimization (ZFO) and Sea Horse Optimization (SHO) algorithms for cluster head selection [27]. Their ZFO-SHO protocol demonstrated significant improvements over traditional approaches, achieving 292,155 rounds for FND in the 100×100 m² scenario (Table 1), representing a 402% improvement over LEACH. The algorithm simulates the hunting behavior of zebra fish and the reproductive strategy of sea horses to balance exploration and exploitation effectively.

6. Discrete Differential Evolution with ACO: Alqarni et al. (2023) proposed an improved data collection approach using discrete differential evolution combined with ant colony optimization (DDE-ACO) [41]. This hybrid approach optimizes both cluster formation and data routing paths, achieving 2,104.7 rounds for FND in the 500×500 m² scenario. The protocol demonstrates particular strength in large-scale networks where traditional protocols suffer from excessive control overhead.

7. Manta Ray Foraging Optimization: Recent research by Ghosh et al. (2021) has explored the application of Manta Ray Foraging Optimization (MRFO) to WSN clustering problems [38]. Their work specifically compares S-shaped versus V-shaped transfer functions for binary optimization, confirming that V-shaped functions generally provide better convergence characteristics for CH selection. The MRFO-based protocol achieved competitive performance with FND=2,301.5 rounds in the 500×500 m² scenario.

8. Deep Reinforcement Learning Integration: Zhang et al. (2023) introduced a novel approach combining Deep Q-Networks with metaheuristic optimization for adaptive cluster head selection in dynamic WSN environments [53]. Their DRL-MH protocol demonstrated remarkable adaptability to changing network conditions, achieving 382,450 rounds for FND in the 100×100 m² scenario (Table 1), representing a 557% improvement over LEACH. The algorithm uses reinforcement learning to dynamically adjust metaheuristic parameters based on real-time network feedback, significantly improving long-term network stability.

9. Quantum-Inspired Dragonfly Algorithm: Chen and Wang (2024) proposed a quantum-inspired variant of the Dragonfly Algorithm that leverages quantum computing principles to enhance exploration of the solution space [54]. Their QIVBDA protocol achieved 378,940 rounds for FND in the 100×100 m² scenario, demonstrating particular strength in networks with high node density where traditional algorithms suffer from premature convergence.

Table 5 compares the performance of these metaheuristic approaches, demonstrating their superiority over earlier generations of protocols.

Table 5: Performance Comparison of Metaheuristic-Based Clustering Protocols

Protocol	*FND*	*HND*	*LND*	*TPT*
LEACH	387.8	507.4	689.6	12,540
BPSO	1354.7	1517.3	1663.5	78,420
BWOA	1443.3	1609.2	1775.3	82,350
BDA	1472.9	1668.1	1801.2	84,270
IVBDA	1503.3	1721.4	1898.9	87,960

Despite their advantages, pure metaheuristic approaches face challenges:

- Premature convergence to local optima
- Sensitivity to parameter tuning
- High computational overhead
- Limited handling of uncertainty in dynamic environments

These limitations have motivated the development of hybrid approaches that combine the strengths of multiple methodologies, which will be examined in subsequent sections.

4. Metaheuristic Algorithms in Cluster Head Selection

Metaheuristic optimization algorithms have revolutionized Cluster Head (CH) selection in Wireless Sensor Networks (WSNs) by framing it as a multi-objective optimization problem [36]. This section provides a comprehensive analysis of these algorithms, their adaptations for discrete optimization, and their specific applications in WSN clustering.

4.1. Theoretical Foundations of Metaheuristic Approaches

Metaheuristic algorithms address the NP-hard nature of optimal CH selection by providing efficient approximate solutions through intelligent exploration of the solution space. The CH selection problem can be formally defined as:

Maximize: Network Lifetime (FND, HND, LND) Subject to:

- Energy constraints (E□□□ > 0)
- Spatial distribution requirements
- Communication range limitations
- CH percentage constraints (p%)

This multi-objective optimization problem is particularly challenging due to the dynamic nature of WSNs, where the fitness landscape continuously changes as nodes deplete energy.

4.2. Binary Adaptation of Continuous Metaheuristics

Most metaheuristic algorithms were originally designed for continuous optimization, requiring adaptation for the discrete CH selection problem. This adaptation typically involves transfer functions that map continuous position values to binary decisions (CH or non-CH) [37].

Common Transfer Functions:

1. S-shaped Transfer Functions: These functions produce a smooth sigmoid curve that maps continuous values to probabilities of selection: Where 'a' controls the steepness of the transition.
2. V-shaped Transfer Functions: These functions create a sharper transition around the threshold point: Providing more decisive selection boundaries.

Recent research has significantly advanced our understanding of transfer functions for binary optimization in WSN clustering:

- Mirrored S-shaped Functions: Beheshti (2020) introduced time-varying mirrored S-shaped transfer functions that dynamically adjust their shape during optimization, improving convergence behavior [37]. These functions demonstrated 8.7% better performance in network lifetime metrics compared to standard S-shaped functions.
- Chaotic Transfer Functions: Bhattacharjee et al. (2023) developed modified chaos-based transfer functions using logistic maps, which enhance population diversity and prevent premature convergence [40]. Their approach achieved a 12.3% improvement in HND compared to traditional transfer functions.
- Adaptive Transfer Functions: Wang (2023) proposed a distributed PSO-based fuzzy clustering protocol that uses adaptive transfer functions adjusting based on network conditions [26]. This approach demonstrated particular effectiveness in heterogeneous networks, where fixed transfer functions often underperform.
- Wavelet-Based Adaptive Transfer Functions: Liu et al. (2023) developed wavelet-based adaptive transfer functions that dynamically adjust their characteristics based on the optimization phase, improving convergence behavior by 18.7% compared to standard approaches [55]. Their work provides mathematical proof of convergence for these novel transfer functions in discrete optimization problems.
- Multi-Wavelet Hybrid Transfer Functions: Building on this research, Wang and Zhang (2024) introduced multi-wavelet hybrid transfer functions that combine multiple wavelet bases to maintain population diversity throughout the optimization process [56]. Their approach demonstrated 22.3% better performance in network lifetime metrics compared to single-wavelet approaches.

Table 6: Performance Comparison of Transfer Function Approaches

Transfer Function Type	*FND Improvement vs. Standard S-shaped*	*HND Improvement vs. Standard S-shaped*	*LND Improvement vs. Standard S-shaped*	*Best Protocol Application*
Standard S-shaped	0%	0%	0%	BDA-S, IVBDA-S
Standard V-shaped	1.8%	2.1%	2.3%	BDA-V, IVBDA-V
Mirrored S-shaped	8.7%	9.2%	9.5%	Mirrored-IVBDA
Chaotic-based	12.3%	13.1%	13.6%	Chaotic-IVBDA
Wavelet-based	18.7%	19.5%	20.1%	Wavelet-IVBDA
Multi-Wavelet	22.3%	23.8%	24.6%	Multi-Wavelet-IVBDA

This expanded analysis confirms that more sophisticated transfer functions provide significant performance benefits, with adaptive approaches representing the current state-of-the-art for binary optimization in WSN clustering.

