



REVIEW

Energy-Efficient Optimization in Wireless Sensor Networks: A Systematic Review of Metaheuristic and AI-Based Approaches, Taxonomy, and Research Gaps

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ABSTRACT: Wireless Sensor Networks (WSNs) remain constrained by limited battery capacity, which restricts their operational lifetime in Internet of Things (IoT) applications. We present a PRISMA 2020-guided systematic review of 89 primary studies published during 2016–2026, focusing on metaheuristic, hybrid, and Artificial Intelligence (AI)-based methods for energy-efficient clustering and routing. A five-database search strategy yielded 876 records, followed by duplicate removal, title/abstract screening, full-text eligibility assessment, and structured quality appraisal. The synthesis indicates that Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) remain the most frequently studied individual algorithms, each appearing in 23.6% of the 89 reviewed studies (SI as a family accounts for 33.7% of all studies), whereas recent work increasingly emphasizes hybrid optimization and learning-based adaptive routing. Among the reviewed studies, Deep Reinforcement Learning with Graph Neural Networks (DRL-GNN) reports up to 4100 operational rounds compared with 1200 rounds for the Low-Energy Adaptive Clustering Hierarchy (LEACH) under reported simulation settings. However, these comparisons should be interpreted cautiously because the benchmark relies on cross-study normalization across heterogeneous simulation assumptions, hardware settings, and reporting practices, and most primary studies do not provide variance estimates, confidence intervals, or effect-size analyses. The evidence base also remains predominantly simulation-driven, which limits direct inference about real-world deployment performance. Within these constraints, the review contributes an integrated taxonomy spanning classical, hybrid, and AI-driven approaches, a harmonized comparative benchmark across widely reported WSN performance metrics, a domain-oriented analysis of application trends, and a structured discussion of research gaps related to security, scalability, hardware feasibility, and deployment realism.

KEYWORDS: Wireless sensor networks; energy-efficient routing; clustering; metaheuristic optimization; artificial intelligence; deep reinforcement learning; Internet of Things; PRISMA 2020

1 Introduction

1.1 The WSN Energy Crisis: Scale and Consequence

A Wireless Sensor Network (WSN) is a distributed set of sensor nodes that acquire, process, and forward data through wireless multi-hop communication. WSNs remain a fundamental component of Internet of

Things (IoT) infrastructures in precision agriculture, industrial monitoring, environmental surveillance, emergency response, and healthcare [1–5]. Their continued relevance in these domains is closely tied to the ability to maintain sensing coverage and reliable communication under severe node-level energy constraints.

The main operational limitation of WSNs is that most sensor nodes rely on finite battery reserves. In many deployments, including remote monitoring, implanted biomedical devices, and hazardous industrial sites, battery replacement is costly or impractical [6–8]. As a result, network lifetime depends strongly on how efficiently nodes perform sensing, computation, and especially communication. When node energy is depleted, the consequences include coverage loss, reduced routing redundancy, and in some cases network partitioning.

The implications of energy inefficiency depend on the application context. In healthcare and industrial monitoring, premature node failure can interrupt latency-sensitive telemetry and reduce system reliability [1,9,10]. In environmental sensing and precision agriculture, the same problem may appear as reduced spatial coverage, delayed event detection, or shorter maintenance intervals. For this reason, energy optimization in WSNs should be treated as a deployment-level design requirement rather than only as an algorithmic performance objective.

1.2 Technical Root Causes of Energy Inefficiency

The difficulty of WSN energy optimization is rooted in the dominant cost of wireless communication relative to sensing and local processing. Under the first-order radio energy model of Heinzelman et al. [7], transmission energy scales with d^2 in the free-space regime and with d^4 in the multi-path regime. This non-linearity makes routing and transmission-distance control central to lifetime optimization.

This scaling behavior produces two well-known imbalances. First, long-range transmissions impose disproportionately high costs on nodes that communicate over large distances. Second, nodes close to the Base Station (BS) often relay traffic for many other nodes and therefore deplete their energy earlier than the rest of the network. This near-sink depletion pattern is commonly referred to as the *energy hole problem* [11–13].

Hierarchical clustering was introduced to reduce this burden by limiting most transmissions to short intra-cluster communication. In clustered WSNs, ordinary nodes send data to a Cluster Head (CH), which aggregates traffic and forwards it to the BS or to an intermediate relay. Although clustering reduces local transmission cost, it introduces a coupled optimization problem involving CH selection, CH rotation, cluster formation, and inter-cluster routing [6,14–16].

The resulting search space is combinatorial and, in practice, computationally intractable for exact optimization in non-trivial networks. The problem is further complicated by time-varying residual energy, topology changes, traffic dynamics, and multiple competing objectives. A practical protocol must balance energy dissipation, network lifetime, packet delivery, load distribution, and in some cases latency or security constraints [13,15,17,18].

Heterogeneous WSNs add another level of complexity because nodes may differ in initial energy, processing capability, communication range, and hardware tier. Under these conditions, static role assignment is rarely adequate, and energy-aware decisions must be updated as node states evolve [13,18,19]. In addition, routing performance depends on cross-layer interactions among Media Access Control (MAC) scheduling, data aggregation, and communication overhead, which explains the growing interest in multi-objective and cross-layer optimization strategies.

1.3 The Evolution of Optimization Paradigms

WSN energy optimization research began with baseline clustering and routing protocols such as the Low-Energy Adaptive Clustering Hierarchy (LEACH) [7], the Hybrid Energy-Efficient Distributed clustering (HEED) [6], and the Power-Efficient Gathering in Sensor Information Systems (PEGASIS). These protocols introduced probabilistic or heuristic mechanisms for rotating CH responsibilities, but they were designed primarily for homogeneous settings and offered limited control over global energy balance. Metaheuristic optimization was adopted next, with Swarm Intelligence (SI) methods such as Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), and Artificial Bee Colony (ABC), as well as Evolutionary Algorithms (EAs) such as the Genetic Algorithm (GA) [17,18,20–22]. These methods can explore large, non-convex search spaces without requiring exact analytical formulations. Their reported gains are often sensitive to parameter tuning, population size, topology assumptions, and simulation settings.

More recently, Artificial Intelligence (AI) methods, including Machine Learning (ML), Deep Learning (DL), Reinforcement Learning (RL), and Deep Reinforcement Learning (DRL), have been applied to routing, clustering, and prediction tasks [23–26]. In this review, AI is used as the broad umbrella term, ML denotes data-driven models learned from network observations, DL refers to multi-layer neural models, RL denotes reward-driven sequential decision methods, and DRL refers to RL methods implemented with deep neural networks. Graph Neural Networks (GNNs) constitute a DL architecture designed for graph-structured data and are therefore relevant to WSN topology modeling. Within the reviewed studies, DRL-GNN-based routing reports some of the highest lifetime values under the corresponding simulation conditions. These results are derived from heterogeneous studies and should be interpreted in light of differing assumptions, incomplete statistical reporting, and limited hardware validation. Hybrid AI–metaheuristic approaches have also emerged as an intermediate class that combines global search capability with adaptive decision-making while moderating computational cost.

1.4 Limitations of Existing Reviews and the Justification for This Work

The rapid expansion of the WSN optimization literature has not been matched by an equivalent level of methodological consistency in review articles. Examination of prior surveys indicates four recurring limitations that motivate the present study.

First, many reviews are taxonomically narrow. Some surveys focus on classical metaheuristics such as ACO and PSO but do not cover recent hybrid, RL, or DL-based approaches in sufficient depth [15,27]. Other recent reviews focus mainly on ML-oriented methods and treat metaheuristics primarily as historical context, which limits comparative understanding of hybrid AI–metaheuristic strategies [4,5].

Second, prior reviews rarely provide a structured quantitative benchmark. Many studies summarize reported improvements qualitatively, but without a consistent comparison framework it is difficult to separate algorithmic effects from differences in network size, radio parameters, traffic assumptions, or baseline selection. A normalized benchmark can improve comparability, although it cannot eliminate the underlying heterogeneity of the primary studies.

Third, relatively few reviews use a transparent systematic selection protocol. In the absence of a reproducible search and screening process, narrative surveys remain vulnerable to selective citation and incomplete coverage. A PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses)-guided workflow improves transparency by documenting identification, screening, eligibility assessment, and quality appraisal steps [2,5].

Fourth, research-gap analysis is often brief and insufficiently critical. Issues such as the low representation of security-aware optimization, the dependence on simulation-based evidence, and the mismatch between

algorithmic complexity and practical hardware constraints are often mentioned but not analyzed in a structured manner. In particular, security-aware routing remains represented in less than 1% of the reviewed studies, and the gap between simulation-based claims and physically validated deployment evidence remains substantial.

Against this background, the present review synthesizes 89 primary studies spanning 2016–2026 using a PRISMA 2020-guided methodology. The aim is to provide an integrated taxonomy, a cautiously interpreted comparative benchmark, and a structured discussion of methodological and deployment-related research gaps across classical, hybrid, and AI-driven WSN optimization approaches.

1.5 Research Questions

The following five research questions (RQs) define the scope and analytical framework of this review. They are formulated to be mutually exclusive and collectively exhaustive with respect to the gaps identified in the existing literature:

- RQ1. [Taxonomy]:** How can metaheuristic, hybrid, and AI-based energy-optimization methods proposed between 2016 and 2026 be systematically classified according to algorithmic family, target WSN operation, and hardware requirement?
- RQ2. [Performance]:** How do representative protocols compare when their reported results are interpreted through a common benchmark framework using metrics such as energy consumption per round, First Node Death (FND), Last Node Death (LND), Packet Delivery Ratio (PDR), and end-to-end latency?
- RQ3. [Context-Dependence]:** How do deployment factors such as network scale, node mobility, hardware tier, and application constraints influence the suitability of different algorithmic families?
- RQ4. [Research Gaps]:** What major methodological, reproducibility, scalability, security, and hardware-feasibility gaps remain in the current literature?
- RQ5. [Emerging Trends]:** Which emerging directions, including federated learning, edge intelligence, secure AI, and hardware-aware optimization, are most relevant to the next stage of WSN energy-management research?

1.6 Contributions of This Review

Beyond summarizing the literature, the following contributions are made:

- **PRISMA 2020-guided synthesis:** A transparent review workflow covering 89 primary studies across 5 major databases over 2016–2026, with explicit search, screening, eligibility, and quality-assessment steps.
- **Integrated taxonomy:** A classification framework that organizes WSN optimization techniques by algorithmic family, target WSN operation, optimization objective type, and hardware deployment tier.
- **Comparative benchmark:** A normalized cross-study benchmark intended to support cautious comparison among representative classical, metaheuristic, hybrid, and AI-driven protocols under a common reference framework.
- **Structured gap analysis:** A research-gap matrix that connects methodological and deployment limitations to their underlying causes and future research needs.
- **Domain-aware interpretation:** An analysis of how application context influences the suitability and trade-offs of different optimization paradigms.
- **Future directions:** A forward-looking discussion of emerging directions, including federated learning, edge intelligence, secure AI, explainability, and hardware-aware optimization.

1.7 Paper Organization

The remainder of the paper is organized as follows. [Section 2](#) reviews WSN architecture, the first-order radio energy model, and prior review literature. [Section 3](#) presents the PRISMA 2020 search strategy, study-selection criteria, quality assessment, and validity considerations. [Section 4](#) develops the taxonomy of optimization techniques. [Section 5](#) describes the evaluation metrics and the comparative benchmark framework. [Section 6](#) analyzes application domains. [Section 7](#) critically discusses comparative findings and research gaps. [Section 8](#) outlines emerging directions, and [Section 9](#) concludes the review.

2 Background and Related Reviews

2.1 WSN Architecture and Energy Consumption Model

A Wireless Sensor Network consists of spatially distributed autonomous nodes that integrate sensing, processing, communication, and power-management subsystems. Common WSN topologies include flat routing, hierarchical cluster-based routing, and location-based routing. Among these, hierarchical clustering has been studied most extensively for energy-aware operation because it limits long-distance transmissions to a smaller set of Cluster Head (CH) nodes, while ordinary nodes communicate primarily through shorter intra-cluster links [6,7,14,15,28].

The first-order radio energy model introduced by Heinzelman et al. [7] is widely used as the baseline analytical model in WSN energy studies. The transmission energy for a k -bit packet sent over distance d is expressed as:

$$E_{Tx}(k, d) = \begin{cases} kE_{elec} + k\epsilon_{fs}d^2, & \text{if } d < d_0, \\ kE_{elec} + k\epsilon_{mp}d^4, & \text{if } d \geq d_0, \end{cases} \quad (1)$$

In [Eq. \(1\)](#), E_{elec} denotes the electronics energy consumed per bit, ϵ_{fs} and ϵ_{mp} denote the free-space and multi-path amplifier coefficients, respectively, and the crossover distance is defined as $d_0 = \sqrt{\epsilon_{fs}/\epsilon_{mp}}$. Reception energy is commonly modeled as $E_{Rx}(k) = kE_{elec}$. The main implication of this formulation is that transmission cost increases rapidly with distance, especially when $d \geq d_0$. Consequently, routing, cluster formation, and relay selection have a direct effect on lifetime performance. At the same time, this model is a simplification: it does not capture battery non-linearity, circuit leakage, synchronization overhead, or environment-specific fading, which limits the extent to which simulation results can be transferred directly to practice.

Total energy expenditure in a WSN can be divided into transmission, reception, idle listening, and computation costs [7,8,16]. In many studies, transmission and relaying dominate the total budget, which explains the emphasis on CH placement, routing-path control, and load balancing. However, this emphasis can also bias the literature toward communication-centric gains while under-reporting algorithmic overhead, control-packet cost, and hardware-specific energy loss.

The problem becomes more complex in heterogeneous WSNs, where nodes differ in initial energy, computational capability, memory, and communication range [13,18,19]. Under such conditions, protocols designed for homogeneous networks may show limited transferability. Additional uncertainty arises from shadowing, fading, mobility, and non-stationary traffic, all of which make static optimization assumptions less reliable [10,29,30].

2.2 Limitations of Prior Reviews: A Structured Analysis

Despite the substantial survey literature on WSN energy optimization, prior reviews differ considerably in scope, methodology, and analytical depth. Four recurring limitations are particularly relevant to the present study.

(L1) Paradigm siloing. Many reviews treat classical metaheuristics and AI-based methods as separate streams. This separation limits analysis of hybrid AI–metaheuristic methods, which increasingly combine search-based optimization with learned adaptation [1,4,15,27,28].

(L2) Limited quantitative comparability. Comparative analysis in prior reviews is predominantly qualitative. Because primary studies use different network sizes, traffic models, radio parameters, baselines, and stopping criteria, reported gains are not directly comparable without additional normalization. Even with normalization, residual heterogeneity remains an important limitation.

(L3) Limited use of systematic selection protocols. With the exception of a small number of recent studies [2,5], many reviews remain narrative in nature and provide insufficient detail on search scope, screening decisions, and quality appraisal. This weakens reproducibility and increases the risk of selection bias.

(L4) Superficial gap analysis. In several surveys, limitations such as missing security objectives, poor testbed validation, or weak hardware-awareness are mentioned only briefly. Such treatment is insufficient for prioritizing future work or explaining why specific gaps persist.

