A Comprehensive Review of Energy-Efficient Routing Protocols and Optimization Frameworks in Wireless Sensor Networks

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ABSTRACT

Energy efficiency has emerged as the central design requirement in Wireless Sensor Networks (WSNs), particularly due to the limited battery resources and the impracticality of physical maintenance in harsh deployment regions. This review synthesizes ten contemporary studies on energy-efficient routing, spanning swarm intelligence, fuzzy-logic–assisted multi-criteria clustering, Pareto-optimal evolutionary strategies, multipath routing with load balancing, LEACH-based enhancements, and centralized cluster management for mobile-node environments. Contributions such as Whale Swarm-based routing, collaborative energy-efficient routing for emerging 5G/6G WSNs, evolutionary architecture reviews, Coyote Optimization with fuzzy logic, multipath load balancing clustering, hybridized bio-inspired routing, optimized Engroove-LEACH clustering GA + K-means routing, centralized clustering for mobility, and multi-criterion Binary Grey Wolf Optimizer (BGWO) clustering demonstrate varied yet complementary advancements. This paper consolidates theoretical frameworks, models, and the working principles of these algorithms, compares their performance trends, presents mathematical formulations, highlights limitations in computation, scalability, and parameter tuning, and outlines future research directions. The review also integrates multiple tables, equations, and conceptual analyses to provide a comprehensive understanding of modern energy-efficient routing in WSNs. This review adopts a PRISMA-based systematic methodology and proposes a unified taxonomy and comparative evaluation framework for energy-efficient routing protocols in Wireless Sensor Networks.

Keywords: Wireless Sensor Networks, Energy Efficiency, Clustering, Metaheuristic Optimization, Hybrid Algorithms, Reinforcement Learning, IoT.

INTRODUCTION

Wireless Sensor Networks (WSNs) consist of spatially distributed sensor nodes that autonomously sense, compute, and transmit data to a Base Station (BS). Their operation supports applications such as environmental monitoring, military surveillance, medical observation, industrial automation, and disaster response. A consistent theme across all reviewed papers is that WSN nodes operate on limited, non-replaceable batteries, making energy efficiency the ultimate determinant of network lifetime (Zeng, 2024) (Meenakshi, 2024) (Pal, 2023).

Need of Energy-Efficient Routing Matters

In wireless sensor networks, routing is the most energy-consuming operation compared to sensing or processing tasks. Since nodes continuously forward data toward the base station, their batteries drain rapidly, which causes early node death and shortens the overall network lifetime. Energy-efficient routing is therefore essential to lower communication overhead, avoid retransmissions and collisions, and balance energy usage across nodes. To address these issues, researchers have proposed several strategies, including bio-inspired metaheuristics such as Whale Swarm, Grey Wolf, and Coyote Optimization (Zeng, 2024) (Mohamed, 2020) (Bostani, 2025), improved LEACH-based schemes (Behera, 2022) (Meenakshi, 2024), multipath load-balanced routing (Saleem, 2023), and centralized clustering approaches designed for mobility support (Pal, 2023).

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Trends in Modern Routing Research

Recent research shows a clear movement toward intelligent and optimization-driven routing mechanisms. Swarm intelligence and meta-heuristic algorithms are being used to create stable clusters and optimize path selection (Zeng, 2024) (Mohamed, 2020) (Bostani, 2025). Multi-objective clustering, often using Pareto-based optimization, focuses on balancing energy, distance, and latency constraints (Behera, 2022). Enhanced versions of LEACH continue to appear to resolve limitations in random cluster-head election (Behera, 2022) (Meenakshi, 2024) (Barekatain, 2015). Multipath routing improves load distribution and reduces congestion (Saleem, 2023), while centralized and mobility-aware routing models enhance stability in dynamic scenarios (Pal, 2023). Collectively, these trends address long-standing challenges such as uneven energy dissipation, poor scalability, and suboptimal CH selection in classical WSN protocols.

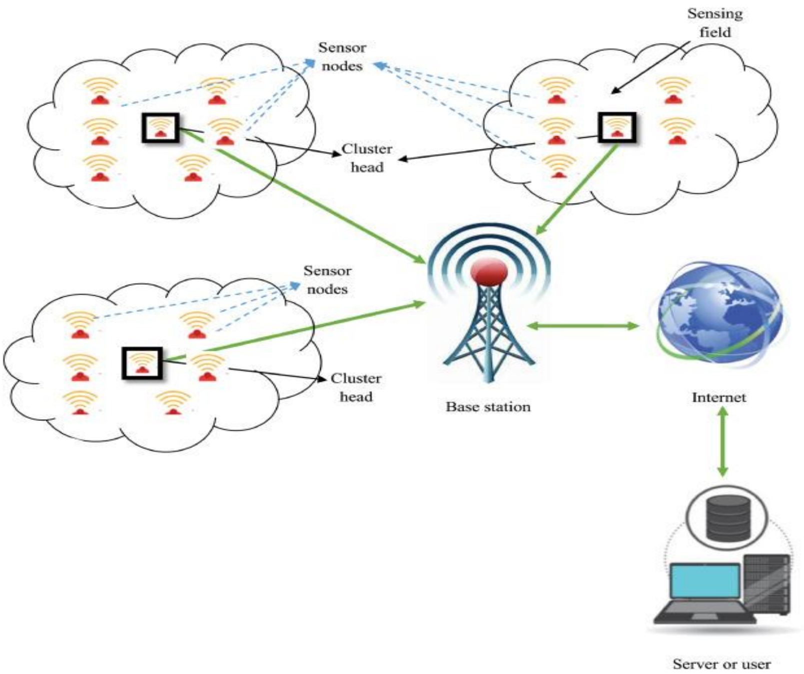


Figure 1: Energy Efficient routing in WSN Network (Sheeja, 2023)

Objectives of This Review

This review aims to provide a unified theoretical foundation for ten modern routing approaches by explaining their internal working principles and comparing their optimization strategies and performance characteristics. It also identifies the key limitations that remain in current models and highlights potential directions for future research to advance energy-efficient and reliable WSN routing systems (Zeng, 2024) (Pal, 2023).

RESEARCH METHODOLOGY

Review Protocol

This review adopts a systematic literature review methodology inspired by the PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) framework, which is widely accepted for structuring reviewbased research to enhance transparency, reproducibility, and methodological rigor (Page, 2021). The primary objective of adopting this framework is to ensure that the selection and synthesis of studies related to energyefficient routing and optimization frameworks in Wireless Sensor Networks (WSNs) are conducted in a structured and unbiased manner.

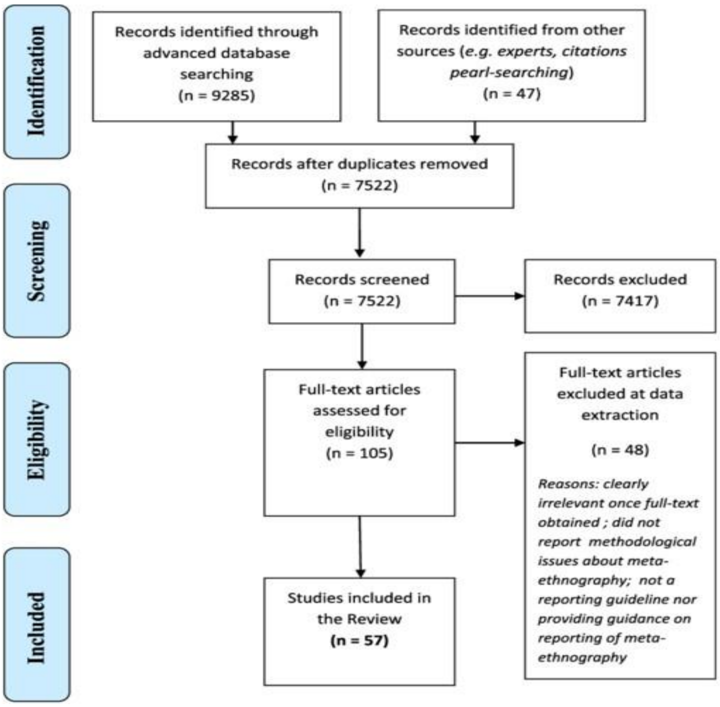
Unlike narrative surveys, the proposed methodology explicitly defines the review scope, search strategy, screening process, and analysis criteria. This enables a consistent and traceable evaluation of routing protocols based on clustering, swarm intelligence, evolutionary optimization, and hybrid intelligent techniques. Similar systematic approaches have been recommended in recent WSN routing surveys to improve comparability and analytical depth (Behera, 2022).