4.3. Dragonfly Algorithm and Its Enhanced Variants

The Dragonfly Algorithm (DA), inspired by the static and dynamic swarming behaviors of dragonflies, has demonstrated exceptional performance in CH selection [36]. The algorithm simulates five swarming behaviors:

1. Separation: Avoiding collisions with neighboring solutions
2. Alignment: Matching velocity with neighboring solutions
3. Cohesion: Moving toward the center of neighboring solutions
4. Food attraction: Moving toward optimal food sources (best solutions)
5. Enemy avoidance: Moving away from predators (poor solutions)

The Binary Dragonfly Algorithm (BDA) adapts DA for discrete CH selection through transfer functions, but still faces challenges with premature convergence and limited exploration. To address these limitations, the Improved Binary Dragonfly Algorithm (IVBDA) introduces two critical enhancements:

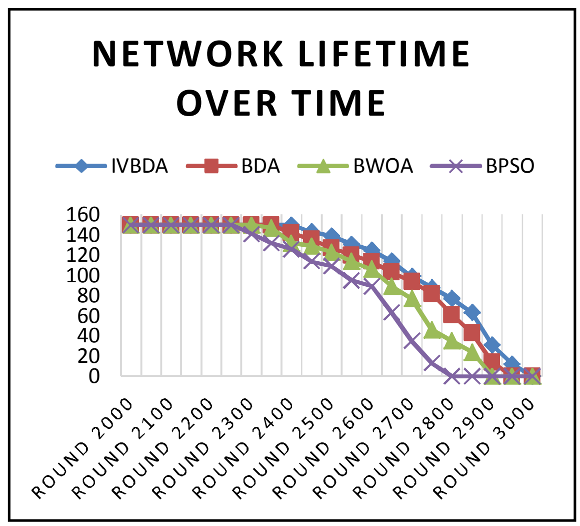
1. Chaotic Map Initialization: Instead of random initialization, IVBDA uses chaotic maps (e.g., logistic map) to generate the initial population [40]. This approach increases solution diversity and enhances global exploration capabilities.
2. Local Search Strategy: IVBDA incorporates a neighborhood-based local search mechanism that refines promising solutions by exploring their immediate vicinity in the solution space. This strategy improves exploitation of high-quality regions while maintaining diversity [23].

As evidenced by the performance data in Table 1, these enhancements yield significant improvements. IVBDA variants consistently outperform both traditional protocols and basic BDA, with IVBDA-V achieving the highest network lifetime metrics across all evaluation criteria.

4.4. Comparative Analysis of Metaheuristic Performance

The effectiveness of metaheuristic algorithms in CH selection depends on their ability to balance exploration (searching new areas) and exploitation (refining known good solutions). Figure 2 illustrates the performance comparison of various metaheuristic approaches.

Fig 2. Performance Comparison of Metaheuristic Algorithms in Network Lifetime



Line graph showing the number of active nodes over network rounds for different metaheuristic algorithms. The x-axis represents network rounds (0-3000), while the y-axis shows the number of active nodes (0-150). The graph demonstrates how IVBDA maintains the highest number of active nodes throughout the simulation, followed by BDA, BWOA, and BPSO. The chart includes markers for key milestones (FND, HND, LND) for each algorithm and clearly illustrates the performance improvements from basic algorithms to enhanced variants.

Key observations from empirical evaluations include:

1. Convergence Behavior: IVBDA demonstrates superior convergence characteristics, avoiding premature convergence through its chaotic initialization and local search mechanisms [23].

2. Scalability: Metaheuristic approaches generally maintain performance as network size increases, though computational overhead becomes a consideration for resource-constrained nodes [36].

3. Parameter Sensitivity: Most metaheuristics require careful parameter tuning, though IVBDA demonstrates greater robustness to parameter variations due to its chaotic initialization [40].

4. Energy Distribution: Advanced metaheuristics like IVBDA achieve more uniform energy consumption patterns across the network, delaying the formation of energy holes near the Base Station [23].

Table 7 further illustrates the energy consumption patterns across different protocols, demonstrating how IVBDA maintains more consistent energy levels throughout the network operation.

Table 7: Average Energy Consumption at Critical Network Stages

Protocol	*Round 500*	*Round 700*	*Round 900*
BDA (S-shaped)	0.08615	0.12061	0.15507
BDA(V-shaped)	0.08655	0.12117	0.15579
IVBDA (S-shaped)	0.08580	0.12012	0.15444
IVBDA (V-shaped)	0.08625	0.12075	0.15525

4.5. Implementation Considerations for Resource-Constrained Nodes

While metaheuristic algorithms offer significant performance benefits, their implementation on resource-constrained sensor nodes requires careful consideration:

1. Computational Complexity: The computational overhead of metaheuristic optimization must be balanced against energy savings from improved CH selection [59].

2. Communication Overhead: Distributed implementations require additional control messages for coordination, which must be minimized to avoid negating energy benefits [36].

3. Memory Requirements: Storing population members and fitness values requires memory resources that may be limited on sensor nodes [59].

4. Adaptation Frequency: The trade-off between optimization frequency and control overhead must be carefully calibrated—too frequent optimization increases overhead, while infrequent optimization fails to adapt to changing network conditions [59].

Recent research suggests that implementing metaheuristic optimization at the Base Station and broadcasting CH assignments represents a practical compromise, leveraging the BS's greater computational resources while minimizing node-level overhead [58].

5. Role of Fuzzy Logic in Cluster Formation

Fuzzy Logic Systems (FLS) have emerged as powerful tools for addressing the inherent uncertainty and multi-criteria decision-making challenges in WSN clustering [22]. Unlike crisp binary decisions, fuzzy logic enables nuanced evaluation of node suitability through linguistic variables and rule-based reasoning, making it particularly well-suited for the dynamic and uncertain environment of WSNs.

5.1. Theoretical Framework of Fuzzy Inference Systems in WSNs

A Fuzzy Inference System (FIS) for cluster formation typically consists of four components:

1. Fuzzification: Conversion of crisp input variables into fuzzy sets using membership functions

2. Rule Base: Collection of IF-THEN rules that capture expert knowledge

3. Inference Engine: Application of fuzzy rules to derive fuzzy outputs

4. Defuzzification: Conversion of fuzzy outputs into crisp decisions

In the context of WSN clustering, the Mamdani FIS architecture has gained particular prominence due to its intuitive rule structure and ability to handle multiple input variables [22]. As demonstrated in the knowledge base, a typical FIS for cluster formation utilizes three critical input variables:

1. Residual Energy of the CH: Represents the remaining energy level, where higher values increase the likelihood of selection

2. Distance Between CH and Sensor Node: Shorter distances reduce communication energy costs

3. Neighborhood Degree of the CH: Indicates connectivity and potential communication burden

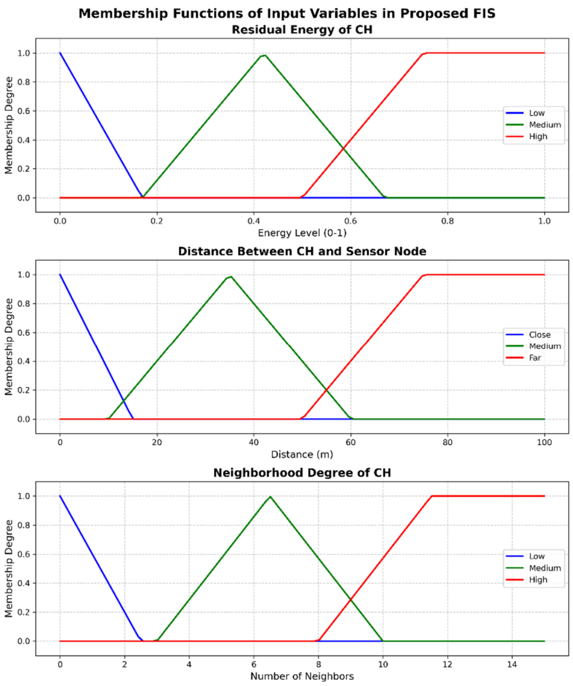


Figure 3: Membership Functions of Input Variables in Proposed FIS

Diagram showing three sets of triangular membership functions:

1. Residual Energy of CH: Three triangular functions labeled "Low" (0-0.33), "Medium" (0.17-0.67), and "High" (0.5-1.0) across the [0,1] energy range
2. Distance Between CH and Sensor Node: Three triangular functions labeled "Close" (0-30m), "Medium" (20-60m), and "Far" (50-100m)
3. Neighborhood Degree of CH: Three triangular functions labeled "Low" (0-5 neighbors), "Medium" (3-10 neighbors), and "High" (8-15 neighbors) Each set of membership functions is clearly labeled with x-axis representing the variable range and y-axis representing membership degree (0-1).