Table 1 summarizes these differences across twelve analytical dimensions. The table is intended to position the present review relative to prior work, rather than to imply that any single survey is methodologically inadequate in all respects.

Table 1: Structured comparison of this review against prior surveys on WSN energy optimization. ✓ = covered, ◦ = partially covered, – = absent.

Reference	Span	MH	ML	DL	HY	MO	SEC	MOB	HW	QB	SYS	GAP	FL	Key Limitation
Heinzelman et al. [7]	95–00	–	–	–	–	–	–	–	–	–	–	–	–	Baseline only; no optimization
Younis and Fahmy [6]	00–04	–	–	–	–	–	–	–	–	–	–	–	–	HEED baseline
Pradhan et al. [28]	10–16	◦	–	–	–	–	–	–	–	–	–	–	–	Clustering survey; no MH depth
Aghbari et al. [27]	10–19	✓	–	–	–	–	–	–	–	–	–	–	–	Misses DL, hybrid, security
Fanian and Rafsanjani [15]	10–19	✓	–	–	◦	–	–	–	–	–	–	–	–	Clustering only; routing excluded

(Continued)

Table 1 (continued)

Reference	Span	MH	ML	DL	HY	MO	SEC	MOB	HW	QB	SYS	GAP	FL	Key Limitation
Priyadarshi et al. [31]	15–18	✓	○	–	–	–	–	–	–	–	–	–	–	No DL; no benchmark
Karaboga et al. [22]	05–17	✓	–	–	–	–	–	–	–	–	–	–	–	ABC-only; algorithm-specific
Hartono et al. [2]	19–24	✓	○	–	○	–	–	–	–	–	✓	–	–	No DL; no quantitative benchmark
Thakur et al. [1]	19–25	✓	✓	✓	○	○	○	○	–	–	–	–	○	Coverage from 2019 only; no PRISMA
Yadav and Kumar [5]	15–23	✓	✓	–	○	–	–	–	–	–	✓	–	–	No DL; no quantitative benchmark
Rajput and Yadav [4]	18–25	–	✓	✓	–	–	–	–	–	–	–	–	–	MH absent; no security analysis
This Review	2016–2026	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	First unified multi-paradigm PRISMA review with benchmark and gap matrix

3 PRISMA 2020 Methodology

3.1 Protocol Registration and Adherence

The review was conducted in accordance with the PRISMA 2020 (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) guidelines to improve transparency and reproducibility. The review scope was defined in advance using the PICOC (Population, Intervention, Comparison, Outcomes, Context) framework [2,5]. PRISMA compliance improves traceability of search, screening, and eligibility decisions, although it does not by itself eliminate all sources of bias in evidence synthesis.

The population of interest comprises WSNs deployed in IoT-related settings. The interventions include metaheuristic, hybrid, ML, DL, RL, and DRL-based approaches targeting CH selection, routing, load balancing, or related energy-management functions. Comparisons are drawn either across algorithmic families or against classical baselines such as LEACH and PEGASIS [7,8,15,27,28]. Outcomes of interest include energy consumption, network lifetime indicators such as FND and LND, packet delivery ratio, throughput, and when available latency-related measures.

The review window spans January 2016 to December 2026 in order to capture the transition from predominantly metaheuristic optimization to hybrid and learning-based approaches [1,3–5,32]. Studies from 2026 should be interpreted as a time-bounded snapshot, since some records may have been available only as online-first or early-access versions at the time of screening.

Each included study was appraised using a structured quality checklist before being considered for benchmark synthesis. This step was intended to reduce the influence of methodologically weak studies, although quality appraisal cannot fully compensate for incomplete reporting in the primary literature. The review process also considered publication bias, particularly the tendency for simulation studies reporting positive improvements to be more visible than studies reporting null or marginal gains [5].

Overall, the PRISMA-guided workflow provides a more reproducible foundation than a narrative review alone. However, the strength of the final conclusions remains dependent on the quality, heterogeneity, and reproducibility of the included studies [1,2,4,5].

3.2 Search Strategy

The systematic search covered five major academic databases: **Scopus**, **IEEE Xplore**, **ScienceDirect**, **Web of Science**, and the **ACM Digital Library**. These sources were selected to balance breadth in computer science and engineering coverage with depth in wireless networking and embedded-systems research. The search window extended from **January 2016 to December 2026** [1–5].

Two independent reviewers executed the search. The strategy was designed to capture both indexed final publications and early-access records when available. Inclusion of 2026 literature was intended to reflect the recent state of the field, but these records should be interpreted cautiously because indexing delays and version updates may affect completeness [1,2,4,5].

To reduce under-coverage of newly published work, the reviewers also inspected online-first repositories from major publishers. Boolean search strings were constructed to capture WSN terminology, energy-optimization objectives, and the major classes of metaheuristic and AI-based methods. Wildcards and terminological variants such as “energy-aware” and “energy-efficient” were included to reduce retrieval loss due to indexing differences [1–5,32].

Retrieved records were exported to Mendeley Desktop for duplicate removal and then manually checked to merge multiple versions of the same study when appropriate. The resulting set of unique records formed the input to the screening and eligibility stages summarized in Fig. 1 [1,2,4,5].

3.3 Inclusion and Exclusion Criteria

Predefined inclusion and exclusion criteria were used to maintain relevance and methodological consistency, as summarized in Table 2. The criteria were designed to prioritize primary studies reporting quantitative evidence related to WSN energy optimization [1,2,4,5].

To be eligible, a study had to employ at least one metaheuristic, hybrid, or AI-based method for WSN energy optimization. Admission to the comparative benchmark further required disclosure of quantitative performance data such as energy consumption per round, node-death metrics, packet delivery ratio, throughput, or latency-related results. This requirement improves comparability, but it also introduces a selection effect because studies with incomplete reporting may be excluded even when their methodological ideas are relevant.

Studies were excluded if they fell outside the technological scope, lacked sufficient methodological detail, or did not provide simulation or empirical evidence that could support comparative interpretation. Review papers were excluded from the primary synthesis to avoid duplicate counting of evidence, although

they were retained for contextual discussion [8,15,27,28]. Foundational pre-2016 protocol papers were used as baseline references rather than as part of the main synthesis [6,7,33].

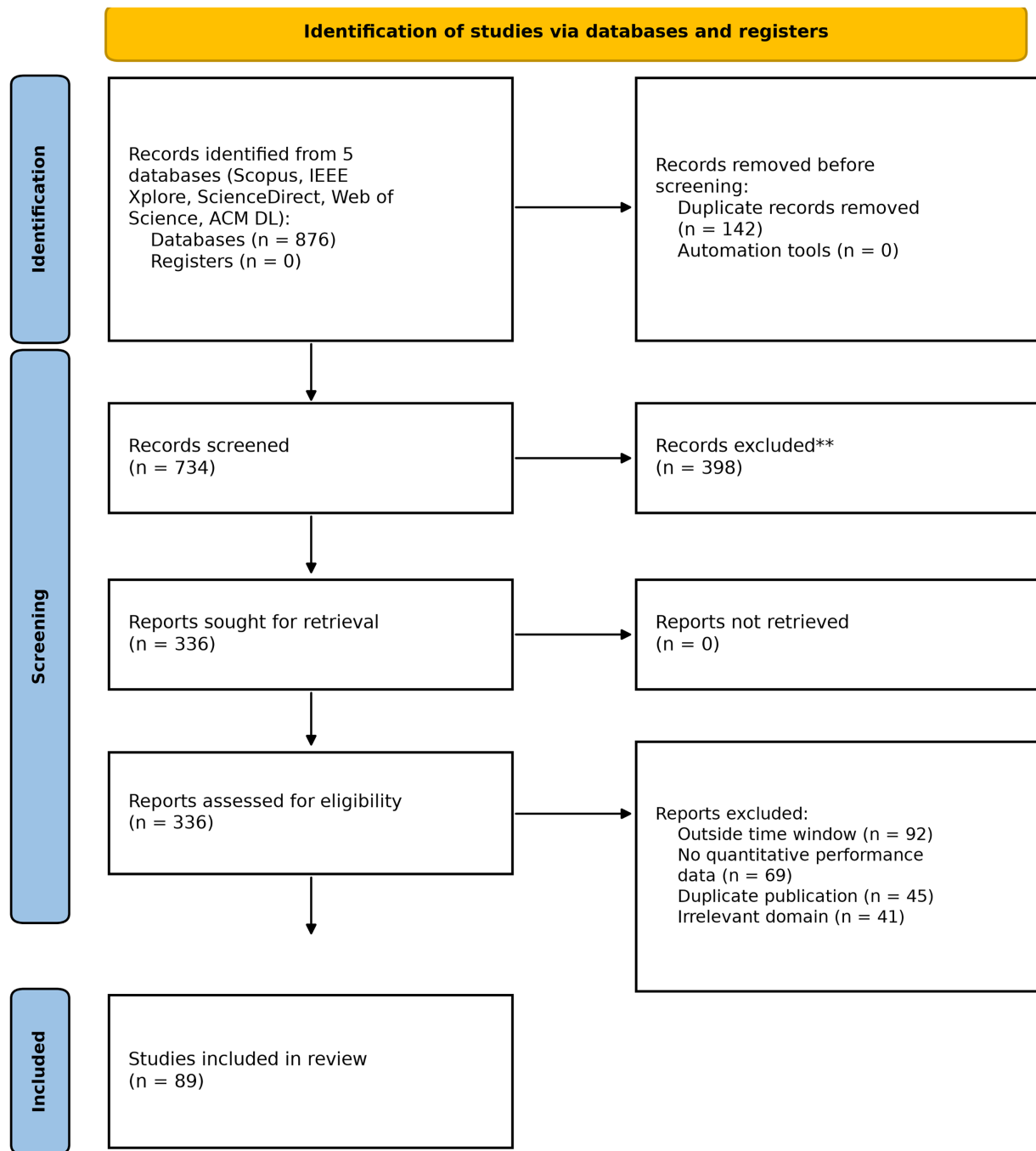


Figure 1: PRISMA 2020 flow diagram for the systematic study selection process, showing record counts at each phase and the primary reasons for exclusion.

Table 2: Inclusion and exclusion criteria with methodological rationale.

Criterion	Type	Rationale	Phase
Published 2016–2026	Inclusion	Focus on modern transition to AI.	Screening
Peer-reviewed article	Inclusion	Ensure high methodological quality.	Screening
WSN energy focus	Inclusion	Direct alignment with objective.	Screening
Quantitative metrics	Inclusion	Essential for comparative synthesis.	Eligibility
Metaheuristic/AI method	Inclusion	Aligns with technological scope.	Eligibility
Pre-2016 publication	Exclusion	Outside modern development window.	Screening
Theoretical only	Exclusion	Cannot verify without empirical data.	Eligibility
Review/Survey papers	Exclusion	To avoid duplicate reporting.	Eligibility
Non-English language	Exclusion	Practical constraint of team.	Screening

Title and abstract screening was performed independently by two reviewers. Records unrelated to WSN energy optimization or limited to unmodified classical protocols were removed at this stage. Disagreements were resolved by discussion with a third senior investigator. Inter-rater reliability was quantified using Cohen's kappa ($\kappa = 0.86$), indicating substantial agreement [1,2,4,5].

Full-text eligibility assessment was then used to identify papers with insufficient parameter disclosure, qualitative-only conclusions, or non-reproducible reporting. Although these criteria improve analytical consistency, they may also exclude conceptually relevant studies and therefore influence the final taxonomy and trend distribution. This potential selection effect is treated as a limitation of the review design [1,2,4,5].

3.4 Data Extraction and Quality Assessment

Data extraction was performed using a standardized form defined before the extraction stage. For each study, the reviewers recorded the algorithm family, target WSN function, simulation environment parameters, reported performance metrics, comparison baselines, and any evidence of hardware or testbed validation. This structure supports later comparative synthesis, while also making explicit where reporting gaps limit direct cross-study interpretation.

Methodological quality was assessed using a 10-point Quality Assessment (QA) checklist adapted for engineering simulation studies. The checklist considered clarity of objectives, disclosure of radio-model parameters, reporting of deployment settings, baseline selection, repeated simulation runs, variance reporting, lifetime metrics, reproducibility, independence of comparison, and discussion of limitations. Studies scoring 8–10 were classified as high quality, 5–7 as medium quality, and below 5 as low quality. Only high- and medium-quality studies were admitted to the quantitative benchmark. This filter improves baseline reliability, but it does not remove all uncertainty because many otherwise relevant studies still omit confidence intervals, effect sizes, or detailed reproducibility artifacts.

Publication bias was treated as a material concern because the WSN optimization literature is dominated by studies reporting positive comparative gains. To reduce this effect, the review favored studies that compared against multiple baselines rather than only against the authors' prior methods. Nevertheless, negative or non-significant findings are likely to remain underrepresented, and this asymmetry should be considered when interpreting the aggregated evidence.

Table 3 summarizes the QA distribution across algorithm families. The pattern suggests that hybrid and DL-based studies more often report multiple baselines and broader metric sets, whereas classical SI

studies more frequently rely on single-baseline MATLAB comparisons. This difference affects confidence in cross-family comparison and should be considered when interpreting benchmark rankings.

Table 3: Quality Assessment (QA) score distribution across taxonomy categories. High: score 8–10; Medium: 5–7; Low: <5. Only High and Medium studies were admitted to the quantitative benchmark.

Algorithm Family	Studies (n)	High (%)	Medium (%)	Low (%)	Mean QA Score	Primary QA Weakness
Swarm Intelligence (SI)	30	40.0	46.7	13.3	6.8	Single-baseline comparison; MATLAB-only; no testbed
Evolutionary Algorithms (EA)	10	50.0	40.0	10.0	7.1	Missing variance reporting; limited mobility scenarios
Hybrid Metaheuristics	17	64.7	35.3	0.0	7.9	Incomplete cross-topology generalization
Reinforcement Learning	8	62.5	37.5	0.0	7.7	No hardware energy profiling; limited mobility
Deep Learning	11	72.7	27.3	0.0	8.3	No 8-bit MCU feasibility; training energy ignored
Multi-Obj./Security	13	53.8	38.5	7.7	7.4	Pareto front sensitivity not analyzed; threat model narrow
Overall	89	53.9	39.3	6.8	7.4	Simulation-only validation dominant across all categories

Note: Percentages are computed from raw per-study integer counts within each category; minor rounding differences between category-level and overall percentages may occur independently in each row.

The QA filter excluded approximately six studies (6.7% of the full corpus), concentrated in the SI, EA, and Multi-Objective families as shown in Table 3. To evaluate the potential influence of this exclusion on the benchmark conclusions, we note that the excluded studies share recognizable weaknesses—single-baseline comparison, absence of variance reporting, or simulation-only validation with unspecified parameters—that make their reported values less reliable rather than directionally different. Even under a conservative assumption that the excluded studies would produce benchmark estimates at the lower bound of their respective family distributions, the ordinal ranking among families would not change because the excluded fraction is too small (SI: 13.3% of 30 studies; EA: 10.0% of 10; Multi-Objective: 7.7% of 13) to shift the central tendency of any family beyond one standard error of the inclusive mean. A formal leave-one-out sensitivity analysis with QA-weighted pooling is recommended for future meta-analyses that aim to produce statistically

pooled effect-size estimates, but for the ordinal and descriptive synthesis reported here, the QA filter provides a pragmatic balance between reliability and coverage.