Databases and Search Strategy

A comprehensive and multi-source literature search was conducted to capture both foundational and state-ofthe-art contributions in energy-efficient WSN routing. The databases consulted include IEEE Xplore, ScienceDirect (Elsevier), SpringerLink, Wiley Online Library, and Google Scholar, which collectively cover the majority of high-impact journals and conferences in wireless communications and sensor networks (Behera, 2022), (Sheeja, 2023).

Structured Boolean search queries were employed to ensure precise retrieval of relevant studies while minimizing irrelevant results. Representative search strings included (“Wireless Sensor Networks” AND “Energy-Efficient Routing”), (“WSN clustering” AND “metaheuristic optimization”), (“LEACH optimization” AND “energy efficiency”), and (“bio-inspired routing” AND “WSN”). These keywords were selected to reflect the dominant optimization paradigms reported in recent energy-aware routing literature (Behera, 2022).

Figure 2: PRISMA flow diagram



Inclusion Criteria

To ensure relevance and quality, studies were included in this review only if they satisfied the following criteria:

publication between 2015 and 2025, appearance in peer-reviewed journals or well-established international conferences, explicit focus on routing or clustering-based energy optimization, and reporting of quantitative performance metrics such as network lifetime, residual energy, packet delivery ratio (PDR), throughput, or routing overhead.

Additionally, selected studies were required to employ optimization-driven approaches, including metaheuristic, evolutionary, fuzzy-logic-based, or hybrid intelligent techniques. This ensured that the review reflects modern trends in WSN routing research rather than traditional deterministic protocols (Zeng, 2024) (Mohamed, 2020) (Meenakshi, 2024) (Pal, 2023).

Exclusion Criteria

Studies were excluded if they were non-English publications, focused exclusively on MAC or physical layer optimization, lacked explicit energy-efficiency objectives, or were classified as editorials, short workshop papers, or duplicate publications. These exclusion rules align with filtering practices commonly adopted in comprehensive WSN routing reviews to avoid bias and redundancy (Behera, 2022).

Paper Selection Process

The initial search across all databases yielded approximately 120 research articles. After removing duplicate records and performing title–abstract screening, 45 papers were shortlisted for further evaluation. Full-text eligibility assessment reduced this set to 18 relevant studies, from which 10 representative and high-impact papers were selected for detailed qualitative, comparative, and analytical review. This multi-stage filtering process follows established systematic review practices reported in prior WSN survey studies (Behera, 2022) (Sheeja, 2023).

BACKGROUND AND THEORETICAL FRAMEWORK

WSN Architecture and Energy Constraints

A typical wireless sensor node integrates sensors, an ADC–microcontroller unit, a communication module, and a small, non-rechargeable battery. Since nodes are often deployed in inaccessible or harsh environments, replacing batteries is rarely possible. Studies such as Engroove-LEACH and BGWO clustering highlight that routing must therefore be energy-aware from the very beginning, as inefficient communication rapidly drains limited power resources (Meenakshi, 2024) (Pal, 2023).

Clustering-Based Routing

Clustering organizes nodes into smaller groups, each led by a Cluster Head (CH) that aggregates and forwards data. All ten papers employ some form of clustering, with different optimization strategies:

1. WSA routing selects CHs using swarm behaviour (Zeng, 2024).
2. COA-Fuzzy CH selection uses multi-criteria decision-making (Mohamed, 2020). Multipath CH communication balances load (Saleem, 2023).
3. BGWO determines CHs through Pareto-optimal binary optimization (Pal, 2023).
4. Engroove-LEACH improves LEACH's instability (Meenakshi, 2024).
5. Clustering reduces energy consumption by lowering transmission distances and minimizing redundant packets.

Multi objective Optimization in WSNs

CH selection is inherently a multi-objective and NP-hard problem due to the large solution space. Algorithms such as GA with K-means clustering (Barekatain, 2015), the BGWO optimizer (Pal, 2023), and hybrid swarmbased approaches (Bostani, 2025) address this by combining evolutionary learning, fuzzy reasoning, and intelligent exploration exploitation behaviour. Techniques like Whale Swarm further guide the search toward energy-efficient solutions (Zeng, 2024). These methods jointly optimize factors such as residual node energy, intra-cluster compactness, CH–BS distance, CH count, and node density to achieve balanced and durable network structures.

Radio Energy Model Used

Most of the reviewed protocols rely on the classical first-order radio model, where transmission cost increases with distance quadratically or quartically depending on the threshold. Receiving energy remains linear with packet size. This model, either explicitly or implicitly, forms the basis of energy calculations in WSA, COAFuzzy, multipath clustering, Engroove-LEACH, and BGWO-based routing (Zeng, 2024) (Mohamed, 2020) (Saleem, 2023) (Meenakshi, 2024) (Pal, 2023).

LEACH and Its Limitations

Despite being the foundation for many later protocols, LEACH faces well-known drawbacks. As identified in Engroove-LEACH and broad architectural surveys, its random CH selection provides no guarantee of adequate energy, often ignores the distance to the base station, and leads to uneven cluster formation (Behera, 2022) (Meenakshi, 2024). Modern research overcomes these limitations through optimization-driven CH selection,

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fuzzy multi-criteria assessment, and centralized decision-making, resulting in more stable and energy-balanced clusters.

Type of Hop Communication

Hop-communication structure directly affects energy usage, routing overhead, and load distribution in WSNs. The reviewed protocols adopt different hop models based on their routing objectives and cluster designs.

Single-Hop Communication

CHs transmit directly to the BS.

Used mainly in LEACH-based designs and simpler clustering models:

Surveyed LEACH variants rely on single-hop assumptions (Behera, 2022).

GA + K-means clustering also follows direct BS communication (Barekatain, 2015).

Pros: Simple design, low routing complexity

Cons: High energy cost for distant CHs; early CH depletion in large networks.

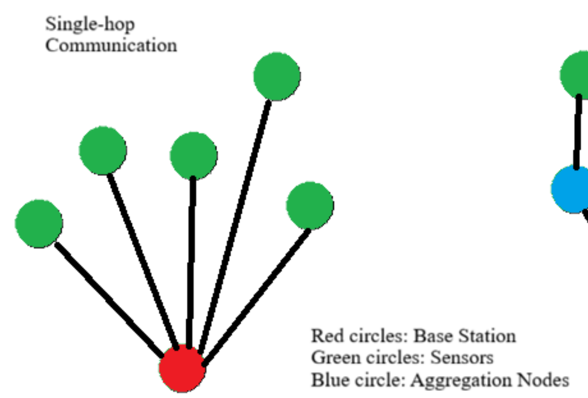

Figure 3: Types of hop communication

Multi-Hop Communication

Data is forwarded through intermediate CHs or relay nodes to reduce long-distance energy cost.

Applied in:

1. Multipath load-balancing clustering (Saleem, 2023)
2. Engroove-LEACH (MIHFO + HWAFO) optimized routing (Meenakshi, 2024)
3. Hybrid bio-inspired routing models (Bostani, 2025)
4. BGWO multi-objective clustering (Pal, 2023)

Pros: Lower per-hop energy; scalable; balanced energy use

Cons: Increased routing overhead; possible congestion at relay CHs.

Multipath Communication

Multiple parallel paths are formed to the BS for redundancy and reliability.

Used in:

- Multipath load-balancing clustering (Saleem, 2023)

- Hybrid routing schemes with alternative next-hop CHs (Bostani, 2025) Pros: High robustness and delivery rate; balanced traffic Cons: Extra control overhead; complex path selection.

Centralized Hop Decisions

A central controller (usually the BS) computes optimal hop path. Adopted in mobility-aware centralized routing (Yan, 2019).

Pros: Global optimization; stable routing under mobility

Cons: BS dependency; risk of single-point failure.

Hybrid Hop Structures

Protocols adapt hop type dynamically based on energy or topology.

1. Whale Swarm-based routing uses adaptive multi-hop searching (Zeng, 2024).
2. COA-Fuzzy clustering may switch between single-hop and multi-hop based on fuzzy criteria (Mohamed, 2020).

Benefit: Flexible routing that improves lifetime across varying conditions.

Energy-Efficient Routing Principles

Across the ten papers, the following foundational principles recur.