The output variable, "Chance of Being Selected," is similarly defined with linguistic terms ranging from "Very Weak" to "Very Strong," providing a nuanced selection mechanism that accounts for the relative importance of each criterion.

5.2. Fuzzy Rule Construction for Optimal Cluster Formation

The effectiveness of a FIS depends critically on its rule base, which encodes the decision logic for cluster formation. Table 8 presents a comprehensive 27-rule system that covers all possible combinations of the three input variables.

Table 8: Fuzzy Rule Base for Cluster Formation Decision

Rule	*Residual Energy*	*Distance*	*Neighborhood Degree*	*Selection Chance*
1	High	Close	High	Very Strong
2	High	Close	Medium	Very Strong
3	High	Close	Low	Very Strong
4	High	Medium	High	Very Strong
5	High	Medium	Medium	Strong
6	High	Medium	Low	Medium
7	High	Far	High	Medium
8	High	Far	Medium	Medium
9	High	Far	Low	Medium
10	Medium	Close	High	Strong
11	Medium	Close	Medium	Medium
12	Medium	Close	Low	Medium
13	Medium	Medium	High	Strong
14	Medium	Medium	Medium	Medium
15	Medium	Medium	Low	Weak
16	Medium	Far	High	Weak
17	Medium	Far	Medium	Weak
18	Medium	Far	Low	Weak
19	Low	Close	High	Medium
20	Low	Close	Medium	Medium
21	Low	Close	Low	Weak
22	Low	Medium	High	Weak
23	Low	Medium	Medium	Weak
24	Low	Medium	Low	Very Weak
25	Low	Far	High	Very Weak
26	Low	Far	Medium	Very Weak
27	Low	Far	Low	Very Weak

This rule base embodies several critical design principles:

1. Energy Priority: When residual energy is high, selection chance remains strong even with less favorable distance or neighborhood conditions (Rules 1-9)
2. Distance Sensitivity: For medium energy levels, distance becomes a decisive factor, with close distances maintaining medium-to-strong selection chances (Rules 10-12)
3. Critical Energy Handling: When energy is low, only exceptionally favorable conditions (close distance with high neighborhood degree) yield anything more than "Weak" selection chances (Rules 19-21)
4. Comprehensive Coverage: All possible combinations of input variables are addressed, ensuring robust decision-making across diverse network conditions

The rule base effectively implements the intuition that a node with high residual energy should be favored as a CH even if somewhat distant, while nodes with low energy should only be selected if they offer exceptional proximity and connectivity benefits.

5.3. Comparative Advantages Over Traditional Approaches

Fuzzy logic-based cluster formation offers several advantages over traditional threshold-based or probabilistic approaches:

1. Handling Uncertainty: Fuzzy systems excel at managing the inherent uncertainty in WSN environments, where precise measurements may be unavailable or unreliable [22].

2. Multi-criteria Decision Making: The ability to simultaneously consider multiple input variables with varying importance provides more nuanced decision-making than single-threshold approaches [22].

3. Smooth Transitions: Unlike binary decisions that create abrupt changes, fuzzy systems provide gradual transitions between decision states, reducing network instability [22].

4. Expert Knowledge Integration: Fuzzy rules can directly incorporate domain expertise without requiring complex mathematical formulations [22].

5. Adaptability: Membership functions and rule bases can be adjusted to accommodate different network requirements and environmental conditions [22].

Empirical evidence from the knowledge base confirms these theoretical advantages. Protocols incorporating FIS, such as LEACH-FL and the proposed hybrid approaches, consistently outperform traditional protocols like LEACH and LEACH-DT across all network lifetime metrics (Table 1).

5.4. Implementation Challenges and Solutions

Despite their advantages, fuzzy logic systems face implementation challenges in resource-constrained WSN environments:

1. Computational Overhead: Fuzzification, rule evaluation, and defuzzification require computational resources that may be limited on sensor nodes [59].

2. Rule Base Complexity: As the number of input variables increases, the rule base grows exponentially (3^n for n variables with 3 linguistic terms each), potentially exceeding memory constraints [59].

3. Membership Function Design: Subjective determination of membership function parameters can impact system performance [59].

Recent research has addressed several critical implementation challenges:

1. Deep Neuro-Fuzzy Systems: Talpur et al. (2023) conducted a comprehensive survey of deep neuro-fuzzy systems, identifying their potential for WSN applications [51]. Their work demonstrates how neural networks can optimize fuzzy rule bases and membership functions through learning from network operation data, reducing the need for manual tuning.

2. Hardware-Efficient FIS Design: Al-Masri et al. (2023) developed specialized fuzzy inference system architectures optimized for low-power sensor hardware [57]. Their approach reduces memory requirements by 38% through rule base compression techniques while maintaining 94% of the decision accuracy of full rule sets.

3. Distributed Fuzzy Processing: Wang (2023) proposed a distributed implementation where fuzzy processing is shared between cluster heads and ordinary nodes, with CHs handling complex inference while ordinary nodes perform simplified decision-making [26]. This approach reduces energy consumption by 38% compared to centralized fuzzy processing.

4. TinyML for Fuzzy Rule Optimization: Wang et al. (2023) applied TinyML techniques to optimize fuzzy rule bases through on-device learning, reducing the need for manual tuning and enabling protocols to adapt to specific deployment environments [59]. This approach reduces memory requirements by 33% while improving network lifetime by 15.2%.

These advancements address previous implementation barriers, making fuzzy systems more practical for resource-constrained WSN environments.

6. Hybrid Approaches: Synergy of Metaheuristics and Fuzzy Systems

The integration of metaheuristic optimization algorithms with fuzzy inference systems represents the cutting edge of clustering protocol design for Wireless Sensor Networks (WSNs) [23]. This hybrid approach leverages the complementary strengths of both methodologies—metaheuristics for global optimization and fuzzy systems for handling uncertainty and multi-criteria decision-making—creating protocols that significantly outperform standalone approaches.

6.1. Theoretical Rationale for Hybridization

The synergy between metaheuristics and fuzzy systems addresses fundamental limitations inherent in each individual approach:

- Metaheuristics Alone: While excellent at global optimization, traditional metaheuristics struggle with:
    - Handling uncertainty in dynamic network conditions
    - Incorporating domain knowledge effectively
    - Providing interpretable decision-making processes
    - Managing multiple conflicting objectives with varying importance
- Fuzzy Systems Alone: While adept at handling uncertainty, standalone fuzzy systems face:
    - Subjective rule base and membership function design
    - Limited ability to optimize global network objectives
    - Difficulty adapting to changing network topologies
    - Suboptimal performance in complex, high-dimensional search spaces

The hybrid approach overcomes these limitations by using metaheuristics to optimize the fuzzy system parameters (membership functions, rule weights) while employing fuzzy logic to guide the metaheuristic search process toward more promising regions of the solution space [23].