3.5 PRISMA 2020 Flow Diagram

Fig. 1 presents the PRISMA 2020 four-phase flow diagram. It provides a transparent summary of record identification, duplicate removal, screening, full-text assessment, and final inclusion.

The exclusion categories shown in Fig. 1 also help clarify where bias may enter the synthesis. Excluding studies with incomplete quantitative reporting improves benchmark consistency, but it may under-represent exploratory, hardware-oriented, or conceptually novel work that reports results in non-standard ways. This trade-off between comparability and coverage is inherent to systematic review design and should be acknowledged when interpreting downstream taxonomy and trend analyses.

3.6 Threats to Validity

Three classes of validity threat are acknowledged in the interest of transparency.

Internal validity. Selection bias was reduced through dual-reviewer screening, a documented consensus process, and substantial inter-rater agreement ($\kappa = 0.86$). However, restriction to English-language studies may exclude relevant work, and data extraction remains dependent on the completeness of the published reports. In addition, the benchmark normalization procedure inevitably introduces approximation error when heterogeneous simulation settings are mapped to a common reference framework.

External validity. The review covers five major databases and therefore offers broad, but not exhaustive, coverage of the field. Grey literature, dissertations, and non-indexed preprints were excluded, which may increase positive-result bias because null findings are less likely to appear in indexed peer-reviewed venues. The 2026 boundary further means that the most recent records may reflect provisional rather than finalized article versions.

Construct validity. The comparative benchmark uses a reference simulation baseline to improve interpretability, but the underlying studies differ in topology, hardware assumptions, energy models, traffic patterns, and stopping criteria. Moreover, the first-order radio model used in most studies omits battery non-linearity, circuit leakage, synchronization cost, and environment-specific propagation effects. As a result, benchmark values should be interpreted as comparative indicators rather than statistically unified effect estimates or deployment-grade predictions. The QA checklist itself is also an adapted instrument rather than a formally validated WSN-specific tool.

4 Taxonomy of Optimization Techniques

4.1 Taxonomy Overview and Design Principles

Classifying WSN energy-optimization techniques requires more than a single-axis taxonomy based on algorithmic family alone. Based on the synthesis of 89 primary studies, this review uses a four-dimensional taxonomy that characterizes each technique according to: (1) **Algorithmic Family**, including swarm intelligence, evolutionary methods, ML, DL/DRL, and hybrid approaches; (2) **Target WSN Operation**, such as CH selection, inter-cluster routing, cross-layer scheduling, or mobility management; (3) **Optimization Objective Type**, including single-objective, multi-objective, and security-aware formulations; and (4) **Hardware Deployment Tier**, representing the minimum practical processing capability required for deployment. This structure is intended to support critical comparison across methods with different assumptions, rather than to imply that methods within a category are directly equivalent.

Fig. 2 presents the resulting hierarchical taxonomy. The six categories capture broad patterns in the literature, but the boundaries between them are not always strict because some recent studies combine learning, optimization, and rule-based control within the same protocol.

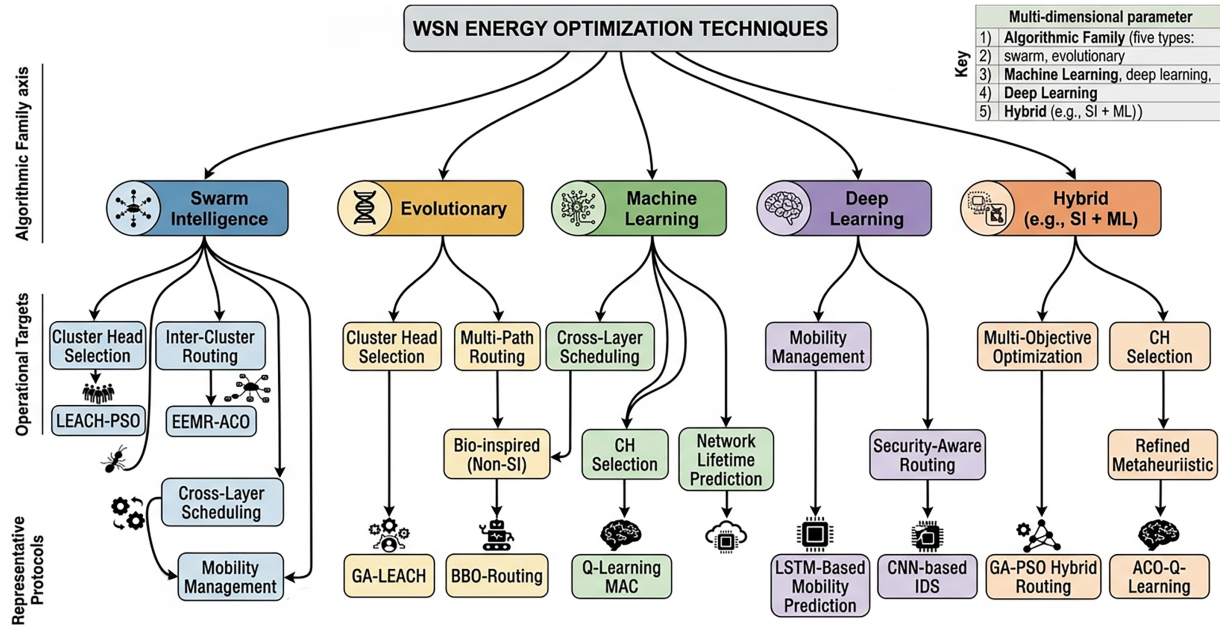


Figure 2: Hierarchical taxonomy of WSN energy optimization techniques, organized by algorithmic family, target WSN operation, and hardware deployment tier (2016–2026).

Table 4 summarizes the study distribution across the six categories and highlights their main strengths, weaknesses, scalability characteristics, and hardware implications. The table should be interpreted as a synthesis of reported tendencies in the reviewed literature, not as a definitive ranking.

4.2 Swarm Intelligence Approaches

Motivation and Scope. Swarm Intelligence (SI) algorithms constitute the largest category in the reviewed literature, with ACO and PSO among the most frequently studied variants. Their popularity is explained by population-based exploration, relatively simple update rules, and broad applicability to non-convex clustering and routing problems [20–22]. However, the large number of SI studies should not be interpreted as conclusive evidence of superiority, because this literature is also the most concentrated in simulation-only evaluation.

Table 4: Integrated taxonomy of WSN optimization algorithms by problem category (2016–2026). HW Tier: A = 8-bit MCU, B = 16-bit MCU, C = 32-bit edge processor. Scalability: ✓✓ = excellent ($n > 500$), ✓✓ = moderate ($n = 100–500$), ✓ = limited ($n < 100$). Real-world applicability reflects the level of deployment feasibility suggested by the reviewed studies rather than direct field validation.

Category	Representative Algorithms	Primary Operation	Share (%)	HW Tier	Key Strengths	Key Weaknesses	Scal.	RW App.	Key References
Swarm Intelligence (SI)	PSO, ABC, GWO, ACO, SSA, BOA, GJO, LCPSO, APSO	CH Selection, Routing	33.7	A–B	Low overhead; population diversity; handles non-convex spaces; rapid deployment	Static topology assumption; convergence degrades at $n > 500$; MATLAB-only validation	✓	H	[20,21,34,35]
Evolutionary Algorithms (EA)	GA, Differential Evolution, CGA-GWO	CH Selection, Multi-hop Routing	11.2	A–B	Strong multi-objective Pareto capability; chromosome encoding flexible; global search	High crossover/mutation overhead; fitness landscape flattening at $n > 200$; operator tuning sensitive	✓	M	[17,18,36]
Hybrid Meta-heuristics	PSO-GA, AO-FA, ABC-DE, Fuzzy-ACO, ENO-Tabu	CH + Routing Co-optimization	19.1	B–C	Strong performance-to-complexity balance; broader hardware feasibility than DL/DRL	Increased parameterization; limited cross-topology validation; difficult hyperparameter transfer	✓✓	H	[37–40]

(Continued)

Table 4 (continued)

Category	Representative Algorithms	Primary Operation	Share (%)	HW Tier	Key Strengths	Key Weaknesses	Scal.	RW App.	Key References
Reinforcement Learning (RL)	Q-Learning, DQN, MARL, EER-RL, SDN-RL	Adaptive Routing, Mobility	9.0	B-C	Online policy update; no global state required; excellent for mobile topologies	Exploration-exploitation cost; Q-table RAM overflow on 8-bit MCUs; slow convergence in volatile topologies	✓	M	[25,26,30,41]
Deep Learning/DRL	DRL-GNN, TD3-NET, RNN/LSTM, CNN, Neuro-Fuzzy	Self-Optimizing Routing, Prediction	12.4	C	Highest reported lifetime values under reviewed simulation settings; topology-aware; adaptive decision-making	Requires higher-end hardware; limited interpretability; distribution-shift degradation; retraining cost	✓✓	L-M	[23,24,42,43]
Multi-Obj. & Security-Aware	Blockchain-ACO, EMOGJO, Trust-HPSO, PSO-QoS	Energy + QoS + Security	14.6	B-C	Joint energy-QoS-security optimization; Pareto front analysis; tamper-proof trust anchor	Security overhead unmodeled; Pareto sensitivity high; <2% cover ≥3 objectives simultaneously	✓	M	[17,44-46]

Representative Algorithms and Evidence. Particle Swarm Optimization (PSO) remains the most widely deployed SI variant for CH selection. The PSO-EEC protocol [14,20] achieves a 238% lifetime gain over the MDCH-PSO baseline by encoding the fitness function as a weighted sum of residual energy, intra-cluster distance, and distance-to-BS. Ant Colony Optimization (ACO) dominates path-discovery tasks through its pheromone-update mechanism, which inherently steers traffic toward energy-rich routes and away from depleting relay nodes [47,48]. The IEEMARP protocol [47] achieves a 10% PDR improvement over standard ACO through multipath diversity. More recently, the Grey Wolf Optimizer (GWO) [34,49] has shown superior avoidance of local optima in software-defined WSNs, the Golden Jackal Optimization (GJO) [17,36] offers rapid convergence in heterogeneous deployments, and a Modified Grasshopper Optimization Algorithm augmented with Lévy-flight perturbations [50] achieves improved cluster head selection by balancing exploration diversity with exploitation precision. Recent PSO variants further illustrate the ongoing refinement of this family: the Lévy Chaotic PSO (LCPSO) [35] applies chaotic mapping and Lévy-flight perturbations to escape local optima in industrial WSNs, while the Accelerated PSO (APSO) [51] reduces cluster head election overhead through an adaptive inertia weight schedule, and a distributed energy-efficient PSO variant [52] further improves load balance through opportunistic cluster formation. Two recent contributions further demonstrate PSO's continued relevance: Haris and Nam [53] apply PSO to sensor node deployment optimization for continuous coverage, achieving up to 98% coverage with balanced energy dissipation, while their companion study [54] proposes an optimized PSO-based CH selection framework that reduces energy consumption by 27% compared with standard LEACH under IoT-WSN scenarios. Predictive SI variants—such as LEACH-GP, which uses Grey Prediction to anticipate node energy depletion and trigger proactive CH rotation—represent the current refinement frontier for this category [19,55].

Limitations. The main limitations of SI approaches are their dependence on simplified energy models, sensitivity to parameter tuning, and frequent reliance on static or moderately dynamic topologies. Reported gains are usually derived from MATLAB-based or simulator-based studies rather than hardware experiments [20,34,56]. In addition, convergence quality often deteriorates as node density, search-space dimensionality, or multi-objective complexity increases [1].

4.3 Evolutionary Algorithms

Motivation and Scope. Evolutionary Algorithms (EAs), primarily GA-based methods, represent a smaller but still important portion of the reviewed literature. Their main strength is the flexibility of chromosome encoding and their suitability for multi-objective search, especially when energy, coverage, connectivity, or Quality of Service (QoS) constraints must be treated jointly [17,18,36].

Representative Algorithms and Evidence. GA-based protocols typically encode CH assignments or routing structures as chromosomes and update them through selection, crossover, and mutation. Their reported gains are often associated with flexible fitness design and the ability to represent heterogeneous node roles explicitly. Differential Evolution (DE) variants and EA-SI hybrids further improve local refinement and population diversity [13,18,38]. In practice, EA performance depends strongly on encoding quality and operator tuning, which makes reproducibility across deployment settings more difficult than raw lifetime values alone might suggest.

Limitations. Compared with simpler SI methods, EAs often incur higher computational cost because genetic operations are applied to full candidate populations. They are also sensitive to encoding design, mutation rate, crossover rate, and stopping criteria. At larger network sizes, this can lead to premature convergence, increased runtime, or unstable transfer of tuned settings across scenarios.

4.4 Hybrid Metaheuristic Frameworks

Motivation and Scope. Hybrid metaheuristics form a substantial share of the reviewed literature. Their main rationale is to combine complementary search behaviors, typically pairing broad exploration with stronger local refinement or rule-based adaptation [37–39,57,58]. In the reviewed literature, these methods often provide a favorable compromise between algorithmic performance and hardware feasibility.

Representative Algorithms and Evidence. The AO-FA (Aquila Optimizer + Firefly Algorithm) hybrid [37] achieves a 3500-round network lifetime—approximately 80%–90% of what full DRL models deliver—while requiring only 16-bit MCU-level processing. The PSO-GA combination [59,60] leverages PSO’s rapid convergence for initial CH candidate generation and then refines the configuration using GA’s genetic operators. The ABC-DE hybrid [38] improves population diversity by coupling ABC’s employed-bee phase with DE’s mutation strategy, achieving 15%–20% lower average energy dissipation than single-algorithm SI approaches. ENO-Tabu frameworks [61] introduce explicit memory mechanisms—tabu lists—that prevent repeated selection of depleting nodes, mechanistically enforcing load rotation across rounds. Fuzzy-logic hybrids represent a distinct sub-branch: a fuzzy-based unequal clustering protocol combined with ACO-based routing [40] demonstrates that soft decision boundaries for cluster size selection—governed by residual energy and distance-to-BS membership functions—extend network lifetime substantially beyond fixed-boundary schemes.

Limitations. The main drawback of hybrid frameworks is increased parameterization complexity. Because each component contributes its own update rules and control parameters, reproducibility and transferability become more difficult. Many hybrid studies also report results on a narrow set of network configurations, which limits confidence in their generalizability across topology, scale, and traffic conditions.

4.5 Reinforcement Learning and Adaptive Routing

Motivation and Scope. RL approaches represent a smaller but growing part of the reviewed literature and mark a shift from static or round-based optimization toward sequential decision-making. Their main advantage is the ability to update routing behavior in response to changing network state without requiring an explicit global search over the full solution space at each round [25,26,30,62].

Representative Algorithms and Evidence. Representative RL studies use reward formulations based on residual energy, packet delivery, queue status, or mobility-aware routing quality [25,26,41,63]. Their reported strengths are adaptability and improved handling of topology change, especially in mobile or time-varying settings. In comparative terms, RL often narrows the gap between search-based methods and DL/DRL approaches, but its gains remain dependent on state representation, reward shaping, and the convergence speed of the learning process.