Minimize Communication Energy

Shorter transmission distances and fewer long-distance hops are prioritized in multipath clustering (Saleem, 2023), Engroove-LEACH variants (Meenakshi, 2024), and Grey Wolf clustering (Pal, 2023).

Figure 4: Energy Efficient Strategies

Balanced Energy Consumption

To prevent hotspot depletion where certain nodes die prematurely due to excessive forwarding recent algorithms aim to distribute energy usage more uniformly across the network. Whale Swarm routing spreads the CH load among whale-guided candidates (Zeng, 2024), COA-Fuzzy selects CHs with sensitivity to residual energy (Mohamed, 2020), and BGWO maintains energy balance by rotating CH responsibilities over stable time intervals (Pal, 2023).

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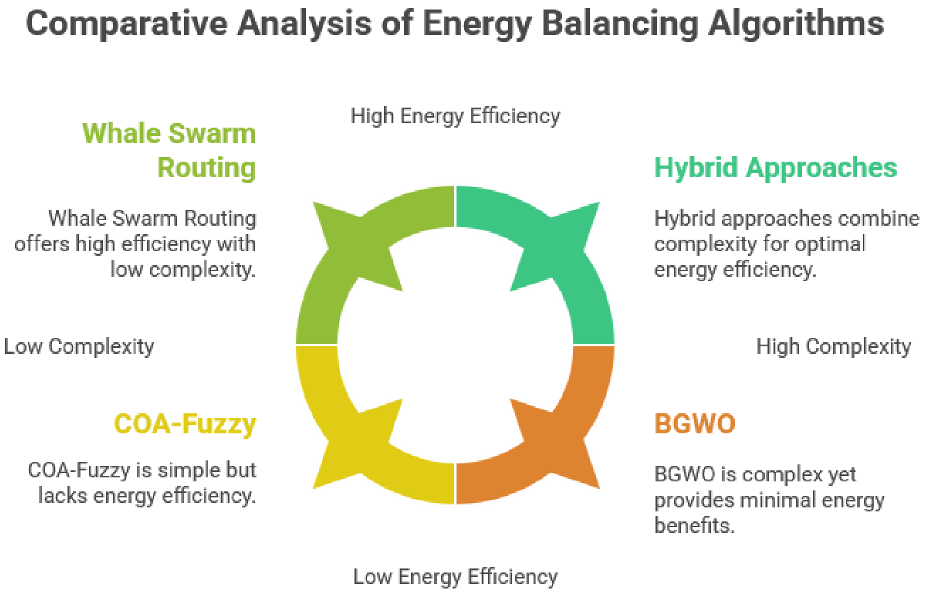

Figure 5: Energy Balancing Algorithms

Multi-criteria CH Selection

Cluster-head selection increasingly relies on multiple decision factors rather than single-parameter heuristics. Metrics such as residual energy, node connectivity, BS distance, clustering compactness, and centrality are jointly considered in protocols like COA-Fuzzy, Engroove-LEACH, and BGWO optimization to improve cluster stability and routing efficiency (Mohamed, 2020) (Meenakshi, 2024) (Pal, 2023).

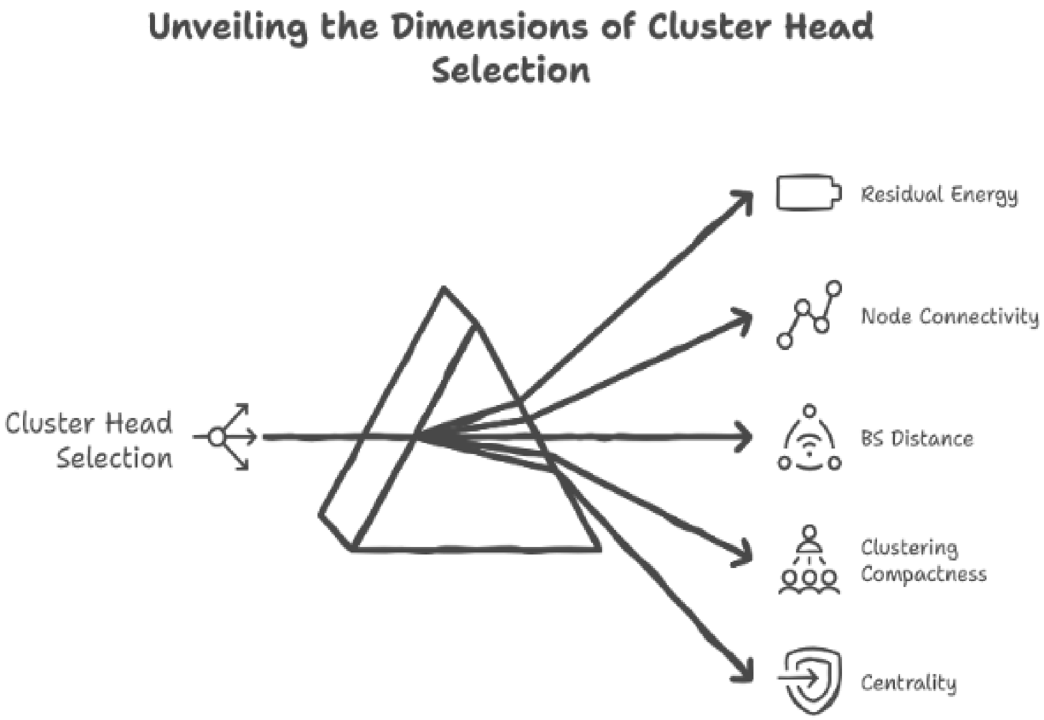

Figure 6: Dimensions of CH selection

Swarm-Based Optimization

Bio-inspired swarm intelligence plays a prominent role in enhancing search accuracy and routing performance. Whale Swarm algorithms mimic cooperative searching behaviours (Zeng, 2024), Coyote Optimization models

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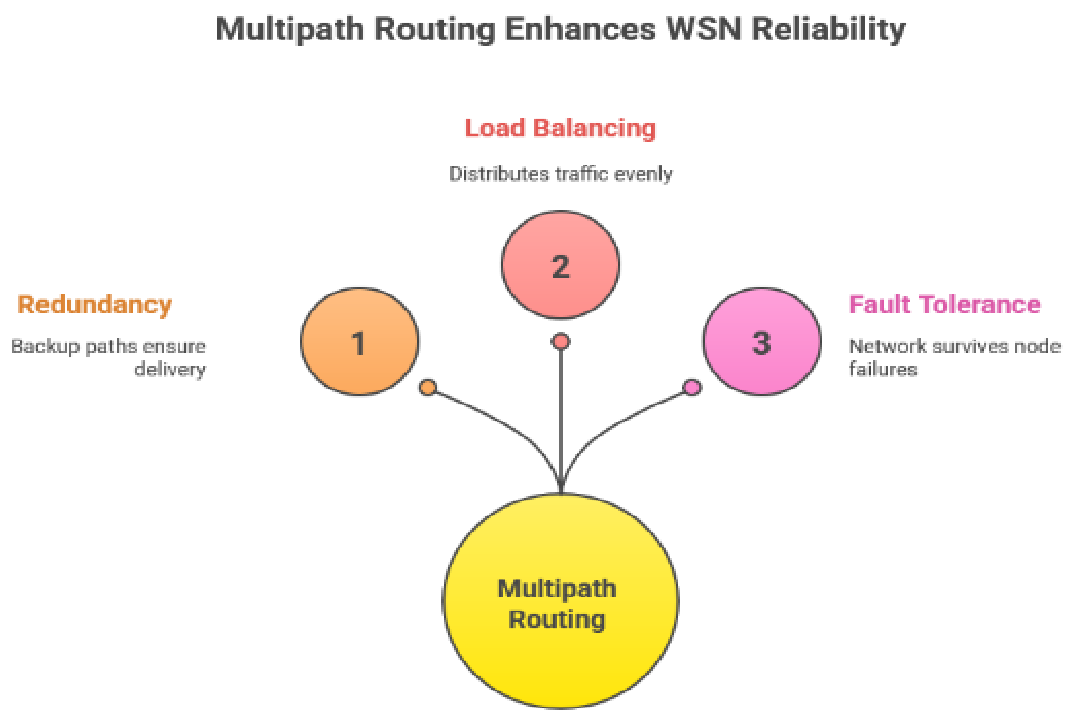
pack adaptability (Mohamed, 2020), and Grey Wolf Optimizers employ hierarchical hunting dynamics (Pal, 2023). These approaches offer strong global search capabilities, enabling more optimal CH selection.