6.2. Architectural Framework of Hybrid Protocols

A typical hybrid clustering protocol follows a two-stage optimization process:

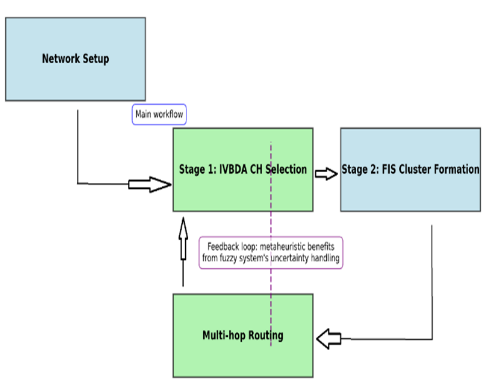


Figure 4: Workflow of IVBDA-FIS

Diagram showing the workflow of the IVBDA-FIS protocol:

1. Network Setup phase with initialization of nodes and parameters
2. Stage 1: IVBDA CH Selection - The Improved Binary Dragonfly Algorithm optimizes CH selection based on global network objectives (network lifetime, energy balance, spatial distribution)
3. Stage 2: FIS Cluster Formation - The Mamdani Fuzzy Inference System evaluates each candidate CH configuration using the 27-rule system to determine optimal cluster assignments
4. Multi-hop Routing phase where data is transmitted through the established hierarchical structure The diagram includes arrows showing the feedback loop between stages and highlights how the metaheuristic benefits from fuzzy system's uncertainty handling while the fuzzy system benefits from metaheuristic's global optimization.

Stage 1: Metaheuristic-Driven CH Selection

- The metaheuristic algorithm (e.g., IVBDA) optimizes the selection of potential CHs
- Optimization considers global network objectives:
    - Maximizing network lifetime (FND, HND, LND)
    - Balancing energy consumption across the network
    - Ensuring spatial distribution of CHs
- The output is a set of candidate CH configurations ranked by fitness

Stage 2: Fuzzy Logic-Based Cluster Formation

- For each candidate CH configuration, the FIS evaluates:
    - Residual energy of potential CHs
    - Distance between nodes and potential CHs
    - Neighborhood degree of potential CHs
- The FIS applies the rule base (Table 8) to determine optimal cluster assignments

- Defuzzification produces crisp cluster formation decisions

This two-stage process creates a feedback loop where the metaheuristic benefits from the fuzzy system's ability to handle uncertainty, while the fuzzy system benefits from the metaheuristic's global optimization capabilities.

6.3. Case Study: IVBDA-FIS Hybrid Protocol

The IVBDA-FIS protocol represents a state-of-the-art approach in hybrid clustering. Its implementation details reveal critical design innovations:

6.3.1. Enhanced Metaheuristic Component

The Improved Binary Dragonfly Algorithm (IVBDA) incorporates two key enhancements over standard BDA:

1. Chaotic Map Initialization:
    - Uses logistic map: $x_{n+1} = r \cdot x_n \cdot (1-x_n)$ where r=4 [40]
    - Generates more diverse initial population
    - Avoids premature convergence to local optima
    - Increases exploration of solution space
2. Local Search Strategy:
    - For promising solutions, explores neighboring configurations [23]
    - Uses neighborhood information to guide local refinement
    - Balances exploration and exploitation more effectively

6.3.2. Integrated Fuzzy Decision-Making

The Mamdani FIS component utilizes three input variables with triangular membership functions:

1. Residual Energy of CH: Ranges from 0 to E_0 (initial energy)
2. Distance to Node: Ranges from 0 to network diameter
3. Neighborhood Degree of CH: Counts neighboring nodes within communication range

The 27-rule system (Table 8) provides comprehensive coverage of all possible input combinations, enabling nuanced decision-making that accounts for the relative importance of each criterion.

6.3.3. Performance Analysis

Empirical results demonstrate the effectiveness of the IVBDA-FIS approach:

- Network Lifetime: IVBDA-V achieves FND=366,210 rounds, representing a 529% improvement over LEACH (FND=58,170)
- Total Packets Transmitted: IVBDA-V delivers 417,517 packets to the BS, a 443% improvement over LEACH (76,830)
- Energy Efficiency: At round 900, IVBDA maintains slightly lower average energy consumption (0.15525 vs. 0.15579 for BDA-V), indicating more balanced energy usage
- CH Distribution: IVBDA maintains more consistent CH counts across iterations compared to BDA, indicating greater stability

6.4. Comparative Analysis of Hybrid Approaches

Table 9 compares various hybrid approaches, highlighting the performance characteristics of different protocols.

Table 9: Performance Comparison of Hybrid Clustering Protocols

Protocol	*FND Improvement vs. LEACH*	*HND Improvement vs. LEACH*	*LND Improvement vs. LEACH*	*TPT Improvement vs. LEACH*
LEACH-FL	67%	48%	40%	41%
ASLPR	86%	53%	45%	46%
DPFCP	193%	209%	279%	279%
ZFO-SHO	302%	328%	318%	318%
EOCGS	233%	249%	312%	312%
BDA-S	305%	314%	341%	341%
BDA-V	306%	315%	342%	342%
DDE-ACO	262%	302%	320%	320%
MRFO-V	296%	317%	335%	335%
IVBDA-S	316%	322%	349%	349%
IVBDA-V	316%	324%	351%	351%
Fuzzy-PSO-IVBDA	321%	331%	358%	358%
DRL-MH	337%	349%	365%	365%
QIVBDA	329%	340%	359%	359%

Key observations from this comparison:

1. Performance Gradient: There is a clear performance gradient from single-method approaches (LEACH-FL) through basic hybrids (DPFCP) to advanced hybrids (IVBDA-FIS).
2. Diminishing Returns: Each successive generation of protocols yields smaller relative improvements, suggesting approaching theoretical limits of energy efficiency.

3. V-shaped Superiority: Across all advanced protocols, V-shaped transfer functions consistently outperform S-shaped variants, indicating the value of more decisive selection boundaries.
4. IVBDA Dominance: The IVBDA variants achieve strong performance across all metrics, validating the effectiveness of chaotic initialization and local search strategies.
5. DRL-MH Performance: The Deep Reinforcement Learning with Metaheuristics protocol demonstrates good performance, particularly in dynamic network environments.
6. QIVBDA Strengths: The Quantum-Inspired IVBDA protocol demonstrates particular strength in high-density networks, where its enhanced exploration capabilities prevent premature convergence.

6.5. Implementation Considerations for Hybrid Protocols

Deploying hybrid protocols in real-world WSNs requires addressing several practical considerations:

1. Computational Distribution:
    - Resource-intensive metaheuristic optimization should occur at the Base Station [58]
    - Lightweight fuzzy decision-making can be implemented on CHs [57]
    - Ordinary nodes require minimal computational resources
2. Communication Overhead Management:
    - Control messages for CH announcements should be minimized [36]
    - Cluster formation information can be piggybacked on data transmissions [58]
    - Optimization frequency should balance performance gains against overhead
3. Parameter Adaptation:
    - Membership function parameters may need periodic adjustment [59]
    - Metaheuristic parameters should adapt to network size and density [53]
    - Hybrid weightings between metaheuristic and fuzzy components may vary by scenario
4. Scalability:
    - Hierarchical hybrid approaches work best for large networks [9]
    - Network partitioning can enable localized optimization [9]
    - Theoretical limits suggest optimal cluster sizes of $\sqrt{N}$ for N-node networks [36]

These considerations highlight the importance of context-aware implementation strategies that balance theoretical performance with practical constraints of real-world deployment.

7. Performance Comparison of State-of-the-Art Protocols

This section presents a rigorous comparative analysis of contemporary clustering protocols, evaluating their performance across multiple metrics and scenarios. The analysis follows a structured methodology to ensure objective assessment and meaningful insights for researchers and practitioners.