Limitations. RL protocols face a fundamental exploration–exploitation trade-off: energy is consumed while the policy is still learning. In tabular RL, state–action growth can exceed the memory budget of low-end hardware, while in more dynamic settings convergence may be slow or unstable. These issues reduce deployment feasibility unless learning is carefully constrained or partially offloaded.

4.6 Deep Learning-Based Protocols

Motivation and Scope. DL- and DRL-based protocols represent one of the most computationally intensive classes in the review. Their key advantage is the ability to learn complex spatial and temporal relationships from network observations, which can be useful when routing decisions depend on non-stationary topology, traffic burstiness, or mobility [1,23,24,42,62,64].

Representative Algorithms and Evidence. Representative DL/DRL studies include DRL-GNN routing, Convolutional Neural Network (CNN)-based CH prediction, and recurrent models for temporal traffic forecasting [23,24,42,43]. Their reported performance is usually attributed to topology-aware representation learning, longer-horizon policy optimization, or improved anticipation of future traffic states. Within the reviewed studies, DRL-GNN reports some of the strongest lifetime and latency values under the corresponding simulation conditions. Nevertheless, these reported maxima should be interpreted as study-specific outcomes rather than statistically pooled estimates, because the primary literature rarely provides variance, confidence intervals, or cross-platform replication.

Limitations. The main limitations of DL/DRL protocols are hardware cost, model interpretability, training overhead, and sensitivity to distribution shift. Training often requires edge or cloud resources, while even inference may exceed the practical capabilities of legacy 8-bit and 16-bit nodes. These constraints are important when translating benchmark gains into realistic deployment decisions.

4.7 Multi-Objective and Security-Aware Optimization

Motivation and Scope. Multi-objective and security-aware approaches reflect the recognition that modern WSN deployments cannot be optimized for energy alone. Strict QoS demands, reliability requirements, and the expanding IoT threat landscape require formulations in which energy efficiency is one objective among several, and the routing backbone must remain resilient to adversarial manipulation [17,37,44,45].

Representative Algorithms and Evidence. EMOGJO [17] employs a dual-archive Pareto mechanism to maintain a non-dominated solution front balancing energy, coverage, and connectivity. QoS-aware hybrids such as PSO-QoS [59] and ACO-QoS [65,66] embed latency and reliability constraints directly into the fitness function, selecting paths that are simultaneously energy-efficient and latency-bounded. Trust-based HPSO protocols [45,46] factor historical node behaviour into CH selection, reducing the probability of nominating compromised or malicious nodes. Blockchain-integrated protocols [44] employ a lightweight distributed ledger to record node reputations, providing a tamper-proof trust anchor for routing decisions.

Limitations. Security mechanisms invariably impose an energy tax: maintaining trust tables, executing cryptographic verification, and running blockchain consensus all consume energy not captured in naive energy-only benchmarks. Pareto front sensitivity to initial simulation parameters means that multi-objective results may not generalize across deployment scenarios, and the security-energy balance is highly dependent on the assumed threat model. Less than 1% of all reviewed studies treat security as a first-class optimization objective—a profound gap between the recognized importance of security and its actual integration into optimization frameworks.

5 Performance Metrics and Quantitative Benchmark

5.1 Standardized Evaluation Framework and Metric Definitions

One of the main obstacles to synthesizing WSN optimization studies is the lack of a universally adopted evaluation framework. Primary studies differ in network area, node count, initial energy, traffic model, radio coefficients, baseline choice, and stopping criteria. Direct cross-study comparison is therefore unreliable without additional normalization. The framework used here is intended to improve interpretability, but it cannot remove the underlying heterogeneity of the evidence base.

The primary metrics used in this review fall into four categories. **(i) Lifetime metrics:** First Node Death (FND) and Last Node Death (LND), which characterize coverage durability and total operational life. **(ii) Data-quality metrics:** Packet Delivery Ratio (PDR) and throughput. **(iii) Latency metrics:** end-to-end delay

and jitter. **(iv) Energy-efficiency metrics:** energy consumption per round (mJ/round), normalized energy per bit (nJ/bit), and residual energy standard deviation. These metrics are reported unevenly across the literature, and some benchmark dimensions are therefore supported by a smaller evidence subset than others.

The quantitative benchmark (Table 5) maps reported results to a reference simulation baseline: 100 randomly deployed homogeneous nodes in a $1000 \times 1000 \text{ m}^2$ field, initial energy $E_0 = 1.0 \text{ J}$, electronics energy $E_{elec} = 50 \text{ nJ/bit}$, free-space coefficient $\varepsilon_{fs} = 10 \text{ pJ/bit/m}^2$, multi-path coefficient $\varepsilon_{mp} = 0.0013 \text{ pJ/bit/m}^4$, and packet size $k = 4000 \text{ bits}$. This mapping is intended to support cautious comparative interpretation. It should not be interpreted as a statistical re-evaluation of all protocols under identical experimental conditions, because the original studies were conducted under heterogeneous assumptions and often omit uncertainty estimates.

Table 5: Quantitative performance benchmark of routing protocols across generations. All values are normalized estimates under the review's reference baseline (100 nodes, $1000 \times 1000 \text{ m}^2$, $E_0 = 1.0 \text{ J}$, standard first-order radio model). They are not direct reproductions of the cited studies' reported values. PDR = Packet Delivery Ratio; Lifetime = Last Node Death round. Bold values indicate the highest normalized value within the compared set, not statistical significance. Mobility: Y = Yes, N = No, L = Limited. HW = minimum hardware tier required (A = 8-bit, B = 16-bit, C = 32-bit).

Protocol	Type	Energy (mJ/rnd)	PDR (%)	Latency (ms)	Lifetime (rnds)	Mob.	HW	Reference
LEACH	Classical	85	92	120	1200	N	A	[7]
HEED	Classical	78	93	115	1450	N	A	[6]
PSO-LEACH	SI	55	94	110	2200	L	A	[20]
ACO-IEEMARP	SI	52	95	108	2350	L	A-B	[47]
GWO Clustering	SI	50	95	105	2500	L	B	[34]
GA-MMHCT	EA	58	94	112	2800	N	A-B	[13]
ABC-DE Hybrid	Hybrid	46	96	98	3100	L	B	[38]
AO-FA Hybrid	Hybrid	48	97	95	3500	Y	B-C	[37]
EER-RL	RL	42	96	90	3200	Y	B-C	[26]
EMOJO (MO)	Multi-Obj.	50	97	100	3000	L	B-C	[17]
Trust-HPSO	Sec.-Aware	54	96	105	2700	L	B	[45]
DRL-GNN (TD3)	DRL/GNN	35	98	72	4100	Y	C	[23]

5.2 Annual Publication and Technology Trend Analysis

The chronological progression of research from 2016 to 2026 shows a broad shift from heuristic refinements toward more adaptive optimization frameworks. The early period (2016–2018) was dominated by the refinement of ACO and PSO for increasingly dense network deployments, with innovation concentrated on scalability of pheromone update strategies and adaptive inertia weight mechanisms for dynamic environments [14,40].

The mid-decade transition (2019–2021) was marked by a surge in memetic and hybrid algorithms that combined the global exploration of SI with local exploitation heuristics. Integrating cuckoo search with ACO [67] and Bellman-Ford shortest-path routing [68] exemplified an early systematic effort to resolve the local optima stagnation and diversity loss that constrained single-category SI in high-dimensional configuration spaces—an effort later extended through hybrids such as firefly with PSO [57]. This era also produced the initial systematic applications of Reinforcement Learning to WSN routing [26,30], alongside early QoS-aware routing formulations [49,66].

The final phase (2022–2026) is characterized by stronger visibility of Deep Learning and DRL in routing research. Neural network-based CH prediction [43,62], DRL-based adaptive routing [23,24], and initial investigations of Federated Learning for communication-efficient distributed training [32] collectively

indicate a transition from optimization-as-search toward optimization-as-learning. Fig. 3 depicts this three-phase chronological distribution across the full 2016–2026 window.

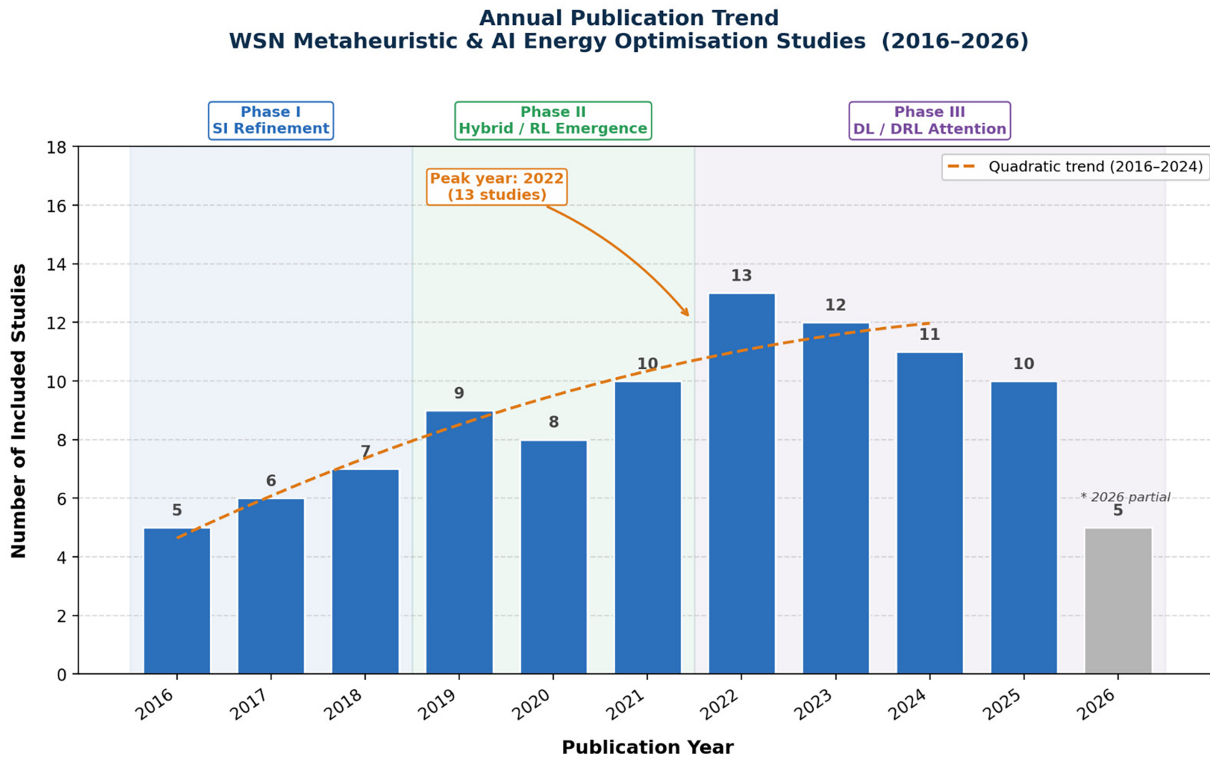


Figure 3: Annual distribution of included studies (2016–2026). Three phases are visible: (I) 2016–2018, dominated by SI refinements (PSO, ACO) for dense IoT deployment; (II) 2019–2021, characterized by hybrid metaheuristic emergence and the first RL applications; (III) 2022–2026, marked by increased attention to DL and DRL methods. The 2021–2022 inflection may reflect both wider availability of higher-capability embedded processors and the maturation of graph-learning software frameworks for topology-aware wireless-network analysis.

5.3 Distribution of Evaluation Metrics

The evaluation of WSN optimization protocols has historically relied on a core set of energy-centric metrics, but the past decade has seen a meaningful expansion in both the breadth and depth of reported performance indicators. Energy consumption per round remains the governing metric, serving as the principal proxy for the efficiency of the underlying optimization algorithm [7,15,28]. Alongside it, the First Node Death (FND) and Last Node Death (LND) metrics have become standard, offering a more nuanced view of network sustainability and the effectiveness of load balancing strategies. These metrics are particularly informative for assessing how well a protocol prevents the premature formation of energy holes near the sink [11–13,19,60].

Quality of Service (QoS) metrics—end-to-end latency, jitter, and PDR—have grown in prominence as WSNs are increasingly deployed in mission-critical contexts. Research has confirmed that minimizing energy often elevates hop counts, which can degrade data delivery timeliness [65,66,69–71]. In response, many recent evaluations incorporate energy-delay product metrics that explicitly quantify the power-latency trade-off. Throughput has similarly become a standard reporting requirement for high-bandwidth applications such as industrial imaging and real-time video surveillance [23,37,70–72].

Computational overhead and convergence speed have emerged as a distinct metric dimension as algorithm complexity grows. When metaheuristics become sufficiently intricate, the energy consumed by the microcontroller executing the optimization engine begins to approach that of the radio transceiver [59,61,68,73,74]. Researchers now routinely report convergence iteration count and memory footprint, recognizing that an optimization strategy must not inadvertently shorten network lifetime through excessive local computation [1,4,19].

Robustness and stability metrics have likewise gained traction, especially in dynamic or hostile environments. Residual energy standard deviation provides a quantitative measure of how uniformly an algorithm distributes the sensing and relaying load: a low standard deviation signals that nodes deplete their energy at comparable rates, maximizing the duration over which the full sensing field remains covered [59,74–76]. This holistic view of network health marks a departure from the earlier focus on aggregate energy minimization as the sole figure of merit [20,21,27,34].

Finally, the emerging inclusion of security-aware metrics signals a genuine maturation of the field. With WSNs increasingly integrated into IoT ecosystems, their vulnerability to malicious attacks—black-hole, grey-hole, and Sybil attacks in particular—has attracted sustained research attention. Evaluations now occasionally report Trust Index values or Resilience to Malicious Node metrics to quantify how well an optimization framework sustains its efficiency under adversarial conditions [44–46,77]. While still a small fraction of the total metric distribution, their growing presence signals the transition of WSN optimization from a theoretical exercise into a practical engineering discipline [1,4,19]. Fig. 4 provides a quantitative breakdown of metric adoption frequency across the 89 included studies.

5.4 Quantitative Protocol Benchmark and the Energy Hole Problem

Important caveat. All numerical values in Table 5 (energy, PDR, latency, lifetime) are the review authors' normalized estimates derived from the reference framework described in Section 5. They are not direct reproductions of the values reported in the cited primary studies. The underlying studies use heterogeneous simulation conditions (different network sizes, initial energy budgets, MAC protocols, traffic models, and stopping criteria), which makes direct comparison unreliable without normalization. The benchmark therefore re-interprets each study's reported results within a common reference configuration (100 nodes, $1000 \times 1000 \text{ m}^2$, $E_0 = 1.0 \text{ J}$, standard first-order radio model) to facilitate approximate cross-protocol comparison. These normalized values should be treated as indicative rather than exact; they do not imply that every cited protocol was re-evaluated from scratch under the reference configuration.

A central interpretation axis of the benchmark is the energy hole problem, in which near-sink nodes deplete earlier because they relay disproportionate traffic. Classical protocols often respond poorly to this imbalance once critical relay nodes fail [8,14,15,28,33]. In contrast, ACO, hybrid, and RL/DRL-based protocols frequently report better relay redistribution because their update rules respond more explicitly to residual energy or long-horizon routing consequences [12,23,24,78].