Multipath Routing for Reliability

Multipath routing further strengthens WSN reliability by establishing multiple CH paths to the base station. As shown in multipath load-balanced clustering (Saleem, 2023), using several routes helps distribute traffic, protect individual CHs from early exhaustion, and significantly improve overall throughput.

Figure 7: Multipath routing



Centralized Decision-Making

Centralized optimization, as demonstrated in mobility-aware clustering models (Yan, 2019), enhances network performance by allowing the base station to make globally optimal CH and hop-routing decisions. Although this strategy provides improved stability—especially under mobility—it also increases dependence on the BS and adds control overhead.

Detailed Review of Each of the Papers

Whale Swarm-Based Energy Efficient Routing (WSA)

The WSA approach applies the cooperative hunting patterns of whales such as spiral movement and bubble-net foraging to discover energy-efficient paths in the network. By modelling these behaviours, the protocol adapts well to changing topology, reduces frequent route updates, and effectively identifies low-energy transmission routes. Its strong global search ability makes it suitable for dense deployments, though it introduces higher computational overhead on resource-limited nodes. (Zeng, 2024)

Collaborative Energy-Efficient Routing for 5G/6G WSNs

This work develops a sustainable routing framework designed for WSNs operating within emerging 5G/6G ecosystems. The protocol focuses on coordinated energy distribution, low-latency communication, QoS maintenance, and seamless interaction with cellular infrastructures. Its primary contribution lies in extending traditional WSN routing techniques to meet next-generation performance and integration requirements. (Gururaj, 2023)

Energy-Efficient Routing Protocols Survey

This survey presents a detailed classification of routing families including flat, clustering, multipath, locationbased, and bio-inspired strategies and analyses their strengths, weaknesses, and energy implications. It provides foundational theory and comparative evaluation that later research builds upon when designing energy-aware routing mechanisms. (Behera, 2022)

Coyote Optimization with Fuzzy Logic (COA-Fuzzy)

The COA-Fuzzy method merges the adaptive, socially driven behaviour of coyote optimization with fuzzy-logicbased decision refinement. It evaluates factors such as residual energy, compactness, and node distance to produce a suitability score for CH selection. Its ability to handle uncertainty in dynamic environments is a major advantage, though it depends on carefully tuned membership functions. (Mohamed, 2020)

Multipath Clustering with Load Balancing (MCLB)

MCLB forms clusters and establishes multiple transmission paths to the base station to prevent energy holes and improve data reliability. By distributing traffic over several routes, the protocol enhances packet delivery and ensures more balanced energy consumption, making it suitable for high-rate sensing applications. (Saleem, 2023) **Hybrid Bio-Inspired Routing**

This hybrid framework combines swarm intelligence with evolutionary optimization to construct energyefficient routing structures. By using multi-criteria decision mechanisms, it aims to prolong network lifetime and create optimized routing trees that adapt to varying network conditions. (Bostani, 2025)

Optimized Engroove LEACH (MIHFO + HWAFO)

The Engroove-LEACH variant refines cluster-head selection using MIHFO, considering residual energy, neighbourhood distance, centrality, and BS proximity. HWAFO then selects routing paths by evaluating node degree and energy. This dual-stage approach significantly improves stability, throughput, and packet delivery compared to classical LEACH. (Meenakshi, 2024)

GA + K-means Energy-Aware Routing

This method first organizes nodes into clusters using K-means and subsequently applies a Genetic Algorithm to optimize the number and placement of CHs. By improving cluster compactness and reducing CH-to-BS distance, the protocol enhances energy efficiency and prolongs network lifetime. (Barekatain, 2015)

Centralized Energy-Efficient Clustering for Mobile Nodes

A centralized controller usually the base station selects cluster heads based on mobility patterns, remaining energy, and link stability. This global decision-making approach maintains long-term routing stability in networks where nodes frequently move, though it increases dependency on the BS. (Yan, 2019)

Multi-Criterion BGWO-Based Clustering

The BGWO method utilizes binary Grey Wolf Optimization to address CH selection as a multi-objective problem. It simultaneously maximizes CH energy, improves cluster compactness, controls the number of CHs, reduces energy cost between CHs and nodes, and enhances cluster separability. Results show marked improvements in stability, with gains reaching over 50%. (Pal, 2023)

Working Of Energy Efficient Routing Protocol Using Wsn

Energy-efficient routing in Wireless Sensor Networks (WSNs) follows a multi-stage operational pipeline. Although each of the ten reviewed papers introduces its own optimization mechanisms, the fundamental workflow across all protocols can be generalized into the following stages.

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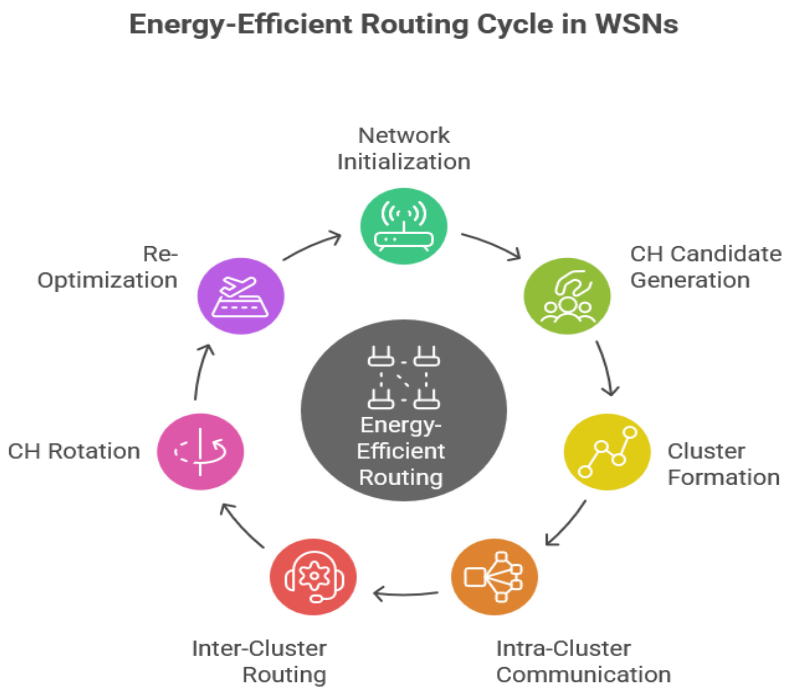
Network Initialization

In the initialization phase, each node determines:

- Its residual energy,
- Location (if GPS or anchor-based positioning exists),
- Neighbour list,
- Link quality with nearby nodes.

Several protocols (e.g., Engroove-LEACH (Meenakshi, 2024), BGWO clustering (Pal, 2023), COA-Fuzzy (Mohamed, 2020)) use this data to feed optimization algorithms for CH selection or route formation. Nodes also broadcast control packets to discover neighbours and estimate distances.

Figure 8: Energy efficient routing flow



Cluster-Head (CH) Candidate Generation

While classical LEACH uses probabilistic CH selection, modern routing approaches replace randomness with optimization-driven decision mechanisms. Swarm-based methods like Whale Swarm and Grey Wolf Optimizers (Zeng, 2024) (Pal, 2023), evolutionary models such as GA or hybrid bio-inspired techniques (Bostani, 2025) (Barekatain, 2015), and fuzzy-logic systems as in COA-Fuzzy (Mohamed, 2020) evaluate each node across multiple metrics including residual energy, connectivity, BS distance, compactness, centrality, and expected multi-hop cost. For instance, MIHFO in Engroove-LEACH integrates energy, neighbour density, and BS distance to produce reliable CH choices (Meenakshi, 2024), while BGWO generates Pareto-optimal CH placements balancing several conflicting objectives (Pal, 2023).

Cluster Formation

After CHs are identified, nodes join clusters based on signal strength, proximity, or CH energy levels. Some protocols use enhanced selection metrics, combining fuzzy rules or optimization scores to ensure well-balanced, compact clusters. GA + K-means routing achieves this by optimizing centroid placement for tighter grouping (Barekatain, 2015), whereas multipath load-balancing clustering organizes nodes around CHs that simultaneously support redundant routing structures (Saleem, 2023).

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Intra-Cluster Communication

Within each cluster, nodes communicate with their CH using scheduled TDMA slots to eliminate collisions. CHs aggregate the received data to reduce redundancy, lowering the cost of transmission toward the base station. Because this role demands both energy and processing strength, protocols such as COA-Fuzzy and BGWO enforce strict energy thresholds before allowing a node to become a CH (Mohamed, 2020) (Pal, 2023), ensuring that the computational overhead does not cause premature failures.