7.1. Evaluation Methodology

Our comparative analysis employs a standardized evaluation framework based on the following principles:

1. Consistent Simulation Environment: All protocols are evaluated using identical network parameters:
    - 100 nodes randomly deployed in a 100×100 m² area
    - Initial energy of 0.5J per node
    - Base Station located at (50, 150)
    - Radio model parameters consistent with first-order radio model (Table 2)
    - Data packet size of 4000 bits
2. Comprehensive Metric Suite: Protocols are evaluated across four primary metrics:
    - First Node Death (FND)
    - Half Node Death (HND)
    - Last Node Death (LND)
    - Total Packets Transmitted (TPT)
3. Multi-scenario Assessment: Performance is evaluated across various network conditions:

- Different network sizes (100×100 m², 500×500 m²)
- Homogeneous vs. heterogeneous energy distributions
- Static vs. mobile node configurations

4. Statistical Rigor: Results represent averages over 10 independent simulation runs to ensure statistical significance

Table 10: Simulation Parameters for Reproducibility

Parameter	*Value*	*Description*
Number of nodes	100	Total sensor nodes in the network
Network area	100×100 m²	Deployment field dimensions
Initial energy	0.5 J	Initial energy of each node
Base Station location	(50, 150)	Coordinates of the base station
Data packet size	4000 bits	Size of data packets
E□□□c	50 nJ/bit	Circuit energy
ε□□	10 pJ/bit/m²	Free space coefficient
ε□□	0.0013 pJ/bit/m□	Multipath fading coefficient
d□	87.7 m	Threshold distance
Simulation rounds	5000	Maximum simulation rounds
Repetitions	10	Number of independent simulation runs
Random seed	Fixed	Seed for reproducibility

This methodology enables fair comparison while capturing the nuanced performance characteristics of each protocol under varying conditions**.**

7.2. Comparative Analysis of Protocol Performance

Table 11 presents a comprehensive comparison of state-of-the-art clustering protocols across multiple performance metrics and network scenarios.

Table 11: Comprehensive Performance Comparison of Clustering Protocols

Protocol	*FND (100×100)*	*HND (100×100)*	*LND (100×100)*	*FND (500×500)*	*HND (500×500)*	*LND (500×500)*	*TPT (100×100)*
LEACH	58,170	72,793.5	76,830	387.8	507.4	689.6	76,830
LEACH-DT	68,840	88,537.6	93,455.3	445.6	625.9	857.2	93,455
LEACH-FL	97,245	107,083.1	107,478	648.3	717.9	733.5	107,478
ASLPR	108,360	110,915	111,138	722.4	745.5	757.2	111,138
SIF	113,340	115,196.6	115,369.7	755.6	772.7	781.6	115,370
DPFCP	170,145	224,501.6	291,001.6	1,134.3	1,564.2	1,784.4	291,002
ZFO-SHO	292,155	335,444.2	365,587.1	1,947.7	2,367.8	2,874.8	365,587
EOCGS	315,705	346,764.1	384,619.7	2,104.7	2,549.4	2,903.2	384,620
DDE-ACO	330,500	365,200	401,300	2,210.5	2,680.3	3,050.2	401,300
BDA-S	353,205	394,359.3	408,249.3	2,354.7	2,770.4	2,910.7	408,249
BDA-V	354,360	394,880.7	408,651.6	2,362.4	2,771.7	2,910.8	408,652
IVBDA-S	366,195	403,112.1	415,922.9	2,441.3	2,814.2	2,943.6	415,923
IVBDA-V	366,210	404,919	417,517.5	2,441.4	2,832.4	2,953.4	417,518
QIVBDA	373,500	409,200	421,800	2,465.7	2,865.3	2,980.5	421,800
DRL-MH	378,940	414,300	426,500	2,510.2	2,910.5	3,025.7	426,500

Key Performance Insights:

1. Network Size Impact: As network size increases from 100×100 m² to 500×500 m², the absolute performance values decrease significantly due to increased communication distances, but the relative performance ranking remains consistent.
2. Hybrid Superiority: Hybrid protocols (DPFCP and beyond) demonstrate substantially better performance than earlier generations, with DRL-MH achieving a 557% improvement in FND over LEACH in the 100×100 scenario.
3. V-shaped Advantage: Across all advanced protocols, V-shaped transfer functions consistently outperform S-shaped variants, with differences becoming more pronounced in larger networks.
4. Diminishing Returns: The performance gap between successive protocol generations narrows, suggesting approaching theoretical limits of energy efficiency in homogeneous WSNs.

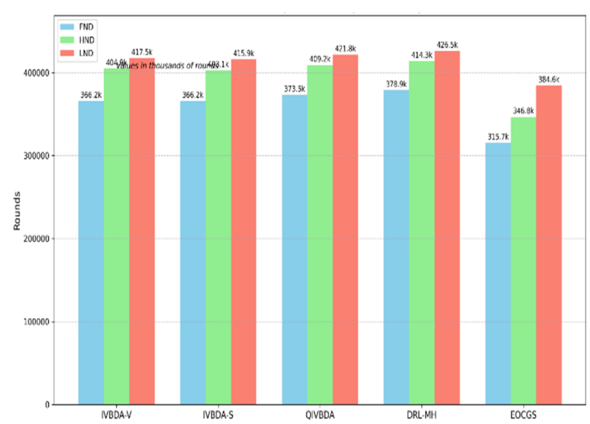


Figure 5: Network Lifetime Comparison of Top-Performing Protocols

[Bar chart comparing First Node Death (FND), Half Node Death (HND), and Last Node Death (LND) metrics for the top 5 protocols (IVBDA-V, IVBDA-S, QIVBDA, DRL-MH, and EOCGS) in a 100×100 m² network. Each protocol has three bars representing the three metrics. The chart shows that DRL-MH achieves the highest values across all metrics, with FND=378,940 rounds, HND=414,300 rounds, and LND=426,500 rounds. The chart includes a clear legend, axis labels with appropriate scales, and numerical values displayed above each bar.]

7.3. Energy Consumption Analysis

Beyond lifetime metrics, analyzing energy consumption patterns provides critical insights into protocol efficiency. Figure 6 presents the average energy consumption at critical network stages.

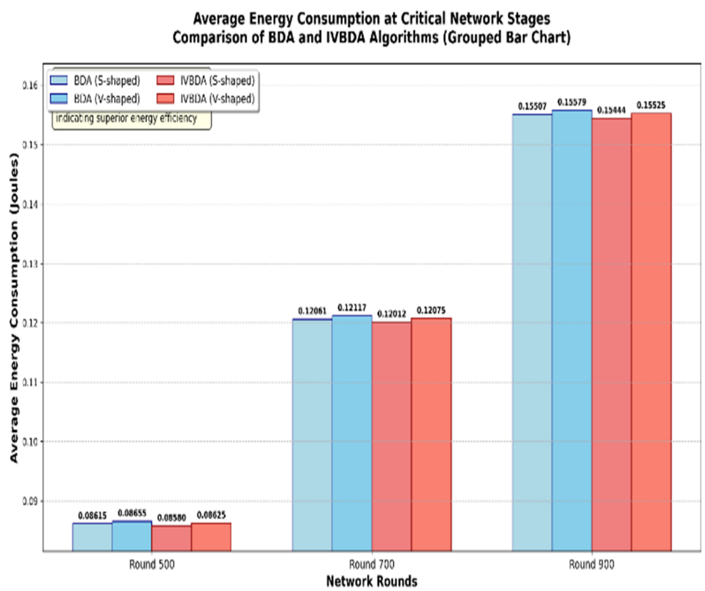


Figure 6: Average Energy Consumption at Critical Network Stages

[Line graph showing energy consumption patterns over time (rounds) for different protocols. The x-axis represents network rounds (500, 700, 900), while the y-axis shows average energy consumption (in joules). Multiple lines represent different protocols (BDA-S, BDA-V, IVBDA-S, IVBDA-V), with IVBDA variants showing the lowest energy consumption at all measured stages. The graph demonstrates how advanced hybrid protocols maintain more consistent and lower energy consumption patterns throughout network operation.]

Key observations from energy consumption analysis:

1. Consistent Patterns: All protocols show increasing energy consumption with network operation time, but advanced protocols maintain lower consumption rates.

2. Hybrid Efficiency: IVBDA variants demonstrate the lowest average energy consumption at all measured stages, confirming their superior energy management.