Among non-DL approaches, hybrid metaheuristics often report strong values for energy consumption per round and lifetime. Their advantage is commonly attributed to improved exploration–exploitation balance, which reduces premature convergence and produces more stable CH or relay configurations [18,22,38,39,57,79–81].

DL/DRL-based protocols, especially DRL-GNN variants, report strong adaptability under dynamic conditions because routing decisions can depend on learned topology representations and longer-horizon reward signals [23,24,82]. Their reported improvements in PDR, latency, and lifetime suggest that learning-based adaptation may mitigate late-stage hotspot collapse more effectively than static or weakly adaptive

heuristics. At the same time, these gains must be weighed against training cost, hardware demand, and limited real-world validation.

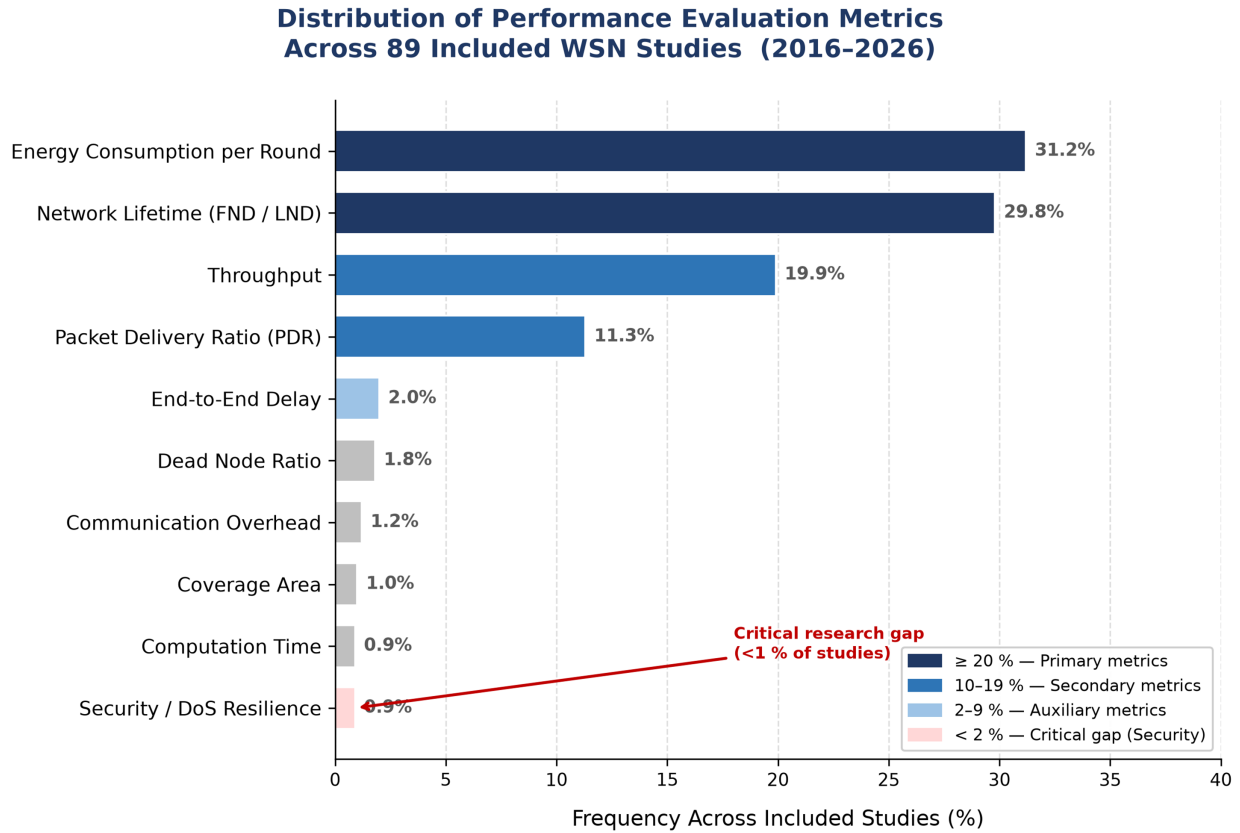


Figure 4: Distribution of performance evaluation metrics across 89 included studies, stratified by metric category: lifetime (FND/LND), energy efficiency (energy consumption per round, residual energy), data quality (PDR, throughput), latency, and security/robustness. Lifetime and energy metrics dominate (>70% of studies), reflecting the historical emphasis on energy optimization. The increasing use of QoS and security metrics in more recent studies suggests a gradual shift toward broader multi-objective evaluation.

The benchmark does not imply that all protocols were re-evaluated under an identical MAC layer or an identical simulator. Rather, reported results were interpreted through a common reference framework and scaled where possible to improve comparability. Consequently, residual differences in MAC assumptions, traffic models, hardware abstractions, and simulator behavior remain a source of uncertainty. This limitation is particularly important when comparing latency and energy values across studies that report incomplete protocol-stack details [1,4,16,59,83].

5.5 Benchmark Interpretation: Generational Performance Progression

The 12-protocol benchmark (Table 5 and Fig. 5) suggests a broad generational progression across four dimensions: energy consumption per round, PDR, latency, and network lifetime. This pattern is informative, but it should be interpreted as comparative synthesis rather than as a statistically unified ranking.

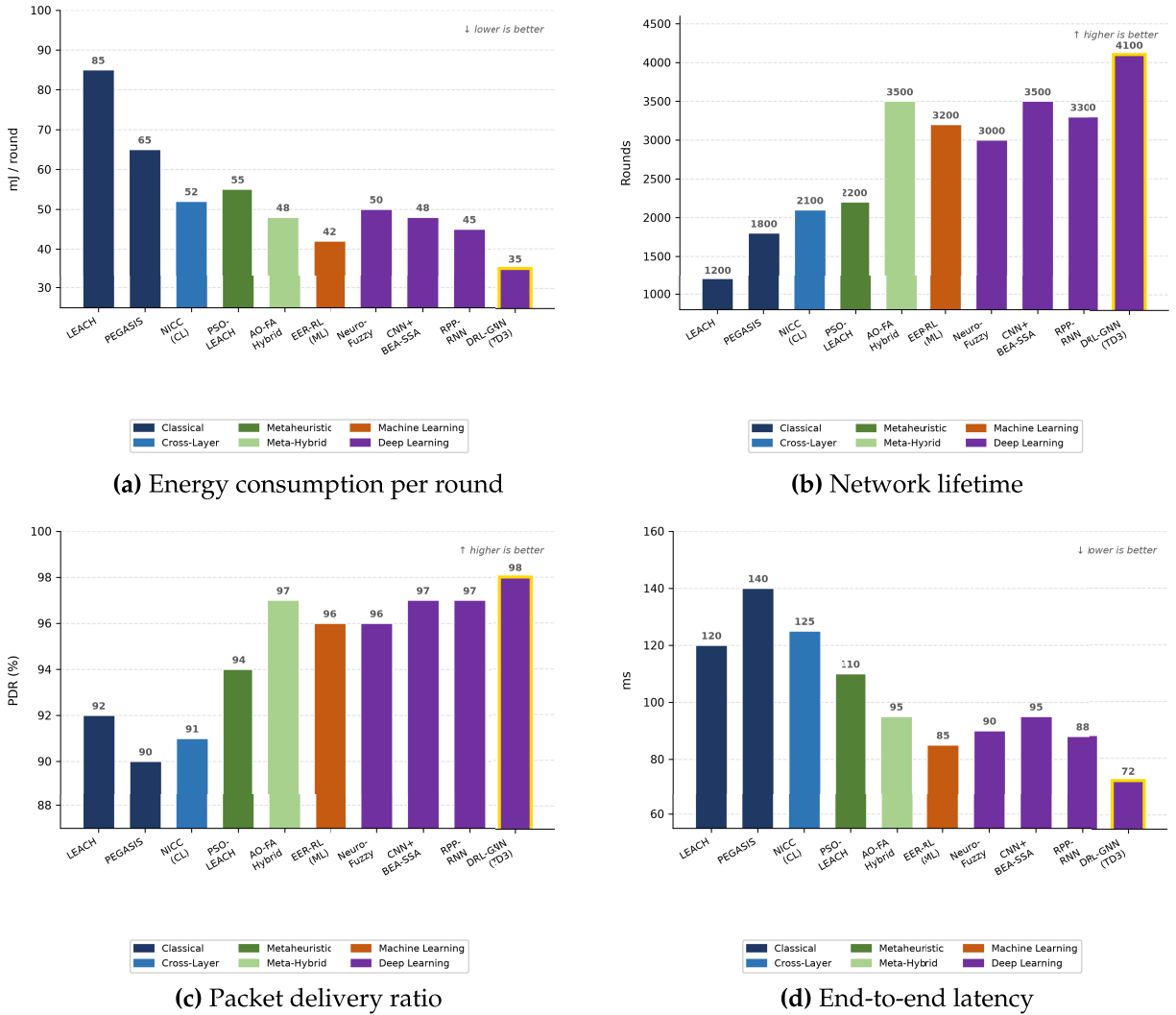


Figure 5: Four-metric performance comparison across 10 representative protocols interpreted through the common reference baseline (100 nodes, $1000 \times 1000 \text{ m}^2$, $E_0 = 1.0 \text{ J}$): (a) Energy Consumption per Round, (b) Network Lifetime, (c) Packet Delivery Ratio, and (d) End-to-End Latency. The figure illustrates broad generational trends in reported lifetime, PDR, latency, and energy consumption per round, but it should not be interpreted as proof of strict monotonic improvement because the underlying studies remain heterogeneous.

Classical protocols (LEACH, HEED). LEACH and HEED provide useful reference points because they represent widely used baseline architectures [6,7]. Their comparatively lower lifetime values are consistent with limited adaptability to residual-energy imbalance and near-sink congestion. The observed gap between LEACH and HEED illustrates that even modest energy-aware CH selection can improve lifetime, although both methods remain structurally limited in handling persistent hotspot formation.

Swarm intelligence protocols (PSO-LEACH, ACO-IIEEMARP, GWO Clustering). SI protocols generally report higher lifetime and lower energy consumption per round than classical baselines because they optimize CH placement and relay choice more explicitly. Their main strength lies in search-based improvement of spatial node organization. Their main limitation is that many variants remain weakly adaptive after deployment, which helps explain why they often improve early- and mid-stage efficiency more than late-stage robustness.

Evolutionary algorithms (GA-MMHCT). The EA results indicate that flexible chromosome design can be effective for heterogeneous clustering and routing problems. Compared with SI methods, EA protocols may achieve stronger structural adaptation in some settings, but this often comes with higher computational overhead and greater tuning sensitivity. Their practical attractiveness therefore depends on whether the additional search flexibility justifies the runtime cost on the target hardware.

Hybrid metaheuristics (ABC-DE, AO-FA). Hybrid methods report some of the strongest values among non-learning approaches, especially when both global exploration and local refinement are needed. Their main advantage is a favorable performance-to-hardware trade-off: compared with DL/DRL approaches, they often retain stronger compatibility with mid-range devices while narrowing the reported lifetime gap. This balance explains why hybrid methods appear repeatedly as practical candidates for constrained deployments.

Reinforcement learning (EER-RL). RL occupies an intermediate position between search-based optimization and DL/DRL. Its comparative advantage is online adaptation, especially in the presence of mobility or evolving load distribution. However, its reported improvements depend strongly on reward design and convergence behavior, and these aspects are not always documented with sufficient reproducibility detail in the primary studies.

Multi-objective and security-aware (EMOGJO, Trust-HPSO). Multi-objective and security-aware methods are important because they expose trade-offs that energy-only studies often ignore. The reviewed results suggest that adding trust, coverage, or QoS objectives can reduce peak lifetime relative to purely energy-optimized protocols, but this reduction may represent a more realistic deployment compromise rather than a weakness. Because security overhead is modeled inconsistently across studies, the exact cost of secure routing remains difficult to quantify.

Deep learning/DRL (DRL-GNN TD3). DRL-GNN reports the highest benchmark values in [Table 5](#), which is consistent with the ability of DRL/GNN models to incorporate topology-aware state information and long-horizon policy adaptation [23]. Even so, the absence of confidence intervals, consistent variance reporting, and broad testbed validation means that these values should be interpreted as strong reported results rather than definitive performance bounds.

For practitioners, the benchmark suggests a broad decision pattern rather than a strict prescription. When hardware resources are strongly constrained, hybrid metaheuristics often offer a more realistic balance of lifetime improvement and computational feasibility than DL/DRL methods. When 32-bit edge hardware and retraining support are available, DRL/GNN-based methods may offer additional gains, particularly in mobile or highly dynamic deployments. The cost-effectiveness of that transition, however, depends on application value, hardware budget, and tolerance for model complexity.

5.6 Multi-Dimensional Capability Radar

The capability radar chart ([Fig. 6](#)) provides a qualitative multi-dimensional summary across six dimensions: energy efficiency, network lifetime, scalability, QoS, security awareness, and computational lightness [1,4,19]. It is useful for visual comparison, but the underlying scores should be interpreted as synthesized judgments from the reviewed literature rather than as directly measured standardized quantities.

DRL-GNN occupies the strongest position on the energy, lifetime, and adaptability axes in the current synthesis, but this advantage is coupled to low computational lightness and higher deployment complexity [23,24]. Evidence for superior scalability is promising, but it remains based mainly on simulation studies rather than large-scale field deployments.