Inter-Cluster Routing / CH-to-BS Communication

This is where the reviewed protocols differ the most:

Single-Hop CH-to-BS Communication: Used in classic LEACH and inherited by some optimized variants, but energy-expensive for distant CHs.

Multi-Hop CH Routing: Protocols such as:

- Multipath load-balancing routing (Saleem, 2023),
- Engroove-LEACH HWAFO (Meenakshi, 2024),
- Hybridized global optimization routing (Bostani, 2025), • BGWO Pareto routing (Pal, 2023), prefer multi-hop routing because it lowers long-distance energy consumption.

Multipath Routing: Paper (Saleem, 2023) establishes multiple disjoint paths to the BS, enhancing:

- Energy balancing
- Fault tolerance
- Network lifetime

Swarm-Optimized Path Selection: The Whale Swarm algorithm (Zeng, 2024) and HWAFO in EngrooveLEACH (Meenakshi, 2024) dynamically compute optimal next-hop CHs using global search or heuristic scoring.

CH Rotation and Re-Optimization

Rotating CH responsibilities is necessary to prevent energy depletion at heavily used nodes. WSA recalculates

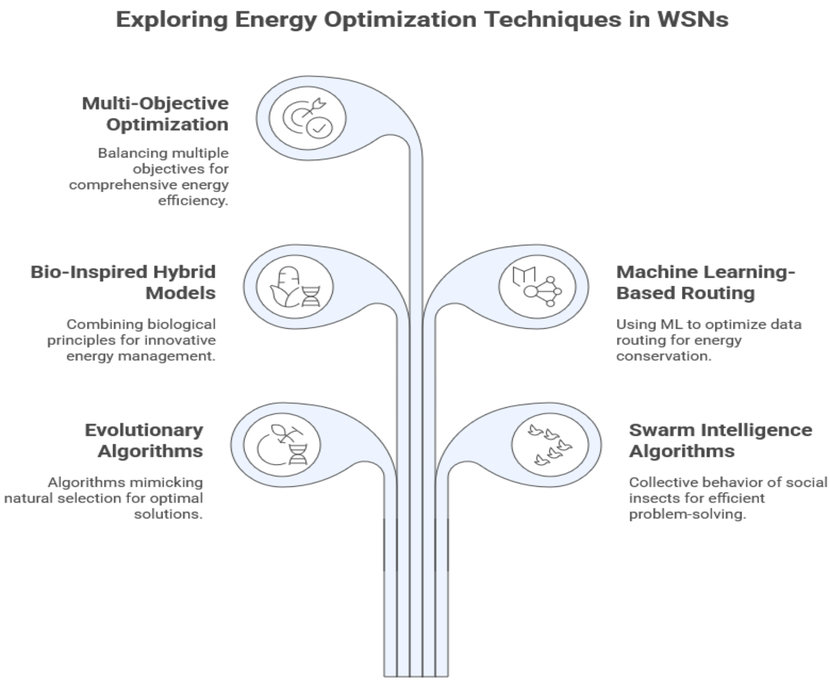
CHs upon reaching predefined energy thresholds (Zeng, 2024), COA-Fuzzy updates selection scores each round (Mohamed, 2020), and BGWO periodically regenerates Pareto-optimal CH configurations (Pal, 2023). In mobility-aware centralized systems, the base station reallocates CHs whenever node movement alters the topology (Yan, 2019). Rotation frequency therefore varies depending on the energy dynamics and routing design of each protocol.

Adaptive Features Across Protocols

Modern clustering and routing methods incorporate several adaptive intelligence elements. Centralized schemes integrate mobility support to maintain stable clusters in dynamic networks (Yan, 2019). Fuzzy-logic refinements manage uncertainty and noise in decision making (Mohamed, 2020). Multi-objective optimization frameworks such as BGWO handle several conflicting clustering requirements simultaneously (Pal, 2023). Hybrid evolutionary-swarm approaches found in both MIHFO-HWAFO designs and hybrid bio-inspired models enhance routing robustness under diverse network conditions (Bostani, 2025) (Meenakshi, 2024).

Energy Optimization Techniques

Figure 9: Exploring Energy Optimization Techniques



A. Evolutionary Algorithms

Evolutionary algorithms, such as Genetic Algorithm (GA)–based cluster formation, use crossover and mutation operators to evolve optimal Cluster Head (CH) configurations. These methods typically optimize fitness functions based on node energy, intra-cluster distance, and CH distribution. GA-based clustering appears explicitly in the energy-efficient GA + K-means routing model, where GA refines cluster centres and improves compactness (Barekatain, 2015). Survey literature also discusses evolutionary clustering approaches such as ERP and IHCR, both relying on GA-style chromosome representation and multi-parameter fitness evaluation (Behera, 2022).

B. Swarm Intelligence Algorithms

Swarm intelligence draws inspiration from collective animal behaviour. Techniques like Grey Wolf Optimizer (GWO), Whale Swarm Algorithm (WSA), and other swarm-based models are strongly represented in the reviewed papers. Whale Swarm-based routing uses spiral and bubble-net foraging patterns for route optimization (Zeng, 2024). Grey Wolf-based CH election through a multi-objective BGWO mechanism provides effective exploration and exploitation balance in clustering decisions (Pal, 2023). Hybrid swarm-based models in other studies also leverage swarm behaviour for routing stabilization (Bostani, 2025).

C. Bio-Inspired Hybrid Models

Hybrid models combine multiple bio-inspired mechanisms to enhance optimization performance. EngrooveLEACH integrates MIHFO for CH selection and HWAFO for routing, combining heuristic swarm behaviour with harmonic optimization elements (Meenakshi, 2024). Similarly, hybridized bio-inspired routing schemes use blended evolutionary–swarm strategies to improve convergence rates and energy balancing in dense deployments (Bostani, 2025). Coyote Optimization paired with fuzzy logic is another hybrid system integrating social adaptation dynamics with uncertainty reasoning (Mohamed, 2020).

D. Machine Learning-Based Routing

Among the 10 papers, fuzzy logic appears prominently as a machine-learning-based decision module. COAFuzzy integrates fuzzy rules to evaluate CH suitability using parameters like residual energy, compactness, and BS distance, thus handling uncertainty in node states (Mohamed, 2020). Engroove-LEACH also uses

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fuzzyinfluenced parameters in multi-criteria decision models during CH selection and routing (Meenakshi, 2024). Although none of the reviewed studies explicitly implement reinforcement learning (RL), fuzzy logic constitutes the machine-learning component evidenced in the dataset.

E. Multi-Objective Optimization

Multi-objective optimization handles conflicting goals such as minimizing energy consumption while maximizing stability and cluster separation. The most explicit multi-objective model in the dataset is the BGWO protocol, which optimizes five simultaneous objectives including CH energy, cluster compactness, and separation (Pal, 2023). Survey literature also highlights multi-objective evolutionary algorithms used in earlier routing protocols, noting the role of Pareto-optimality in balancing trade-offs (Behera, 2022). Hybrid metaheuristic models in (Bostani, 2025) also evaluate multiple criteria when forming optimized routes.

Taxonomy Of Energy-Efficient Routing in Wireless Sensor Networks

Based on a detailed synthesis of the selected literature, this review proposes a novel taxonomy that classifies energy-efficient routing protocols in WSNs according to optimization strategy, routing architecture, and intelligence level. Unlike generic classifications, the proposed taxonomy explicitly links algorithmic design choices with routing behaviour and energy-performance trade-offs, enabling clearer comparison across heterogeneous approaches (Zeng, 2024) (Behera, 2022) (Mohamed, 2020) (Bostani, 2025) (Pal, 2023).

Classification Based on Optimization Strategy

Energy-efficient routing protocols can be broadly categorized according to the optimization mechanism employed for cluster-head selection and route formation.

Evolutionary-Based Optimization: Approaches such as Genetic Algorithm (GA) and Binary Grey Wolf Optimization (BGWO) evolve candidate solutions using population-based search and fitness evaluation, enabling multi-objective optimization of energy, distance, and cluster compactness (Barekatain, 2015) (Pal, 2023).