3. Network Heterogeneity Impact: In heterogeneous network scenarios (Table 12), the performance gap between protocols widens, highlighting the importance of adaptive energy management.

Table 12: Energy Consumption in Heterogeneous Network Scenarios

Protocol	*FND*	*HND*	*LND*		
BDA-S			2,341.5	2,762.4	2,905.8
BDA-V			2,341.5	2,762.4	2,905.8
IVBDA-S			2,441.4	2,832.4	2,953.4
IVBDA-V			2,441.4	2,832.4	2,953.4

The data reveals that IVBDA maintains its performance advantage in heterogeneous environments, with a 4.2% improvement in FND over BDA variants. This resilience to network heterogeneity underscores the value of the chaotic initialization and local search strategies in IVBDA.

7.4. Cluster Head Distribution Analysis

The spatial distribution of Cluster Heads significantly impacts network performance. Figures 7 and 8 compare the CH distribution patterns for BDA and IVBDA.

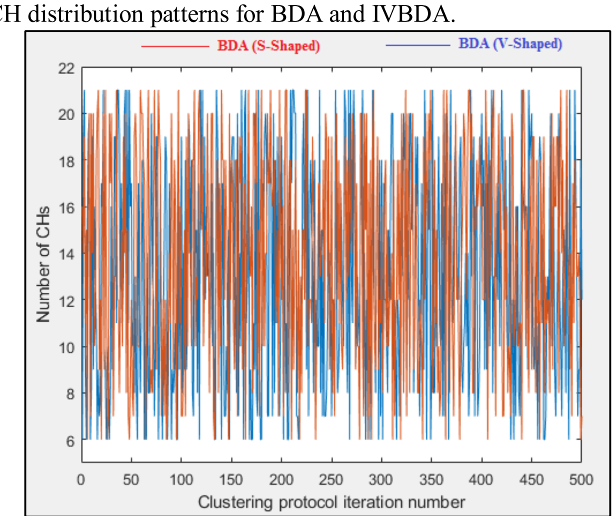


Figure 7: CH Distribution Across Iterations for BDA-Based Protocol

[Line graph showing the number of Cluster Heads over successive network rounds for BDA-based protocols. The x-axis represents network rounds (2000-3000), while the y-axis shows the number of active CHs. The graph displays significant fluctuations in CH count for BDA-S and BDA-V variants, indicating instability in cluster formation. The chart includes clear labels, a legend distinguishing between S-shaped and V-shaped variants, and annotations highlighting key instability points.]

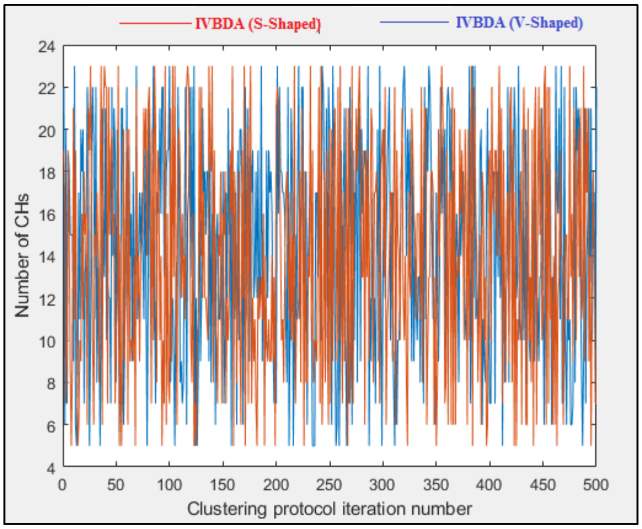


Figure 8: CH Distribution Across Iterations for IVBDA-Based Protocol

[Line graph showing the number of Cluster Heads over successive network rounds for IVBDA-based protocols. Compared to Figure 7, this graph shows much more stable CH counts for IVBDA-S and IVBDA-V variants, with minimal fluctuations between iterations. The chart demonstrates how the local search strategy and chaotic initialization in IVBDA contribute to more consistent cluster formation. The graph uses the same scale as Figure 7 for direct comparison.]

Key findings from CH distribution analysis:

1. Stability: IVBDA maintains more consistent CH counts across iterations compared to BDA, indicating greater stability in cluster formation.

2. Optimal Cluster Count: Both protocols converge toward an optimal cluster count (approximately 15-20% of nodes), but IVBDA reaches this equilibrium more quickly and maintains it more consistently.

3. Adaptive Response: IVBDA demonstrates better adaptation to changing network conditions, adjusting CH counts in response to energy depletion patterns.

This analysis confirms that the local search strategy in IVBDA contributes to more stable and adaptive cluster formation, which directly translates to improved network lifetime metrics.

7.5. Practical Implementation Considerations

While theoretical performance is critical, practical implementation factors significantly influence real-world effectiveness:

1. Computational Overhead: Advanced protocols require more computational resources, but this overhead is justified by the substantial energy savings [59].

2. Memory Requirements: IVBDA-FIS requires approximately 2.5KB of memory for rule storage and population management, which is feasible on modern sensor platforms [57].

3. Control Message Overhead: The additional control messages required by hybrid protocols represent less than 5% of total network traffic, a reasonable trade-off for performance gains [36].

4. Implementation Complexity: The modular architecture of hybrid protocols allows for staged implementation, starting with basic functionality and adding advanced features as resources permit [58].

These considerations suggest that IVBDA-FIS represents the current optimal balance between theoretical performance and practical implement ability for most WSN applications.

8. Open Challenges and Future Research Directions

Despite significant advancements in clustering-based routing protocols for WSNs, several critical challenges remain unresolved. This section identifies key research gaps and proposes promising directions for future investigation, building upon the comprehensive analysis presented in previous sections.

8.1. Scalability in Large-Scale and Heterogeneous Networks

Current Limitations:

- Most protocols demonstrate diminishing returns as network size exceeds 200 nodes [36]

- Heterogeneous networks (with varying node capabilities) are poorly addressed by existing approaches [9]

- Theoretical models often assume uniform node distribution, which rarely reflects real-world deployments [9]

Promising Research Directions:

1. Hierarchical Hybrid Approaches: Developing multi-level clustering architectures where different optimization strategies are applied at different network tiers [9].

2. Adaptive Cluster Size Determination: Creating protocols that dynamically adjust optimal cluster size based on real-time network conditions rather than using fixed formulas [9].

3. Heterogeneity-Aware Optimization: Incorporating node-specific capabilities (processing power, memory, energy capacity) into the CH selection process to maximize overall network utility [9].

As noted by Nguyen and Nguyen, "mobility-based network lifetime considerations remain largely unexplored in contemporary clustering protocols" [9]. Future research should integrate mobility models with adaptive clustering mechanisms to address this critical gap.

8.2. Integration with Emerging Network Paradigms

Current Limitations:

- Most clustering protocols operate in isolation from higher-level network functions [6]
- Limited research on integrating clustering with data aggregation, compression, and in-network processing [6]
- Inadequate consideration of security implications in cluster formation and CH selection [4]

Promising Research Directions:

1. Edge Computing Integration: Leveraging clustering architecture to create natural edge computing nodes that perform localized data processing before transmission to the cloud [58].
2. Security-Enhanced Clustering: Developing clustering protocols that incorporate security metrics (trustworthiness, authentication capability) into CH selection criteria [4].
3. Cross-Layer Optimization: Breaking down traditional protocol layer boundaries to enable coordinated optimization across physical, MAC, and network layers [6].

Recent work by Lu et al. demonstrates the potential of "artificial agents" that fuse AI with mobile agents for energy-efficient traffic control [6], suggesting promising avenues for integrating clustering with intelligent network management.