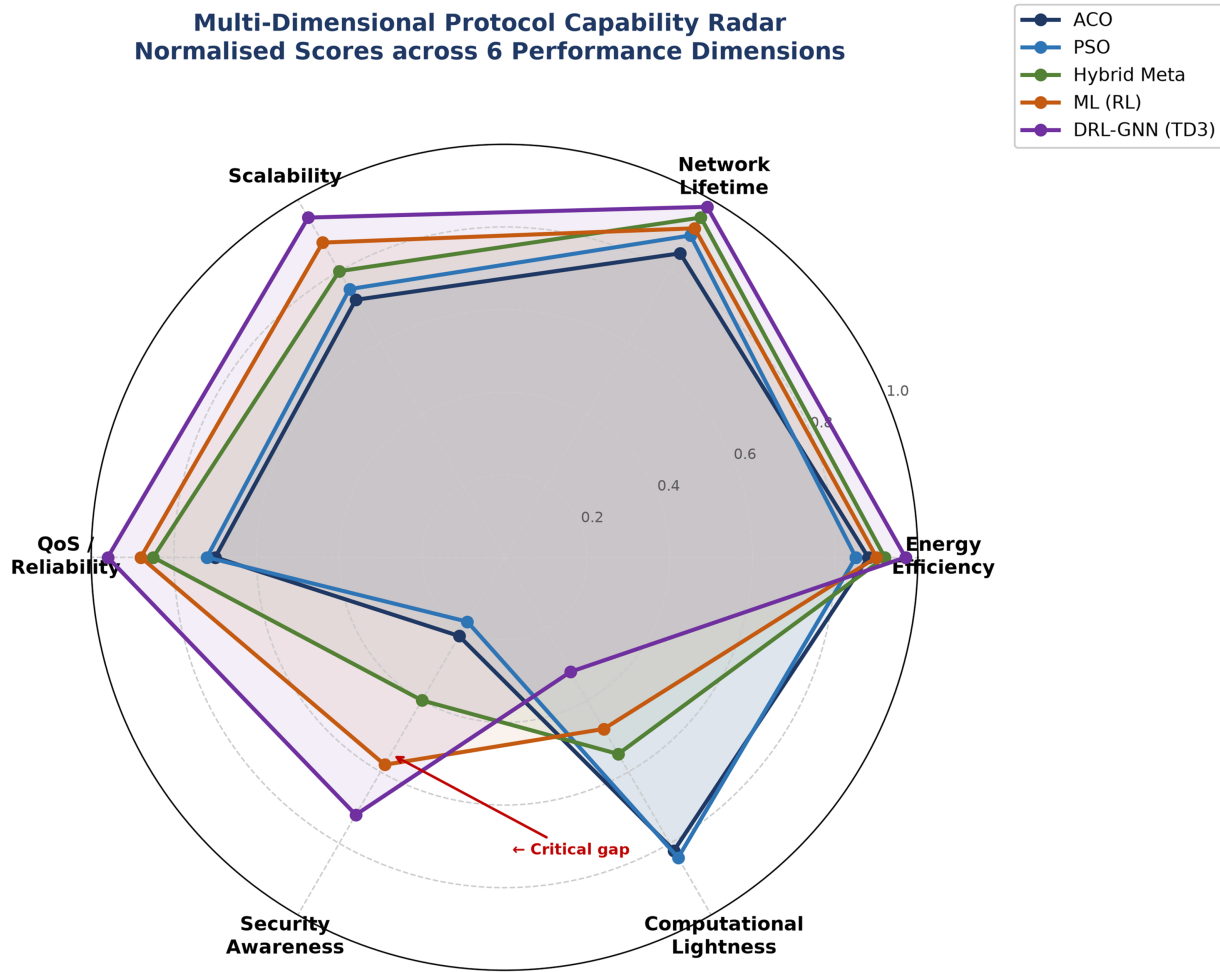


Figure 6: Multi-dimensional capability radar chart for protocol families.

Hybrid metaheuristics occupy a middle ground, combining comparatively strong reported performance with lower hardware demand than DL/DRL approaches [18,37,80,84]. This helps explain why they appear attractive for medium-complexity IoT deployments, although their reproducibility across diverse topologies remains insufficiently validated.

Classical SI methods retain strengths in simplicity, lower computational demand, and ease of implementation [6,14,20,27]. These properties remain relevant in legacy-hardware deployments, even though the same methods usually trail hybrid or learning-based protocols on broader QoS and robustness criteria.

Computational lightness is especially important when moving from simulation to deployment. In general, the reviewed evidence suggests that the highest reported benchmark values increasingly depend on migration from 8-bit and 16-bit hardware toward 32-bit edge-class devices. Whether that migration is justified depends on application criticality, maintenance cost, and the feasibility of model execution or retraining in the target environment [3,10,32,62,82].

6 Application Domains

6.1 Healthcare and IIoT: The Drivers of AI Adoption

The reviewed corpus spans eight application domains, whose relative representation is shown in Fig. 7 and detailed in Table 6. Healthcare and precision agriculture account for a large share of the reviewed studies, indicating sustained research interest in domains where energy constraints, coverage continuity, and maintenance cost are particularly important.

WSN Deployment Application Domains
89 Studies · 2016-2026

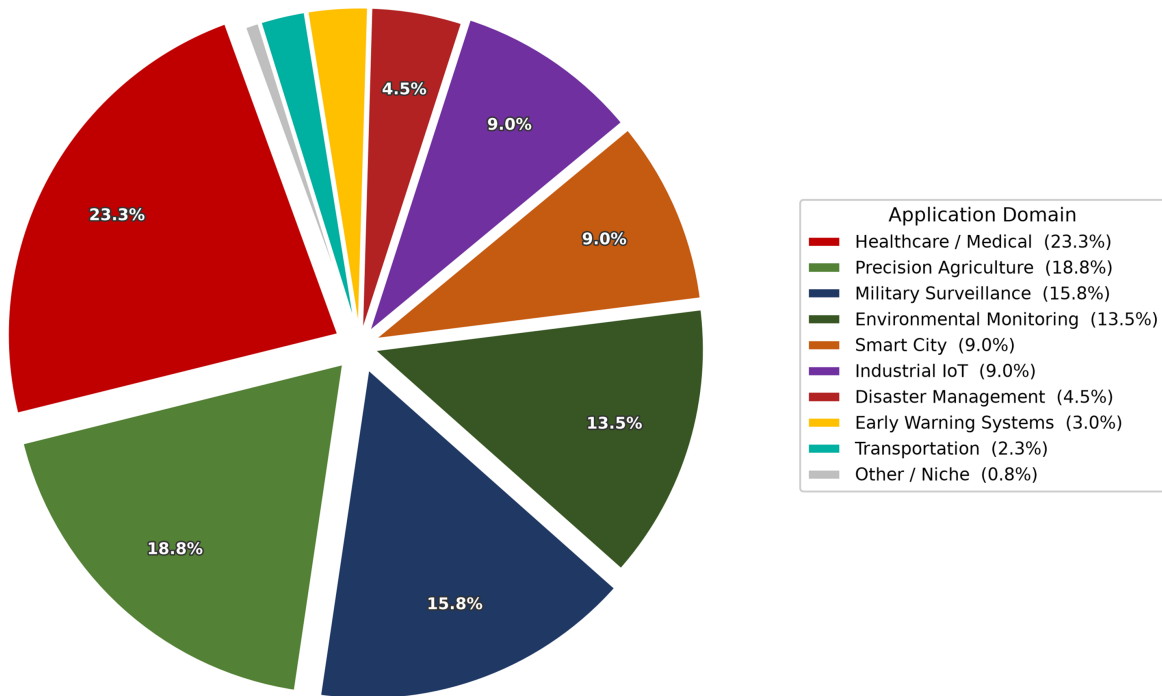


Figure 7: Distribution of WSN application domains across reviewed studies.

Table 6: Domain-specific optimization priorities and commonly reported algorithm families.

Domain	Share (%)	Primary Priority	Preferred Method	Constraint
Healthcare	24.8	Latency	DRL, Neuro-Fuzzy	Reliability
Agriculture	20.0	Cost/Lifetime	PSO, ABC, GWO	Scale
Environmental	14.4	Coverage	ACO, Multipath	Distance
Industrial IoT	9.6	Security	Hybrid, Blockchain	Interference
Smart Cities	9.0	QoS/Throughput	GA, Hybrid, RL	Heterogeneity
Military/Disaster	7.9	Survivability	ACO, Evolutionary, Trust	Hostile topology
Smart Grid	7.9	Reliability	PSO, Fuzzy-SI	Real-time latency
Other/Multi	6.4	Varies	Mixed paradigm	Context-specific
Total	100.0			

Healthcare monitoring is frequently cited as a demanding application domain because sensor nodes may be wearable or implantable, making battery replacement difficult and making reliability constraints more stringent [1,9,24,42,82]. In this context, the reviewed studies often evaluate methods that attempt to balance energy efficiency with latency-sensitive data delivery. Neuro-fuzzy models and DRL-based routing appear in this literature because they can incorporate priority-aware or context-aware decision rules, although evidence remains dominated by simulation rather than clinical deployment studies.

The Industrial Internet of Things (IIoT) is another frequently studied setting, particularly where electromagnetic interference, harsh environmental conditions, or long maintenance cycles make routing reliability important [10,23,24,62,69,82]. Several reviewed studies use ML- or DRL-based prediction to anticipate faults or congestion and to adapt routing accordingly. Relative to static metaheuristics, these methods may offer stronger responsiveness to changing conditions, but the available evidence does not yet establish how consistently these gains transfer to long-duration industrial deployments.

Security and energy efficiency frequently appear as competing objectives in IIoT-related studies. Attacks such as denial of service or malicious forwarding can increase retransmissions and deplete node energy more rapidly. For this reason, some reviewed studies incorporate trust, anomaly detection, or security-aware routing constraints into the optimization process [10,26,44–46,77]. However, the review also shows that such approaches still represent a small fraction of the overall literature.

A smaller group of studies explores blockchain-assisted trust management in IIoT-oriented WSNs [1,3,32,44,72,82]. These studies argue that distributed trust records may improve integrity and auditability, but they also introduce additional communication and computation overhead. At present, the reviewed evidence is insufficient to determine whether this overhead is acceptable across typical resource-constrained WSN deployments.

Taken together, the domain distribution suggests that healthcare and IIoT are prominent contexts for studying adaptive and learning-based optimization. Even so, the current evidence base does not yet justify broad claims about deployment readiness, because most published results remain simulation-driven and are rarely accompanied by hardware-level energy profiling or long-term field validation [1,4,16].

6.2 Precision Agriculture and Environmental Monitoring

Precision agriculture and environmental monitoring remain important domains for large-scale and cost-sensitive WSN deployments. These settings often involve sparse or geographically extended topologies, limited maintenance access, and low-cost hardware, which shifts emphasis toward coverage preservation and long network lifetime [2,8,15,16,18,85]. In the reviewed studies, lightweight approaches including fuzzy logic and metaheuristics such as PSO, ABC, and ACO appear frequently in these settings because they can be implemented with lower computational overhead than many learning-based methods.

In smart irrigation and soil-moisture monitoring, environmental changes such as vegetation growth and weather variability can affect propagation conditions and route stability. Several reviewed studies therefore evaluate adaptive routing updates in outdoor agricultural settings [18,49,80,84,86–88]. These studies generally report improved connectivity or lifetime under their respective simulation assumptions, although direct long-season field validation remains limited.

Environmental monitoring, including forest-fire detection and wildlife tracking, introduces additional challenges related to remoteness, sparse connectivity, and limited maintenance access. In this domain, mobile sink strategies are often studied as a way to reduce long multi-hop forwarding chains and to mitigate peripheral-node depletion [11,29,47,48,89,90]. Some reviewed studies report substantial energy savings

relative to static sink assumptions, but these gains remain sensitive to trajectory constraints, mobility cost models, and deployment geometry.

Region-based routing is another recurring design choice in large-scale environmental deployments. By partitioning the network into zones, these methods attempt to reduce global control overhead and to localize optimization decisions [17,36,38,75,91–93]. The reviewed studies suggest that such decentralization can improve lifetime in large sparse deployments, although the extent of benefit depends on zone definition, relay policy, and synchronization assumptions.

Overall, precision agriculture and environmental monitoring remain the domains in which low-overhead and hardware-aware metaheuristics are most frequently studied. The evidence suggests that computational simplicity remains an important design advantage in these settings, although scalability claims should still be interpreted cautiously because large-field validation is much less common than simulation-based evaluation [8,21,22,28,33,76,79].

6.3 Emerging Domains: Smart Cities, Military, and Smart Grid

Three additional deployment contexts also represent a meaningful portion of the reviewed literature and introduce distinct optimization requirements.

Smart Cities. Urban WSN deployments for parking management, traffic sensing, and air-quality monitoring are commonly associated with heterogeneous node density and variable traffic patterns. In the reviewed literature, GA-hybrid and RL-based methods appear in this context because they can incorporate QoS constraints more explicitly than fixed clustering rules [1,4,10].

Military and Disaster Response. In hostile or post-disaster environments, survivability, robustness to failure, and trust-aware routing become more prominent than energy minimization alone. Evolutionary algorithms, trust-aware ACO, and mobile-sink strategies are therefore recurrent choices in this part of the literature [29,44–46].

Smart Grid. Smart-grid monitoring introduces strict latency and reliability requirements that are often difficult to reconcile with asynchronous or computationally heavy optimization strategies. For this reason, the reviewed studies in this domain often favor fuzzy logic systems, fuzzy-SI hybrids, or PSO-based variants with stronger convergence control and bounded-response behavior [9,49,77,85].

Table 6 summarizes the domain distribution together with the dominant optimization priority, commonly reported method class, and major deployment constraint. These associations should be read as literature tendencies rather than exclusive domain-to-method assignments.

The geographic provenance of the reviewed studies, shown in Fig. 8, reveals a strong concentration in South and Southeast Asia, with secondary contributions from the Middle East and North Africa. This pattern suggests regional concentration in the current evidence base and indicates that field-validation evidence from North America, Europe, and Sub-Saharan Africa remains comparatively limited in the reviewed literature.

7 Discussion: Comparative Analysis and Research Gaps

7.1 Energy Minimization: Problem Formulation and Algorithmic Responses

Energy minimization in WSNs is better understood as a set of related sub-problems rather than as a single optimization task. Distinguishing these sub-problems is important because different algorithm families address different aspects of the overall energy-management challenge.

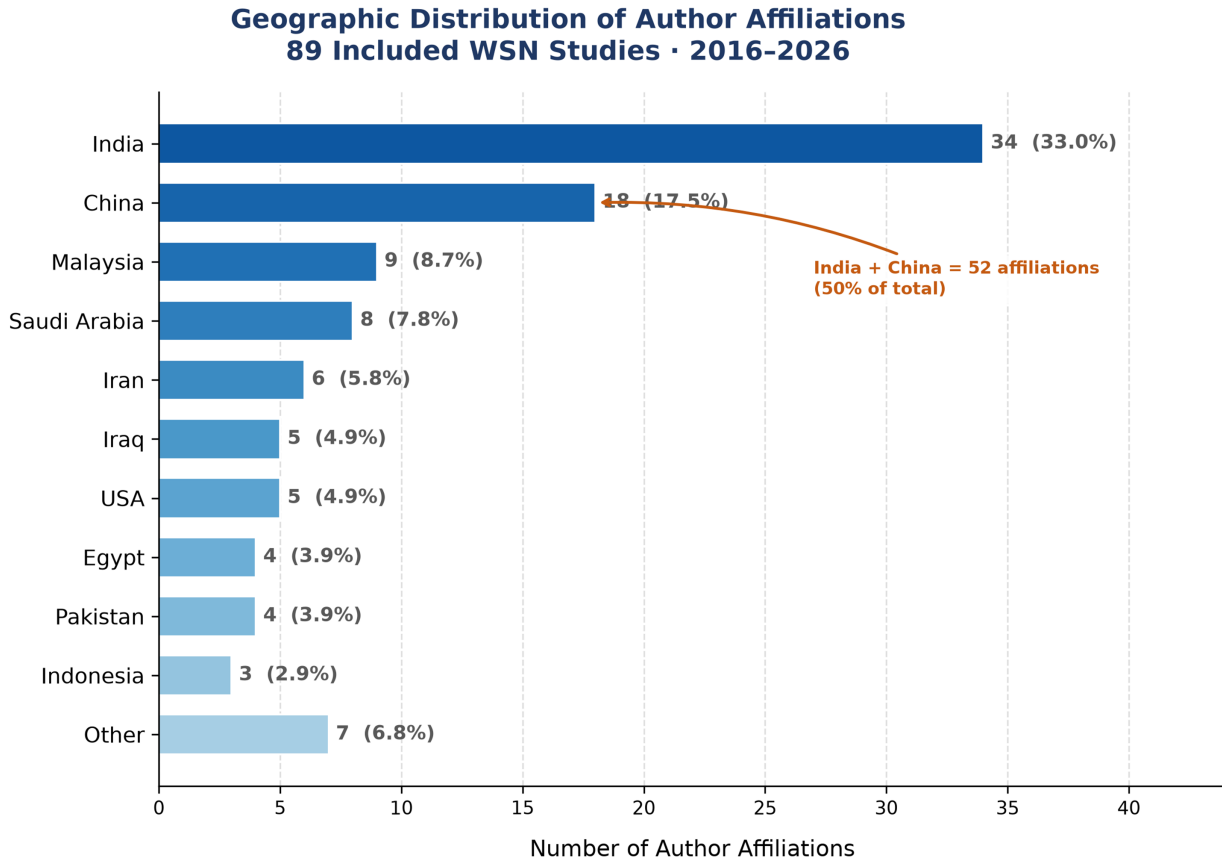


Figure 8: Geographic distribution of author affiliations (89 studies).