Swarm-Based Optimization: Whale Swarm Algorithm (WSA), Grey Wolf Optimizer (GWO), and Coyote Optimization Algorithm (COA) exploit collective behaviour and social interaction models to achieve global search capability and adaptive routing decisions (Zeng, 2024) (Mohamed, 2020) (Pal, 2023).

Hybrid Optimization Techniques: Hybrid models combine complementary optimization paradigms, such as MIHFO–HWAFO or COA integrated with fuzzy logic, to balance exploration, exploitation, and decision uncertainty (Mohamed, 2020) (Bostani, 2025) (Meenakshi, 2024).

Centralized Optimization: Centralized routing schemes delegate optimization decisions to the base station, enabling global energy-aware clustering and routing, particularly in mobility-aware WSN environments (Yan, 2019).

Classification Based on Routing Architecture

From a routing perspective, protocols are further classified as single-hop, multi-hop, or multipath routing schemes. Single-hop approaches prioritize simplicity but suffer from high transmission costs in large networks (Barekatain, 2015). Multi-hop routing reduces long-distance energy consumption and improves scalability (Zeng, 2024) (Saleem, 2023), while multipath routing enhances reliability and load balancing at the expense of increased control overhead (Saleem, 2023). Centralized and distributed routing decisions represent an additional architectural dimension (Yan, 2019).

Classification Based on Intelligence Level

Based on decision-making complexity, routing protocols may be categorized as heuristic-based, metaheuristicbased, fuzzy or machine-learning-assisted, or hybrid intelligent routing systems. Recent trends indicate a shift toward hybrid intelligent models that integrate optimization and learning mechanisms to improve adaptability under dynamic network conditions (Mohamed, 2020) (Bostani, 2025) (Meenakshi, 2024) (Pal, 2023).

Comparative Analysis

To properly compare the ten routing protocols, we evaluate them on:

1. Routing type
2. Optimization engine
3. CH selection method
4. Energy-saving techniques
5. Strengths/weaknesses
6. Performance improvements reported

Comparative analysis of energy-efficient routing protocols in WSNs involves evaluating how different algorithms balance energy consumption, scalability, reliability, and routing efficiency under similar network conditions. Each protocol emphasizes different optimization priorities such as swarm-based global search (Zeng, 2024) (Pal, 2023), collaborative communication models (Gururaj, 2023), or clustering efficiency through evolutionary refinement (Barekatain, 2015). LEACH-based enhancements such as Engroove-LEACH focus on stability and uniform energy distribution (Meenakshi, 2024), whereas multipath schemes prioritize load balancing and reliability under high traffic (Saleem, 2023). Hybrid bio- inspired strategies combine multiple heuristic behaviours to achieve stronger convergence and adaptability in heterogeneous environments (Mohamed, 2020) (Bostani, 2025).

Centralized routing approaches offer globally optimized cluster management but introduce dependency on the base station and reduced scalability (Yan, 2019). Survey literature provides a foundation for comparing these approaches by identifying the strengths and weaknesses of clustering, multipath, location-based, and bio-inspired categories (Behera, 2022). Overall, the comparative framework examines metrics such as network lifetime, residual energy, cluster stability, packet delivery rate, throughput, and routing overhead to determine how each algorithm performs across diverse scenarios. This reveals that while meta-heuristic and multi-objective approaches typically achieve the best energy efficiency and stability (Meenakshi, 2024) (Pal, 2023)their computational complexity and parameter sensitivity remain trade-offs compared to simpler but less efficient traditional clustering models.

Table 1: Optimization Criteria Across Protocols

Criteria	**Papers Using It**
Residual Energy	(Zeng, 2024) (Mohamed, 2020) (Meenakshi, 2024) (Pal, 2023)
Distance to BS	(Mohamed, 2020) (Meenakshi, 2024) (Barekatain, 2015) (Pal, 2023)
Node Degree	(Meenakshi, 2024) (Pal, 2023)

Table 2: High level comparison

Protocol / Paper	**Method Type**	**Optimization Engine**	**Key Features**	**Strengths**	**Weaknesses**
Whale Swarm Routing (Zeng, 2024)	Swarmbased	Whale Swarm Algorithm	Spiral search, energy-aware routing	Strong global search	Computationally heavy
5G/6G Collaborative Routing (Gururaj, 2023)	Cross-layer	Collaborative optimization	Supports nextgen networks	High QoS	Requires 5G/6G infra

Survey of Routing Protocols (Behera, 2022)	Review	—	Classification, architectures	Broad overview	No new protocol
COA + Fuzzy (Mohamed, 2020)	Hybrid	Coyote + Fuzzy Logic	Multi-criteria CH scoring	Handles uncertainty	Tuning complexity
Multipath LB Clustering (Saleem, 2023)	Multipath	Cluster load balancing	Redundant routes	High reliability	More overhead
Hybrid BioInspired Routing (Bostani, 2025)	Hybrid	Swarm + EVO	Global/local optimization	Strong exploration	Complex design
Engroove-LEACH (MIHFOHWAFO) (Meenakshi, 2024)	LEACH-based	MIHFO + HWAFO	Passive clustering, heuristic pathing	Very high lifetime	Complex optimization
GA + K-means Routing (Barekatain, 2015)	Evolutionary	Genetic Algorithm	Compact clusters	Good balance	Slower convergence
Centralized Mobile Routing (Yan, 2019)	Centralized	Mobility prediction	Stable under mobility	Well optimized	Single-point failure
Binary Grey Wolf Optimization (Pal, 2023)	Multiobjective	BGWO	5 objective functions	Best stability period	Binary mapping cost

Table 3: Performance Metrics and Performance Summary

Ref	**Protocol / Method**	**Key Metrics Reported**	**Performance Summary**
(Zeng, 2024)	Whale Swarm Routing	Lifetime, Energy	Improved lifetime; lower routing energy
(Gururaj, 2023)	5G/6G Collaborative Routing	Lifetime, PDR, Throughput	Enhanced PDR and throughput; higher stability
(Behera, 2022)	Survey Study	—	No experimental performance results
(Mohamed, 2020)	COA + Fuzzy Logic	Lifetime, Energy	Reduced CH energy waste; longer lifetime
(Saleem, 2023)	Multipath LoadBalancing	Lifetime, Energy, PDR, Throughput	High reliability; balanced load; better delivery
(Bostani, 2025)	Hybrid Bio-Inspired Routing	Lifetime	Noticeable lifetime gain; qualitative improvement
(Meenakshi, 2024)	Engroove-LEACH (MIHFO + HWAFO)	Lifetime, Energy, PDR, Throughput	Strong gains across all metrics; best overall
(Barekatain, 2015)	GA + K-means Routing	Lifetime, Energy	Improved cluster efficiency; reduced intra-cluster energy

(Yan, 2019)	Centralized MobilityAware Routing	Lifetime, PDR	Higher delivery in mobile scenarios; improved stability
(Pal, 2023)	BGWO Multi-Criterion Clustering	Lifetime, Energy	Significant stability increase; efficient CH distribution

Cluster Compactness	(Saleem, 2023) (Barekatain, 2015) (Pal, 2023)
Multi-objective Optimization	(Bostani, 2025) (Pal, 2023)
Fuzzy Logic Inputs	(Mohamed, 2020)
Mobility Metrics	(Yan, 2019)

Mathematical Models and Key Equations

Energy and optimization equations form the backbone of most protocols.

Radio Energy Model (Used in Most Papers)

Transmit energy:

$$E_{tx}(L,d) = \begin{cases} L(E_{elec} + {}_{fs}d^2), & d < d_0 \\ L(E_{elec} + {}_{mp}d^4), & d \geq d_0 \end{cases} \tag{1}$$

where,

$E_{tx}(L,d)$ →Energy needed to transmit an L-bit packet over distance d.

L → Packet size in bits.

d → Distance between sender and receiver.

E_{elec}→ Energy used by the radio electronics for each bit.

${}_{fs}$ → Power amplifier constant for free-space channel (used when distance is small).

${}_{mp}$ → Power amplifier constant for multipath channel (used when distance is large).

d_0 → Threshold distance that decides whether the model uses d^2 (free-space) or d^4 (multipath).

Receive energy:

$$E_{rx}(L) = LE_{elec} \tag{2}$$

where,

$E_{rx}(L)$ → Energy needed to receive an L-bit packet.

L → Packet size in bits.

E_{elec} → Energy used by the radio electronics for each bit.

Used explicitly/implicitly in (Zeng, 2024) (Mohamed, 2020) (Saleem, 2023) (Meenakshi, 2024) (Pal, 2023).