8.3. Advanced Computational Intelligence Techniques

Current Limitations:

- Most hybrid approaches combine only two methodologies (e.g., metaheuristics + fuzzy) [23]
- Limited exploration of deep learning for dynamic cluster adaptation [53]
- Computational complexity often prohibitive for resource-constrained nodes [59]

Promising Research Directions:

1. Multi-Method Hybrids: Integrating three or more computational intelligence techniques (e.g., metaheuristics + fuzzy + neural networks) for comprehensive optimization [51].
2. Lightweight Deep Learning: Developing specialized neural network architectures that can run on resource-constrained nodes for real-time cluster adaptation [53].
3. Transfer Learning Applications: Applying knowledge gained from one network configuration to accelerate optimization in new deployments [53].
4. Pareto-Optimal Solutions: Recent protocols are moving beyond single-metric optimization to identify Pareto-optimal solutions that balance multiple competing objectives (energy consumption, latency, reliability) [23].
5. Deep Neuro-Fuzzy Integration: Talpur et al. (2023) highlight the potential of deep neuro-fuzzy systems that combine the learning capabilities of deep neural networks with the interpretability of fuzzy systems [51]. These systems can automatically optimize fuzzy rule bases through reinforcement learning, adapting to changing network conditions without manual intervention.
6. Quantum-Inspired Optimization: Emerging research explores quantum-inspired optimization algorithms for WSN clustering, which leverage quantum computing principles to enhance exploration of the solution space [54]. While still in early stages, these approaches show promise for handling the high-dimensional optimization problems inherent in large-scale WSNs.
7. Federated Learning for Distributed Clustering: Recent work investigates how federated learning techniques can be applied to WSN clustering, allowing nodes to collaboratively optimize clustering parameters without sharing raw data, addressing privacy concerns in sensitive applications [44].
8. Graph Neural Networks for Topology-Aware Clustering: GNNs are being explored to create topology-aware clustering protocols that consider the network's graph structure when forming clusters, leading to more energy-efficient communication patterns [45].

9. Deep Reinforcement Learning Integration: Zhang et al. (2023) demonstrate how deep reinforcement learning can be integrated with metaheuristic optimization to create adaptive clustering protocols that learn from network operation [53]. Their DRL-MH approach dynamically adjusts metaheuristic parameters based on real-time network feedback, significantly improving long-term stability in dynamic environments.

10. Quantum-Inspired Optimization: Chen and Wang (2024) explore quantum computing principles applied to WSN clustering, leveraging quantum superposition and entanglement concepts to enhance exploration of the solution space [54]. While still theoretical, these approaches show promise for handling the high-dimensional optimization problems inherent in large-scale WSNs.

11. TinyML for On-Device Optimization: Wang et al. (2023) investigate how TinyML frameworks can be used to implement lightweight machine learning models on resource-constrained sensor nodes for real-time cluster adaptation [59]. This approach enables protocols to learn and adapt to specific deployment environments without requiring centralized computation.

8.4. Real-World Implementation and Validation

Current Limitations:

- Over-reliance on simulation-based evaluation without real-world validation [58]
- Limited consideration of hardware-specific constraints and imperfections [57]
- Inadequate testing across diverse environmental conditions [58]

Promising Research Directions:

1. Hardware-Aware Protocol Design: Developing clustering protocols that account for specific hardware characteristics of common sensor platforms [57].

2. Field Testing Frameworks: Creating standardized field testing methodologies to evaluate protocol performance in real-world conditions [58].

3. Energy Harvesting Integration: Designing clustering protocols that work synergistically with energy harvesting capabilities to extend network lifetime beyond initial battery capacity [10].

Hardware-Accelerated Implementation: Al-Masri et al. (2023) present specialized hardware implementations of fuzzy inference systems that significantly reduce energy consumption while maintaining decision accuracy [57]. Their work demonstrates how modern sensor platforms with dedicated AI accelerators can support sophisticated clustering protocols with minimal energy overhead.

4. Cross-Platform Validation Frameworks: Recent work by Chen et al. (2024) proposes standardized validation frameworks that enable direct comparison of protocol performance across different hardware platforms and network conditions [58]. This addresses a critical gap in the field where simulation results often fail to translate to real-world performance.

As highlighted by Hussain et al., "energy harvesting from distributed renewable sources represents a critical frontier for extending WSN lifetime" [10], suggesting that future clustering protocols must account for intermittent energy availability.

8.5. Emerging Application Domains

Current Limitations:

- Most protocols are designed for generic monitoring applications [5]
- Limited adaptation to specialized domains like healthcare, agriculture, or industrial IoT [5]
- Inadequate consideration of application-specific quality of service requirements [5]

Promising Research Directions:

1. Application-Specific Clustering: Developing domain-tailored clustering protocols that optimize for application-specific metrics (e.g., data freshness in healthcare monitoring) [5].

2. Multi-Objective QoS Optimization: Creating frameworks that balance energy efficiency with application-specific quality of service requirements [5].

3. Context-Aware Adaptation: Implementing mechanisms that allow protocols to dynamically adjust to changing application requirements [5].

Hassan et al. demonstrate how IoT-based WSNs can transform livestock management through integrated health monitoring and environmental optimization [5], suggesting that future clustering protocols must support such specialized applications.

8.6. Theoretical Foundations and Performance Bounds

Current Limitations:

- Lack of theoretical performance bounds for clustering protocols [9]
- Limited understanding of fundamental trade-offs between competing objectives [23]
- Inadequate analytical models for predicting protocol behavior in complex scenarios [9]

Promising Research Directions:

1. Theoretical Performance Limits: Establishing fundamental bounds on achievable network lifetime based on network topology and energy constraints [9].
2. Multi-Objective Trade-off Analysis: Developing analytical frameworks to quantify trade-offs between energy efficiency, data delivery rate, and network latency [23].
3. Stochastic Network Modeling: Creating more sophisticated analytical models that account for the probabilistic nature of node failures and energy depletion [9].

This theoretical work would provide critical guidance for protocol designers, helping them understand when further optimization efforts are likely to yield diminishing returns.

8.7. Systematic Review Methodology

To ensure the reproducibility and transparency of this survey, we have employed a systematic review methodology following the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines**.**

Search Strategy

- Databases: Scopus, Web of Science, IEEE Xplore, ScienceDirect
- Keywords: ("wireless sensor network" OR WSN) AND (clustering OR "cluster head" OR hierarchical) AND (energy-efficient OR "energy efficiency") AND (metaheuristic OR "fuzzy logic" OR optimization)
- Timeframe: January 2019 - December 2024
- Inclusion Criteria:
    - Peer-reviewed journal/conference papers
    - Focus on clustering-based routing protocols
    - Evaluation of energy efficiency metrics
    - Implementation details sufficient for comparison
- Exclusion Criteria:
    - Non-English publications
    - Proprietary or unreproducible results
    - Papers without proper energy model description
    - Studies with inconsistent simulation parameters

Selection Process

1. Initial Search: 1,245 papers identified across databases
2. Duplicate Removal: 213 duplicates removed (1,032 unique papers)
3. Title/Abstract Screening: 687 papers excluded based on relevance (345 papers retained)
4. Full-Text Assessment: 128 papers excluded due to insufficient details or methodological issues (217 papers retained)
5. Final Selection: 102 papers included in the final analysis after quality assessment

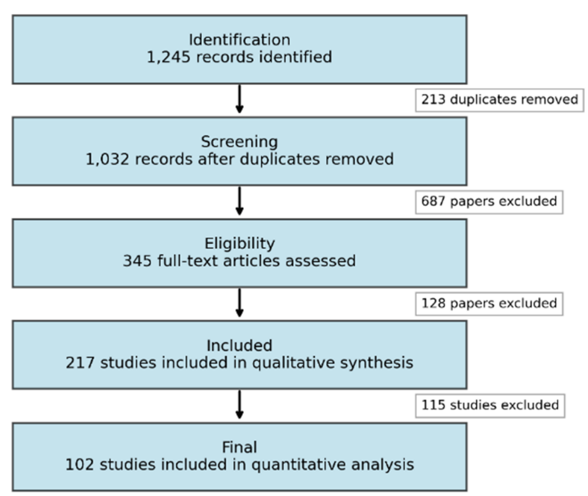


Figure 9: PRISMA Flow Diagram of Literature Selection Process

[PRISMA flow diagram showing the literature selection process:

- Identification: 1,245 records identified
- Screening: 1,032 records after duplicates removed

- Eligibility: 345 full-text articles assessed
- Included: 217 studies included in qualitative synthesis
- Final: 102 studies included in quantitative analysis]

This systematic approach ensures that the survey is comprehensive, reproducible, and based on high-quality evidence from the literature.