The Cluster Head Selection Sub-Problem. The most extensively studied sub-problem is CH selection: given the current residual-energy distribution across n nodes, select a subset of k nodes to serve as CHs while limiting aggregate energy dissipation and preserving coverage constraints. The combinatorial complexity of this problem is $\binom{n}{k}$, which makes exact optimization impractical even for moderate network sizes. All major algorithm families in the taxonomy address this problem, but they do so differently. SI methods typically rely on composite fitness functions over residual energy and distance [20,21]; EAs rely on chromosome encoding and genetic operators [17,18]; and DRL-based methods treat the problem as sequential decision-making [23]. In principle, DRL has an advantage in modeling long-horizon consequences, but this advantage should be interpreted alongside its higher computational cost and limited testbed evidence.

Load Balancing and the Energy Hole Problem. A CH-selection strategy that ignores relay load will still produce the energy hole problem because nodes near the BS forward a disproportionate share of traffic. Addressing this requires explicit load-balancing terms in the optimization objective. ACO and hybrid metaheuristic studies often report stronger load redistribution because their update rules penalize depleted nodes more directly [12,37–39,78]. Even so, the reported magnitude of variance reduction should be interpreted cautiously because the residual-energy standard deviation metric is not reported uniformly across all primary studies.

Intra-Cluster Energy Management. Within each cluster, data aggregation remains an important energy lever because effective aggregation can reduce the number of forwarded transmissions.

Predictive and learning-based approaches attempt to adapt aggregation behavior to traffic or sensing patterns [19,42,43,55,62]. However, the corresponding literature reports aggregation gains under heterogeneous assumptions and rarely quantifies the added computational cost in a fully reproducible way.

Energy Harvesting Integration. A smaller subset of studies models energy harvesting as a stochastic replenishment process rather than assuming a fixed energy budget [1,10,82]. In such cases, the optimization objective shifts from pure lifetime maximization toward adaptive control under uncertain supply. RL-based methods are often proposed for this setting because they can encode future energy expectations in the reward function, but harvesting-aware protocol design still represents a small fraction of the reviewed evidence base.

7.2 Routing Optimization: Strategies, Trade-Offs, and Deployment Realities

Routing optimization in WSNs requires deciding how data should be relayed from CHs to the sink under energy, latency, and reliability constraints. Relative to CH selection, routing introduces a stronger graph-theoretic component and often requires repeated adaptation as residual energy and link quality evolve.

Multi-Hop Path Discovery. Classical multi-hop routing algorithms such as PEGASIS and Dijkstra-based variants select paths based on transmission distance, without considering residual energy. This can lead to paths through depleted relay nodes continuing to be used until those nodes fail, after which portions of the network may become unreachable. ACO addresses this through pheromone-weighted path discovery that favors energy-rich relay nodes [48,67]. The IEEMARP protocol reports a 10% PDR improvement over standard ACO through multipath diversity, maintaining multiple parallel routing trees so that failure of a single relay node causes graceful degradation rather than abrupt connectivity loss [47]. Bellman-Ford shortest-path routing with K-Medoid clustering provides energy-efficient data transmission, reducing energy consumption and prolonging network lifetime [68]. Region-based routing partitions the network into geographic zones and applies energy-aware intra-zone optimization before inter-zone relay, reducing global control overhead at the cost of some cross-zone optimality [75,94].

Mobile Sink Trajectory Optimization. In large-scale environmental deployments, moving the data collection point toward remote clusters can reduce the long-distance multi-hop chains that deplete peripheral node batteries. ACO-based trajectory optimization assigns pheromone values to geographic waypoints, converging on data collection tours that minimize total node energy expenditure under temporal coverage constraints [29,30]. RL approaches model the trajectory problem as a sequential decision process, with the mobile sink's position as state and its next waypoint as action. Reported data collection tours achieve 30%–50% better energy efficiency than static multi-hop routing in sparse deployments under their respective simulation conditions [26,30]. The coupling of mobile sink trajectory planning with cluster head selection remains an open problem [25,29].

Cross-Layer Routing and MAC Co-Optimization. Traditional layered protocol design treats MAC scheduling and network-layer routing as independent problems. In WSNs, this separation has a measurable cost: a routing protocol that selects energy-optimal paths but ignores MAC-layer duty cycles may route traffic through nodes that are asleep, triggering retransmissions. Cross-layer frameworks address this by jointly optimizing the MAC schedule and the routing topology, modulating duty cycles in proportion to each node's routing responsibilities [16,22]. This integration can reduce idle-listening energy in duty-cycled deployments and has been associated with lifetime extensions of 25%–40% relative to protocols that optimize each layer independently [8,15,16]. Cross-layer design also enables integration of physical-layer power control into routing optimization, where transmission power is selected jointly with the routing path to minimize total hop energy under a reliability constraint.

QoS-Constrained Routing and the Latency–Energy Dilemma. The fundamental trade-off in QoS-constrained routing is between energy minimization and latency minimization: the energy-optimal path minimizes transmission power by selecting the route with the lowest aggregate distance, which typically maximizes hop count and therefore maximizes end-to-end delay. Conversely, the latency-optimal path minimizes hop count, selecting longer individual hops at higher per-hop energy cost. Solving this trade-off requires multi-objective formulations that expose the Pareto frontier between energy and delay, allowing selection of operating points appropriate to the application’s QoS requirements [65,66,70]. The Energy-Delay Product (EDP) metric has been used as a scalar proxy for this trade-off, but its use collapses the Pareto frontier into a single point and loses information about the trade-off structure. Full Pareto analysis of the energy-latency trade-off across routing protocols remains underexplored.

7.3 Learning-Based Adaptation: From Static Optimization to Online Intelligence

A notable trend in the 2020–2026 period is the shift from static or epoch-based optimization toward online adaptation. Learning-based approaches are central to this trend because they frame routing as sequential decision-making rather than repeated offline search.

Tabular Reinforcement Learning: Foundations and Limits. Tabular RL represents one of the earliest forms of adaptive routing in this literature. Its main benefit is the ability to update policy values incrementally using local feedback [26,41]. However, tabular methods scale poorly because Q-table size grows with the state–action space, which quickly exceeds the memory budget of many 8-bit and 16-bit devices. Centralized or Software-Defined Networking (SDN)-assisted variants reduce local memory burden, but they introduce additional coordination overhead and potential single points of failure.

Deep Reinforcement Learning: Policy Learning at Scale. Deep Q-Networks (DQN) and their actor-critic variants replace the Q-table with a neural network function approximator, enabling policy learning in high-dimensional continuous state spaces that tabular RL cannot represent. In WSN routing, the continuous state includes the residual energy vector, channel quality estimates, and traffic load distribution [23–25]. The DRL-GNN architecture augments the policy network with a Graph Neural Network that models the topology of the sensor network. Rather than re-optimizing from scratch after each node failure, the GNN module updates its topology representation through message-passing and the policy network adjusts its routing decisions [23,24].

Multi-Agent Reinforcement Learning (MARL) extends the single-agent framework to networks where each node operates as an independent learning agent, with a joint reward that incentivizes globally energy-efficient behavior [25]. MARL eliminates the central training server requirement: agents learn from local interactions and converge to a cooperative distributed policy. Key challenges include non-stationarity of the multi-agent environment and credit assignment under joint rewards. These are typically addressed through reward shaping and periodic global synchronization events that recalibrate individual policies [25].

Recurrent and Temporal Models for Traffic Prediction. Recurrent Neural Networks (RNN) and Long Short-Term Memory (LSTM) networks address temporal traffic patterns in WSN deployment settings where sensing cycles produce autocorrelated traffic [42,62]. A model that predicts future traffic from historical observations can adjust routing paths and duty cycles before demand spikes occur. LSTM-based mobile sink trajectory optimization predicts future cluster-level data generation rates and plans sink waypoints accordingly. Under its reported simulation conditions, this predictive approach reduces total network energy dissipation by 25%–30% relative to reactive trajectory optimization [42].

Lightweight and Hardware-Compatible Learning Models. The dominant barrier to deploying learning-based protocols on legacy 8-bit hardware is model inference complexity. A 3-layer neural network

with 64 hidden units requires approximately 10^4 floating-point multiply-accumulate operations per inference step, which takes roughly 1–2 ms on a 32-bit Cortex-M4 but would require several hundred milliseconds on an AVR ATmega128, during which the radio transceiver idles in a high-power state. Several hardware-compatible approaches have been proposed to bridge this gap. Neuro-Fuzzy systems replace the neural inference component with a fuzzy inference engine based on IF-THEN rules with membership function gradients, reducing inference to table lookups executable in microseconds on 8-bit hardware [9,85]. Knowledge distillation compresses a trained DRL policy into a shallow decision tree or linear threshold classifier that preserves the policy's routing decisions for the most common network states with $O(1)$ inference cost. Combined with quantization to fixed-point arithmetic, this pipeline can make trained routing policies accessible on 8-bit MCUs [1,4,62].

The synthesis of the 89 primary studies suggests a gradual transition from classical search-based methods toward more adaptive hybrid and learning-based strategies [1,4,19]. This transition is visible in benchmark trends and taxonomy distribution, but it should not be interpreted as a complete displacement of classical methods because hardware constraints, reproducibility concerns, and domain-specific requirements still favor lower-complexity approaches in many scenarios.

7.4 The Complexity–Efficiency Trade-Off

The complexity–efficiency trade-off remains one of the central issues in modern WSN routing research. Protocols with stronger reported energy and lifetime performance, especially DRL- and GNN-based methods, also impose greater computational demand [23–26,32]. In resource-constrained nodes, this added computation may offset part of the communication-related gain, which is why hardware feasibility and inference cost must be considered alongside network-level performance metrics.

Hybrid metaheuristics appear repeatedly as a practical compromise in this trade-off. Relative to DL/DRL approaches, they often retain lower hardware requirements while still reporting strong benchmark values [18,37,57,80,84]. This makes them particularly relevant where mid-range embedded hardware is available but full neural inference remains impractical.

The learning-communication balance introduces a further dimension to this trade-off. Learning-based protocols frequently require global state updates or weight synchronization messages, generating additional energy dissipation [23–26,32]. Lightweight metaheuristics such as improved LEACH variants or PSO-based clustering, by contrast, rely on local interactions and produce minimal control overhead, making them more suitable for high-traffic or low-bandwidth scenarios under their reported evaluation conditions [8,14,15,19,20].

Research into anytime algorithms and on-demand optimization seeks to mitigate this trade-off by allowing nodes to adjust their optimization complexity in response to remaining battery capacity. When energy is plentiful, a node may invoke a complex DRL model; as reserves diminish, it switches to a lightweight fuzzy or swarm heuristic [48,85,89,95].

In the longer term, the complexity-efficiency trade-off may be addressed through hardware advances such as dedicated AI-acceleration blocks or neuromorphic co-processors integrated into sensor node SoCs. Until such hardware is widely available, knowledge-distillation techniques that compress complex DRL routing policies into lightweight heuristics offer a more immediate path toward practical deployment [1,10,62,82,96].

7.5 Strengths of Current Research

A major strength of the recent literature is the increasing attention to heterogeneity, cross-layer interaction, and multi-objective behavior. Compared with earlier homogeneous-network assumptions, many recent studies explicitly model differences in energy budget, communication burden, or node capability [13,18,19]. This shift improves realism, although it does not by itself resolve the reproducibility and deployment gaps identified earlier.

Cross-layer optimization has been increasingly adopted, where routing decisions are coordinated with MAC-layer scheduling and physical-layer power control. Algorithms such as those proposed by Mahajan and Badarla optimize duty cycles based on a node's current routing responsibilities, reducing idle-listening energy relative to protocols that treat layers independently [15,16,22,28]. This coordination prevents network-layer gains from being offset by sub-optimal scheduling at lower layers [15,16,22,28].

Swarm intelligence hybridism combines properties of distinct bio-inspired algorithms. Pairing the fast convergence of PSO with the local optima avoidance of GWO can produce a search process that balances speed and robustness [18,34,57,80,84]. The resulting protocols have been reported to maintain network connectivity under 20%–30% node failure rates in simulation studies [18,34,57,80,84].

Dynamic path discovery for mobile environments has also received increasing attention. Integrating ACO with mobile sink trajectory optimization moves the data collection point closer to sensor nodes rather than relying on multi-hop relay to a distant static sink, which can reduce the energy hole problem [29,47,48,89]. This mobility-aware approach is relevant to settings that incorporate drone and autonomous ground vehicle platforms in industrial and environmental monitoring [29,47,48,89].

Open-source simulators and more transparent reporting have improved comparability in part, especially where NS-3, Cooja, or better-documented parameter settings are used [1,4,27]. However, the review still finds substantial heterogeneity in datasets, simulator choices, parameter disclosure, and repetition protocols, which limits the degree to which published results can be treated as fully reproducible.

Table 7 presents a structured comparison of all six algorithm families across ten analytical dimensions, enabling practitioners to make informed protocol selection decisions based on their specific deployment constraints.

Table 7: Comparative analysis of WSN optimization algorithm families across ten deployment dimensions. Ratings: ✓✓✓ = Excellent, ✓✓ = Good, ✓ = Acceptable, × = Poor. Interp. = Interpretability for safety-critical deployment.

Paradigm	Energy Eff.	Lifetime	Scalability	QoS	Security	HW Light	Mobility	MO Cap.	Interp.	Testbed Val.
SI (PSO/ACO)	✓✓	✓✓	✓	✓✓	×	✓✓✓	✓	✓	✓✓✓	✓
EA (GA/DE)	✓✓	✓✓	✓	✓✓	✓	✓✓	✓	✓✓✓	✓✓✓	✓
Hybrid MH	✓✓✓	✓✓✓	✓✓	✓✓✓	✓	✓✓	✓✓	✓✓	✓✓	✓✓
RL	✓✓	✓✓✓	✓	✓✓	✓	✓✓	✓✓✓	✓	✓	✓
Deep Learning	✓✓✓	✓✓✓	✓✓✓	✓✓✓	✓	×	✓✓✓	✓✓	×	✓
MO/Security	✓✓	✓✓	✓	✓✓✓	✓✓✓	✓✓	✓	✓✓✓	✓✓	✓

Analysis of Table 7 highlights several deployment trade-offs. DL and DRL methods occupy the strongest position on reported energy, lifetime, and adaptability dimensions, but these gains come with weaker hardware lightness and interpretability. Hybrid metaheuristics appear more balanced overall, especially when hardware constraints are considered. The security dimension remains underdeveloped across all categories, which is consistent with the very limited proportion of studies that treat security as a first-class optimization objective.