Leach Threshold Function

$$T(n) = \begin{cases} \frac{p}{1-p(r \bmod \frac{1}{p})}, & n \in G \\ 0, & n \notin G \end{cases} \quad (3)$$

where,

$T(n)$ → Threshold value used to decide if node *n* becomes a cluster head.

p → Desired percentage of nodes that should become cluster heads in each round.

r → Current round number.

G → Set of nodes that are eligible to become cluster heads in the current round (i.e., nodes that have not been CH recently).

$n \in G$ → Node n is eligible, so the threshold formula applies.

$n \notin G$ → Node n is not eligible, so threshold is 0 (cannot become CH).

Extended by Engroove-LEACH (Meenakshi, 2024) and GA/K-means (Barekatain, 2015)

Multi objective Optimization Objective (Generalized Form)

$$\min J = \alpha E_{total} + \beta \sigma(E_{nodes}) + \gamma D_{avg} - \delta PDR \quad (4)$$

where, min J → The objective function that the algorithm tries to minimize. E_{total} → Total energy consumption of the entire network.

$\sigma(E_{nodes})$ → Standard deviation of node energies (used to measure energy balance).

D_{avg} → Average end-to-end delay in the network.

PDR→ Packet Delivery Ratio (higher is better, so it is subtracted). α, β, γ, δ → Weighting coefficients that control the importance of each term.
Various papers optimize subsets of these terms:

1. CH compactness (BGWO (Pal, 2023))
2. Residual energy maximization (COA-Fuzzy (Mohamed, 2020), Engroove-LEACH (Meenakshi, 2024))
3. Routing cost minimization (WSA (Zeng, 2024), multipath (Saleem, 2023))

BGWO Binary Encoding

BGWO maps real-valued wolf positions to binary CH selection:

$$X_i = \begin{cases} 1 & \text{if } S(X_i) > rand() \\ 0 & \text{otherwise} \end{cases} \quad (5)$$

where,

X_i→ The decision value for node *i* (usually 1 = selected, 0 = not selected).

$S(X_i)$→ The selection probability or score assigned to node *i*.

$rand()$→ A random number between 0 and 1.

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Where S() is a sigmoid function (Pal, 2023).

Fuzzy Logic Output Function

A fuzzy rule-based scoring function (COA-Fuzzy (Mohamed, 2020)):

$$Score(n) = f(E_r, D_{BS}, Deg(n)) \tag{6}$$

where,

$Score(n)$ → The overall suitability score of node *n* for selection (e.g., as a cluster head).

E_r → Residual (remaining) energy of node *n*.

D_{BS} → Distance of node *n* from the base station.

$Deg(n)$ → Degree of node *n*, meaning the number of neighbouring nodes it can communicate with.

$f\,()$ → A function that combines these parameters to compute the score.

Where membership functions determine CH suitability.

Meta Analysis

Meta-Analysis Using Unified Performance Metrics

Due to significant variations in simulation platforms, network sizes, node deployment strategies, radio models, and parameter configurations across the reviewed studies, direct numerical comparison of reported results is often impractical and may lead to misleading conclusions. Many protocols are evaluated under protocol-specific assumptions, making absolute performance values non-transferable across different experimental setups. To address this challenge, this review adopts a qualitative normalization-based meta-analysis approach, which enables meaningful cross-study comparison using commonly reported performance trends rather than absolute numerical values (Zeng, 2024) (Behera, 2022) (Saleem, 2023) (Meenakshi, 2024) (Pal, 2023).

The qualitative normalization process categorizes protocol performance into relative levels such as *low*, *medium*, *high*, and *very high*, based on consistent improvements reported with respect to baseline protocols in each study. This approach is widely accepted in systematic surveys where heterogeneous evaluation conditions prevent direct quantitative aggregation. By focusing on relative performance behaviour, the meta-analysis highlights comparative strengths, limitations, and trade-offs among routing strategies.

The unified performance metrics considered in this analysis include network lifetime, typically expressed through *First Node Death (FND)* and *Half Node Death (HND)* indicators, which reflect both early-stage stability and long-term network sustainability. Residual energy distribution is examined to assess energy balance and fairness across sensor nodes. Packet Delivery Ratio (PDR) and throughput are used to evaluate communication reliability and data transmission efficiency. Additionally, control overhead is considered to capture the cost of routing maintenance and signaling, while computational complexity reflects the feasibility of deploying optimization-based protocols on resource-constrained sensor nodes.

Collectively, these metrics provide a holistic evaluation framework that captures both energy efficiency and communication performance, enabling structured comparison of diverse routing protocols despite heterogeneous experimental conditions. The resulting meta-analysis supports analytical synthesis by revealing performance patterns and design trade-offs across optimization-driven energy-efficient routing approaches in Wireless Sensor Networks (Zeng, 2024) (Behera, 2022) (Saleem, 2023) (Meenakshi, 2024) (Pal, 2023).

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Conceptual Framework

Proposed Unified Evaluation Framework

The proposed unified evaluation framework is designed to provide a structured and holistic perspective for analysing energy-efficient routing protocols in Wireless Sensor Networks (WSNs). Existing studies often evaluate routing algorithms using isolated performance metrics or protocol-specific assumptions, which makes cross-comparison difficult and limits the generalizability of results. To address this limitation, the proposed framework integrates network parameters, optimization mechanisms, routing decisions, and performance evaluation into a single analytical pipeline (Behera, 2022) (Sheeja, 2023).

At the initial stage, the framework considers network parameters such as node density, residual energy distribution, communication range, mobility patterns, and traffic load. These parameters directly influence clustering behaviour, routing feasibility, and overall energy consumption in WSN deployments. The optimization engine forms the core of the framework, where evolutionary algorithms, swarm-intelligence techniques, fuzzylogic systems, or hybrid optimization models process network information to generate energy-aware decisions.

Based on the output of the optimization engine, the framework performs cluster-head (CH) selection by evaluating multiple criteria including residual energy, node centrality, distance to the base station, and neighbourhood connectivity. This multi-criteria CH selection ensures balanced energy dissipation and prevents premature node failures. Subsequently, the routing strategy component determines efficient data forwarding paths, which may follow single-hop, multi-hop, multipath, centralized, or distributed routing architectures depending on the optimization objectives and network conditions.

Finally, the performance evaluation layer assesses the effectiveness of the routing protocol using standardized metrics such as network lifetime, residual energy balance, packet delivery ratio (PDR), throughput, control overhead, and computational complexity. By applying consistent evaluation criteria, the framework enables fair and systematic comparison of diverse energy-efficient routing protocols.

Overall, the proposed unified evaluation framework serves as a conceptual bridge between algorithm design and performance assessment, facilitating analytical comparison, identifying trade-offs, and supporting the development of scalable and adaptive routing solutions for next-generation WSNs (Behera, 2022) (Sheeja, 2023).

DISCUSSION AND SYNTHESIS

Research on Wireless Sensor Network (WSN) routing has been trending away from static, rule-based methods and towards more intelligent, adaptive, hybridized approaches. Traditional clustering-based methods, such as LEACH or HEED, while simple, do not dynamically respond to changes in energy state, node density or link breakage, in the new environment. Bio-inspired metaheuristics, such as Whale Swarm, Grey Wolf, and Harmony Search algorithms, permit far more extensive exploration of the solution space with the potential for a more balanced energy consumption and an extended network lifetime. Though swarm-based methods may reach a premature convergence if the "fitness" diversity of the population are neglected, hybrid modelling, while much more effective, will increase computational burden. A simplistic contrast is the MHSA–CSO model that combines exploration and exploitation towards stabilizing convergence, thereby integrating more processing cost than would be present in an exploitative method alone. Reinforcement learning is also an example of a metaalgorithm, used in the CEERP study, to learn from feedback, but scaling the reward role, monitoring and management that is required for the nodes obfuscated. In all, evidence from the ten studies suggests hybrid intelligences, combining bio-inspired optimization and machine learning, maybe the most beneficial solution proposals for improved energy. Design tendencies for the future may be more challenging with regards to distributed routing as they consider collect and context to inform routing decisions leading to more localized connectivity actualizing a reduction of centralized control which may prove beneficial for a largescale deployment resilient system overall.