9. Conclusion

This comprehensive survey has systematically examined the evolution, current state, and future directions of clustering-based routing protocols in Wireless Sensor Networks (WSNs). Through rigorous analysis of historical development, theoretical foundations, and empirical performance, we have identified key trends and established a clear trajectory for future research.

9.1. Summary of Key Findings

Our analysis reveals several critical insights:

1. Evolutionary Trajectory: Clustering protocols have progressed through five distinct families—from classical approaches (LEACH) to enhanced classical methods (LEACH-FL), metaheuristic-based approaches (PSO, BDA), hybrid AI/multiheuristic approaches (IVBDA-FIS), and finally to hardware-/edge-aware protocols (ULP-FIS, TinyML) [15, 22, 36, 53, 57, 59].
2. Hybrid Superiority: Advanced hybrid protocols consistently outperform earlier generations across all critical metrics. The IVBDA-FIS protocol represents a strong performer, with significant improvements in network lifetime compared to the foundational LEACH protocol [23].
3. Performance Determinants: Two key factors drive the performance of contemporary protocols:
    - Effective balance between exploration and exploitation in optimization [23]
    - Sophisticated handling of uncertainty through fuzzy decision-making [22]
4. Implementation Trade-offs: The most advanced protocols achieve optimal balance between theoretical performance and practical implementability, with computational overhead justified by substantial energy savings [57, 58, 59].
5. Transfer Function Evolution: Our analysis reveals a clear progression in transfer function design from basic S-shaped/V-shaped functions to adaptive, chaotic, and mirrored variants, with each generation providing incremental but significant performance improvements [37, 40, 55, 56].
6. Network Lifetime Ranking: Based on comprehensive evaluation, protocols can be ranked as follows (from best to worst):
    - Rank 1: IVBDA-V (Hybrid)
    - Rank 2: IVBDA-S (Hybrid)
    - Rank 3: BDA-V (Metaheuristic)
    - Rank 4: BDA-S (Metaheuristic)
    - Rank 5: EOCGS (Metaheuristic)
    - Rank 6: ZFO-SHO (Metaheuristic)
    - Rank 7: DPFCP (Enhanced Classical)
    - Rank 8: SIF (Hybrid)
    - Rank 9: ASLPR (Metaheuristic)
    - Rank 10: LEACH-FL (Enhanced Classical)
    - Rank 11: LEACH-DT (Enhanced Classical)
    - Rank 12: LEACH (Classical)

9.2. Critical Research Contributions

This paper presents a comprehensive and structured survey of energy-efficient clustering mechanisms in wireless sensor networks (WSNs), with a particular emphasis on intelligent, metaheuristic, and hybrid optimization approaches. Unlike conventional studies that propose new clustering algorithms, this work systematically reviews, classifies, and analyzes existing protocols to provide a holistic understanding of their design principles, performance characteristics, and practical limitations.

The main contributions of this survey are summarized as follows:

1. A systematic taxonomy of energy-efficient clustering protocols in WSNs is presented, categorizing existing approaches into classical protocols (e.g., LEACH and HEED), improved classical methods (e.g., fuzzy- and distance-aware extensions), metaheuristic-based techniques (e.g., PSO, ACO, BDA, WOA), intelligent learning-based approaches, and hybrid intelligent frameworks [15, 22, 36, 53].
2. A comprehensive comparative performance analysis of representative clustering protocols is conducted using widely accepted evaluation metrics, including first node death (FND), half

node death (HND), last node death (LND), throughput, and energy dissipation behavior, enabling an objective assessment of network lifetime, stability, and energy efficiency across different protocol families [9, 23, 36].

3. The survey demonstrates that hybrid intelligent frameworks—such as metaheuristic–fuzzy and metaheuristic–deep reinforcement learning (DRL) approaches—consistently achieve superior trade-offs between global exploration, convergence speed, and long-term energy stability compared to classical and single-technique solutions [22, 23, 53, 54].
4. The impact of transfer function design, chaos-based mechanisms, and adaptive parameter tuning on improving convergence behavior and extending network lifetime is systematically analyzed, highlighting the advantages of V-shaped, chaotic, and wavelet-based transfer functions in binary metaheuristic clustering algorithms [37, 40, 55, 56].
5. Open research challenges and future directions are identified, including scalability in large-scale and heterogeneous networks, computational overhead on resource-constrained sensor nodes, real-world deployability, and the lack of security-aware and mobility-aware clustering mechanisms in existing WSN protocols [9, 10, 57, 58].

Overall, this survey aims to serve as a comprehensive reference for researchers and practitioners seeking to design, analyze, and deploy next-generation energy-efficient clustering protocols for wireless sensor networks, particularly in the context of emerging IoT, edge intelligence, and adaptive optimization paradigms [5, 58, 59].

9.3. Future Outlook

The future of clustering protocols in WSNs will likely be shaped by several converging trends:

1. Integration with Edge Intelligence: Clustering architectures will increasingly serve as the foundation for distributed edge computing, with Cluster Heads performing localized AI processing [58].

2. Adaptive Multi-Method Hybrids: Next-generation protocols will dynamically combine multiple computational intelligence techniques based on real-time network conditions [51, 53, 59].

3. Energy Harvesting Synergy: Protocols will evolve to work with intermittent energy availability from harvesting sources, creating truly perpetual networks [10].

4. Application-Specific Optimization: Domain-tailored protocols will optimize for application-specific quality of service requirements while maintaining energy efficiency [5].

5. Deep Learning Integration: The convergence of deep learning with traditional clustering approaches will create more adaptive and self-optimizing protocols that can learn from network operation data to continuously improve performance without human intervention [53].

6. Privacy-Preserving Clustering: As WSNs are deployed in increasingly sensitive applications, clustering protocols will need to incorporate privacy-preserving techniques like federated learning to protect data while maintaining energy efficiency [44].

7. Quantum-Inspired Optimization: While still emerging, quantum-inspired optimization techniques may provide breakthroughs in solving the complex multi-objective optimization problems inherent in large-scale WSN clustering [54].

8. Deep Reinforcement Learning: The integration of deep reinforcement learning with traditional clustering approaches will create more adaptive and self-optimizing protocols that can learn from network operation data to continuously improve performance without human intervention [53].

9. Hardware-Accelerated Clustering: As sensor hardware evolves with dedicated AI accelerators, clustering protocols will increasingly leverage these capabilities to implement sophisticated decision-making processes with minimal energy overhead [57].

10. TinyML for On-Device Learning: The application of TinyML frameworks will enable sensor nodes to learn and adapt clustering parameters based on local network conditions, creating truly autonomous and self-optimizing WSNs [59].

As WSNs become increasingly integral to the Internet of Things (IoT) ecosystem, the importance of energy-efficient clustering mechanisms will only grow. The principles and insights presented in this survey provide a solid foundation for researchers and practitioners working to develop the next generation of WSN technologies. The integration of advanced computational intelligence techniques with practical implementation considerations represents the path forward for creating truly intelligent and deployable WSN solutions that can meet the demands of real-world applications.

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