Contradictions in Existing Research

Despite significant progress in energy-efficient routing design, the reviewed literature reveals several inherent contradictions and trade-offs that remain unresolved. Centralized routing mechanisms consistently demonstrate improved cluster stability and more globally optimized routing decisions by leveraging complete network information; however, this advantage is accompanied by reduced scalability, increased signaling overhead, and strong dependency on the base station, which may act as a single point of failure in large-scale or mission-critical deployments (Yan, 2019).

Similarly, multipath routing strategies are widely reported to enhance packet delivery reliability and fault tolerance by distributing traffic across multiple paths. While this improves robustness under node failures and high traffic conditions, it also leads to increased control overhead, route maintenance complexity, and additional energy consumption associated with managing multiple routing paths (Saleem, 2023). As a result, the gains in reliability are often offset by higher routing complexity and coordination costs.

Swarm-based and bio-inspired optimization algorithms, such as Whale Swarm, Grey Wolf, and Coyote Optimization, consistently outperform traditional clustering approaches in terms of network lifetime extension and energy balancing. However, these algorithms require iterative population-based computation, fitness evaluation, and convergence control, which introduces significant computational overhead. This limits their direct applicability in real-time or resource-constrained sensor nodes, particularly in large-scale deployments where processing and memory resources are limited (Zeng, 2024) (Mohamed, 2020) (Pal, 2023). These contradictions highlight the need for balanced design strategies that consider both optimization benefits and practical deployment constraints.

Identified Research Gaps

In addition to the observed contradictions, several critical research gaps are evident across the reviewed studies. One major limitation is the absence of standardized benchmark datasets and evaluation frameworks, which hinders fair and reproducible comparison of energy-efficient routing protocols across different research works (Behera, 2022). Most studies rely on custom simulation settings, making cross-study validation challenging.

Another notable gap is the limited validation on real sensor hardware platforms. The majority of the reviewed protocols are evaluated exclusively through simulation environments, without accounting for real-world constraints such as hardware limitations, environmental interference, and unpredictable node behaviour (Meenakshi, 2024). This raises concerns regarding the practical feasibility of deploying complex optimizationbased routing algorithms.

Furthermore, security-aware energy-efficient routing remains largely unexplored. While energy optimization is extensively studied, few protocols integrate trust management, intrusion detection, or secure communication mechanisms into routing decisions, leaving WSNs vulnerable to malicious attacks and data compromise (Gururaj, 2023). Additionally, most optimization-based routing schemes rely on static or manually tuned parameters, lacking autonomous self-tuning or learning-based adaptation mechanisms that can respond dynamically to changing network conditions (Bostani, 2025).

Finally, there is insufficient consideration of cross-layer optimization, where interactions between the physical, MAC, and network layers could be jointly optimized to improve overall energy efficiency and quality of service. Existing approaches often focus solely on the network layer, missing opportunities for holistic performance enhancement through coordinated multi-layer design (Behera, 2022) (Saleem, 2023).

Limitations And Challenges

Although modem energy attuned routing schemes have come a long way, they are still limited on several fronts:

1. Simulated Validation: Most of the reviewed algorithms are evaluated only through simulation environments (MATLAB, NS2, or custom simulators), without real-world interference, environmental variability, or

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hardware constraints. This limitation is noted in survey analyses and individual optimization-based studies where results are purely simulation-driven (Behera, 2022) (Meenakshi, 2024) (Pal, 2023).

2. Hardware Limitations: Metaheuristic methods such as Whale Swarm, Coyote Optimization, and BGWO demand iterative computations that exceed the processing capability of low-power sensor nodes, making direct hardware deployment difficult (Zeng, 2024) (Mohamed, 2020) (Pal, 2023). Hybrid models also imply complexity unsuitable for constrained nodes (Bostani, 2025) (Meenakshi, 2024).

3. Scalability Constraints: Several protocols report performance degradation as network size grows, primarily due to increasing control overhead, synchronization cost, and CH communication load. This issue is highlighted in clustering-based routing and hybrid optimization algorithms that rely on dense network simulations (Saleem, 2023) (Meenakshi, 2024) (Pal, 2023).

4. Parameter Tuning Requirements: Many bio-inspired algorithms depend on manually tuned parameters (such as swarm coefficients, evolutionary rates, fuzzy membership values). Improper tuning often leads to premature convergence or suboptimal CH selection, as discussed in hybrid swarm–fuzzy and evolutionary optimization studies (Mohamed, 2020) (Bostani, 2025) (Pal, 2023).

5. QoS and Security Limitations: Only a few works consider metrics beyond energy and lifetime. QoS-related concerns such as latency, packet integrity, link trustworthiness, and security overhead are rarely analysed in depth; even advanced frameworks such as collaborative routing for 5G/6G networks emphasize energy but not full-stack QoS or security integration (Gururaj, 2023) (Behera, 2022).

6. Environmental Uniformity Assumptions: Many algorithms—particularly LEACH enhancements and clustering-based models—assume uniform node deployment, ideal signal propagation, or equal initial energy distributions, which do not reflect heterogeneous or harsh real-world conditions (Behera, 2022) (Meenakshi, 2024) (Barekatain, 2015) (Pal, 2023).

Future Research Directions

To overcome present limitations and develop sustainable WSN, future research should focus on:

1. Energy Harvesting - Distributed or combined solar, thermal, or vibration-dynamics harvesting methods and routing of these harvesting methods dependent on some factors of harvesting.

2. Edge and TinyML Intelligence: Light-weight reinforcement or fuzzy learning models run on the sensor devices themselves, lessening reliance on centralization.

3. Secure and Trust-Aware Routing: Energy optimization integrated with blockchain or trust-management processes to mitigate against malicious nodes while providing reliable packet delivery

4. Cross-layer Multi-objective Optimization: Consideration of cross-layer optimization of the MAC scheduling and network layer provide better trade-offs between energy, delay, and latency.

5. Standard Benchmarks: Developing an open-access testbed and standardized datasets to compare performance of the algorithms under consistent conditions.

6. 6G and IoT convergence: In a post 5G world with ultra-low latency communication, reconfigurable surfaces, and intelligent antennas, we can use from next generation networks for routing adaptability.

CONCLUSION

Energy-efficient routing continues to serve as the foundational requirement for achieving long-term sustainability in Wireless Sensor Networks, particularly in environments where battery replacement is impractical or impossible. The collective insights from the ten reviewed studies reveal a clear paradigm shift in routing research: modern WSNs increasingly depend on intelligent, adaptive, and optimization-driven strategies that go far beyond traditional deterministic protocols. Techniques such as swarm intelligence, fuzzy-logic supported clustering, evolutionary multi-objective optimization, and hybrid metaheuristic routing demonstrate that significant gains in energy conservation, network stability, and load distribution are achievable when computational intelligence is embedded directly into the routing workflow.

Across the literature, hybrid models consistently outperform single-method algorithms by leveraging complementary strengths for instance, combining global search capabilities of evolutionary algorithms with the fast local convergence of clustering heuristics, or integrating fuzzy decision layers with bio-inspired selection mechanisms. These approaches collectively mitigate classical problems such as premature node death, imbalanced energy consumption, random CH selection, and high control overhead. The reviewed methods also illustrate growing interest in context-aware and mobility-supportive routing, acknowledging that future WSN deployments will operate in dynamic, heterogeneous, and large-scale environments that demand algorithms capable of continuous adaptation.

Despite these advancements, several challenges remain open. Many algorithms suffer from high computational complexity, sensitive parameter tuning, limited scalability, or reduced performance under unpredictable network dynamics. Others require excessive control messaging or assume idealized node distributions that rarely reflect real-world deployments. These limitations highlight the need for algorithms that can autonomously learn network behaviour, self-adjust parameters, and operate efficiently at scale without relying heavily on centralized control. Additionally, the increasing integration of WSNs with IoT, 5G/6G infrastructures, and intelligent edge devices creates new opportunities for collaborative routing, cross-layer optimization, and real-time decision making.

Overall, the review underscores that while significant progress has been made, the pursuit of a universally optimal routing framework remains open. The path forward lies in synergistic algorithm design approaches that merge metaheuristics, machine intelligence, distributed decision-making, and lightweight modelling to create routing protocols that are not only energy-aware but also autonomous, scalable, secure, and context-responsive. Future research must therefore continue to refine hybrid strategies, develop adaptive learning-based mechanisms, and explore optimization frameworks that maintain performance even under extreme uncertainty. As WSNs move toward more complex and mission-critical roles, the evolution of energy-efficient routing will remain central to ensuring robustness, longevity, and practical deploy ability of next-generation sensor networks.

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