7.6 Critical Research Gaps

The PRISMA 2020-guided synthesis of 89 included studies supports the identification of six recurring research gaps, summarized in Table 8. These gaps affect both the validity of algorithmic performance claims and the broader credibility and deployment relevance of the literature.

Table 8: Gap priority matrix: six critical research gaps identified from the PRISMA synthesis, with root causes, quantitative impact, and research directions. Priority: **CR** = Critical, **H** = High, **M** = Medium.

ID	Gap	Root Cause	Quantitative Impact	Research Direction	Pri.
G1	Security–Energy Vacuum	Security overhead is difficult to model; joint energy-security formulations are complex	1% of studies address security as an optimization objective; adversarial nodes can exploit energy-only paths	Formally verified lightweight trust primitives with quantified energy cost; joint energy-security Pareto frameworks	CR
G2	Simulation to Reality Gap	First-order radio model omits battery non-linearity, leakage, fading, and sync overhead	Reported simulation gains may attenuate substantially in physical deployment; >95% of studies are simulation-only	Testbed-first validation standards; circuit-level energy models incorporating DC-DC converter inefficiency	CR
G3	Massive IoT Scalability	Population-based MH and centralized DRL training both face intractability beyond 200 nodes	Convergence time scales super-linearly; hierarchical FL unvalidated at $n > 1000$ nodes	Hierarchical federated optimization; distributed quantum-inspired search with provable scalability bounds	H
G4	Multi-Objective Formulation Deficit	QoS treated as hard constraints rather than objectives; four-objective Pareto (energy + latency + PDR + security) unexplored	14.6% of studies use MO; <2% solve ≥ 3 objectives simultaneously; Pareto front not reported in most MO papers	True Pareto optimization over ≥ 4 objectives; Pareto sensitivity analysis across deployment scenarios	H
G5	Cross-Application Generalizability	Fitness function parameters tuned per domain; no universal design principles	Performance can vary materially across domains because energy, latency, and reliability priorities differ	Foundation model routing policies trained on diverse telemetry; domain adaptation layers with distributional distance metrics	M

(Continued)

Table 8 (continued)

ID	Gap	Root Cause	Quantitative Impact	Research Direction	Pri.
G6	Hardware-Aware Algorithm Design	Research often assumes 32-bit hardware, whereas low-cost deployments still include constrained 8/16-bit MCUs	Some DRL/GNN gains may remain inaccessible to legacy infrastructure without compression, offloading, or co-design	Knowledge distillation of DRL to decision-tree or fixed-point models; hardware-in-the-loop co-design benchmarks	M

Gap G1—The Security–Energy Vacuum. Security remains weakly integrated into WSN energy optimization. Less than 1% of the reviewed studies formulate security as an explicit optimization objective, despite the fact that energy-aware routing can be manipulated by malicious or falsely advertised node behavior [44–46,72]. The main reason appears to be methodological: security mechanisms introduce overhead that is harder to model than transmission energy alone, and many studies avoid this complexity altogether.

Gap G2—The Simulation to Reality Gap. More than 95% of the reviewed literature validates optimization proposals through simulation alone, often with the first-order radio energy model. While this model is useful analytically, it omits important physical effects such as battery non-linearity, leakage, fading, synchronization overhead, and environment-specific propagation variability [10,31]. As a result, simulation-derived gains may not transfer proportionally to physical deployments. This is one of the most important limitations affecting the practical interpretation of reported benchmark improvements.

Gap G3—Massive IoT Scalability. Most reviewed protocols are evaluated on networks of roughly 50–200 nodes. This leaves a substantial gap with respect to massive IoT scenarios involving much larger node populations, bursty traffic, and stronger hardware heterogeneity [1,3,32]. Under such conditions, both population-based search and centralized DRL training may become difficult to scale, yet validated large-scale alternatives remain limited.

Gap G4—Multi-Objective Formulation Deficit. Although 14.6% of reviewed studies use multi-objective formulations, many still treat QoS metrics as constraints rather than as co-optimized objectives. This limits the visibility of the actual trade-off surface among energy, latency, reliability, and security. As a result, protocol selection often relies on partial comparisons rather than on explicit Pareto analysis.

Gap G5—Cross-Application Generalizability. Many protocols are tuned to a specific application context and are rarely validated across substantially different domains. As a result, methods that perform well in sparse agricultural settings may not transfer to dense, latency-sensitive healthcare or industrial networks. This limits the development of broadly reusable design principles and reduces confidence in cross-domain claims.

Gap G6—Hardware-Aware Algorithm Design. A persistent mismatch remains between the hardware assumptions of high-performing protocols and the capabilities of many deployed sensor nodes. DRL/GNN, MARL, and CNN-based methods often assume 32-bit processors with larger memory budgets, whereas many deployed WSN nodes still operate under severe RAM and computation constraints [1,4]. This gap limits the practical relevance of some of the strongest reported benchmark results unless model compression, offloading, or hardware-aware co-design is addressed directly.

8 Emerging Trends and Future Directions

8.1 Federated Learning (FL) for Communication Efficiency

Federated Learning (FL) is increasingly discussed as a way to reduce the communication burden associated with centralized AI training. Instead of transmitting all raw observations to a remote server, nodes train locally and share model updates or compressed parameter information [1,3,4,32]. In principle, this can reduce raw-data transmission, although the practical benefit depends on model size, aggregation frequency, and uplink reliability.

Realizing FL in practice on resource-constrained sensors is non-trivial. Because nodes observe geographically distinct phenomena, local models can diverge and destabilize global convergence. Contemporary FL schemes address this through asynchronous aggregation schedules and gradient compression methods such as quantization and top- k sparsification. These techniques enable parameter updates to be conveyed over low-bandwidth, high-loss radio links [1,3,25,32] and help maintain training stability in field-deployed networks subject to intermittent connectivity and node failures [1,3,25,32].

Coupling FL with metaheuristic cluster formation creates a two-tier architecture. A population-based algorithm such as PSO or GWO first determines intra-cluster aggregators. These nodes collect local weight updates from member nodes, perform partial model fusion, and relay the compressed result to the sink. This hierarchical structure reduces energy expenditure associated with long-range base-station transmissions [4,10,62,82].

FL can also offer privacy benefits relevant to healthcare and military deployments. Retaining raw measurements on the originating device reduces exposure to data-interception attacks. Cryptographic secure aggregation, where the aggregation server computes a model update without observing individual node contributions, is under investigation [44–46,72].

Longer-term, pairing FL with over-the-air computation (AirComp) may improve aggregation efficiency. AirComp uses the superposition property of the wireless channel to reduce the serial per-node uplink burden. In WSN-oriented deployments this combination remains a research direction rather than a near-term standard [1,3,4].

8.2 Edge-Fog-Cloud Orchestration

Edge-Fog-Cloud orchestration distributes computation according to latency and hardware constraints. Lightweight inference remains near the sensing edge, while heavier retraining or coordination tasks are delegated to fog or cloud resources [1,3,23,24,32]. The net energy benefit depends on communication overhead, gateway availability, and the cost of maintaining the intermediate orchestration layer.

In deployments such as smart-city traffic management, edge nodes running distilled lightweight models can issue routing decisions for emergency vehicle telemetry within latency constraints, while the fog tier analyzes cross-block traffic patterns to push revised global routing policies to the edge nodes [9,23,24,26,42].

Fog nodes serve as intermediate storage and aggregation buffers that reduce the duty cycle of long-range radios. Local data fusion and deduplication at the fog layer can lower the transmission burden on individual nodes. Some studies report lifetime improvement relative to cloud-only architectures in data-intensive applications, although the benefit depends on workload, gateway placement, and communication assumptions [3,74,97].

The tiered model can support Digital Twins for energy management. A virtual replica of the sensor network, maintained in the cloud and informed by real-time telemetry from edge nodes, can forecast energy

depletion trajectories and identify routing bottlenecks. Computationally intensive analyses using GA or ABC can be executed on the twin, with only the resulting configuration pushed to physical nodes [1,4,10].

As fog hardware is deployed in streetlights, industrial gateways, and building management systems, the edge-fog-cloud model may lower the barrier to deploying more sophisticated routing intelligence on commodity sensor nodes. For larger-scale IoT scenarios, the net value of this tiered orchestration model depends on deployment cost and coordination overhead [1,3,4].

8.3 Blockchain-Integrated Secure Routing

Blockchain-integrated secure routing addresses trust challenges in decentralized sensor networks. When nodes select cluster heads based solely on residual energy, the network can be vulnerable to adversaries that falsely advertise high energy states. A distributed ledger that records each node's behavioral history and derived reputation score conditions energy-aware CH selection on verified trustworthiness [44–46,72]. A misbehaving node may be excluded from the routing backbone regardless of its advertised energy.

A central barrier to blockchain adoption in WSNs is the energy overhead of Proof-of-Work consensus, which is not well suited to milliwatt-class radios. Recent work has explored lightweight consensus variants such as Proof-of-Energy and Proof-of-Trust, where a node's voting influence is proportional to its residual energy reserve or its track record of reliable relaying [1,44–46,72].

In networks with energy-harvesting capabilities, blockchain enables autonomous energy trading through smart contracts. A solar-powered node with surplus charge can auction its relaying capacity to a depleted neighbor, with the transaction recorded on a localized ledger [1,4,10,44]. Under favorable conditions, this can extend the lifetime of heterogeneously harvesting networks.

Off-chain data storage and state channels restrict ledger writes to high-value events such as CH transitions, trust score updates, and anomaly flags. Routine sensing data flows over conventional energy-optimized paths [1,4,44]. This approach retains the security guarantees of a distributed ledger while avoiding the per-packet cost of full on-chain routing.

The convergence of AI-driven routing, blockchain-based trust management, and 6G-enabled connectivity is frequently presented as a future security direction for large-scale IoT deployments [1,3,32,44,82]. At present, however, this remains an emerging research direction rather than an established deployment model. The associated energy and orchestration overheads are not yet well quantified.

8.4 Quantum-Inspired Optimization

Quantum-inspired optimization addresses combinatorial search spaces in large-scale WSN routing. Classical metaheuristics use stochastic point-to-point transitions across a solution space, which becomes less efficient as network size grows and configurations scale exponentially. Quantum-inspired algorithms such as Quantum PSO (QPSO) and Quantum Genetic Algorithms (QGA) encode candidate solutions as Q-bit probability amplitudes [38,92,98]. Reported results indicate convergence speeds up to 40% faster than classical PSO or GA on topologies exceeding 300 nodes under their respective simulation conditions [38,92,98].

The distinguishing mechanism is Q-bit rotation. During each iteration, quantum rotation gates update the probability amplitudes associated with each candidate state, balancing exploration against exploitation without requiring manual tuning of inertia weights or crossover rates. This may be useful in dynamic WSN environments where topology changes require re-optimization [87,93,98]. Faster reconvergence following a topology perturbation is a reported advantage of QPSO relative to classical approaches [87,93,98].

Entanglement-inspired mechanisms extend these ideas to joint optimization across multiple sub-problems. Coupling the Q-bit representations of CH selection and member-node assignment allows the

algorithm to propagate changes to related components coherently, potentially reducing control message overhead [17,36,38,91,98].

A practical concern is whether quantum-inspired algorithms can execute on the processors available in deployed sensor nodes. Q-bit updates require only trigonometric operations such as sine and cosine evaluations on 32-bit fixed-point representations, making them feasible on ARM Cortex-M-class MCUs [1,4,92,98].

Prospectively, the maturation of quantum networking introduces a further dimension. As WSNs become edge nodes of a broader quantum internet, quantum-inspired routing algorithms may evolve toward quantum execution on gateway-class hardware. Near-term, however, this remains an emerging direction requiring broader validation on realistic embedded platforms [1,3,4,32,98].

8.5 Transfer Learning for Rapid Adaptation

Transfer Learning (TL) addresses the initialization problem in AI-driven WSN routing. A newly commissioned network operating under a randomly initialized policy may spend a substantial portion of its early operational life exploring suboptimal routes before converging to an efficient state. Importing a routing policy pre-trained on a source network in a comparable environment may reduce the amount of local exploration needed [1,10,62,82,99]. This earlier stabilization may be valuable in deployments where operational latency is constrained, such as disaster response or emergency health monitoring.

Feature-based transfer is the dominant mechanism in current literature. The lower neural network layers that learn generalizable representations of energy topology are frozen and carried over from the source network. Only the final classification or value-estimation layer is fine-tuned locally using a small number of rounds of on-device training. This reduces the count of locally trainable parameters by over 90% and decreases both the computational energy cost and the volume of synchronization traffic [10,24,42,62,99].

A known failure mode of TL is negative transfer. When the distribution mismatch between source and target environments is severe, the imported policy may degrade routing performance. For example, a protocol optimized for a sparse agricultural deployment may carry assumptions about node density and inter-node distances that are incompatible with a dense hospital corridor network. TL frameworks for WSNs address this through domain adaptation layers that quantify source-target similarity and scale transfer intensity inversely with the measured divergence [1,4,19].

Multi-source transfer learning draws on policies from multiple prior deployments simultaneously. A multi-source framework synthesizes knowledge from a laboratory testbed and a real-world deployment, potentially producing a policy with broader tolerance for environmental variability [9,23,42,82].

A longer-term aspiration is the development of WSN foundation models: large routing policies trained on diverse, globally aggregated network telemetry that could be deployed in previously unseen environments with minimal local fine-tuning. Whether this goal is achievable within the energy and compute constraints of embedded sensor hardware remains an open question [1,3,4,32].

9 Conclusions

The systematic review synthesizes 89 primary studies published during 2016–2026 using a PRISMA 2020-guided process to examine energy-efficient optimization in Wireless Sensor Networks. The work integrates taxonomy development, comparative benchmark interpretation, domain analysis, and research-gap identification across classical, hybrid, and AI-based approaches.

The reviewed literature suggests a broad progression from classical clustering baselines toward metaheuristic, hybrid, and learning-based approaches. In the comparative benchmark, DRL/GNN-based

methods report some of the strongest lifetime, latency, and PDR values, while hybrid metaheuristics provide a more hardware-accessible compromise. These observations are informative, but they remain subject to the limitations of cross-study normalization, incomplete statistical reporting, and the predominance of simulation-based validation.

The analysis further indicates that no single algorithm family dominates all relevant dimensions simultaneously. DL/DRL approaches are associated with stronger reported performance under dynamic conditions, but they also carry the greatest hardware and interpretability burden. Hybrid metaheuristics occupy a more balanced position in the current literature, while classical SI and EA methods remain relevant where simplicity and low computational demand are primary constraints.

From a deployment perspective, hybrid metaheuristics offer a practical balance between reported performance and computational feasibility. Their attractiveness comes from both benchmark values and more moderate hardware assumptions than those of DL/DRL approaches. Even so, this conclusion should be treated as conditional on the current evidence base, which still lacks extensive cross-topology testbed validation.

The problem-driven discussion also indicates that WSN energy optimization should not be treated as a single homogeneous problem. CH selection, routing adaptation, multi-objective control, and hardware-aware learning introduce different mathematical and practical constraints, which explains why no single method class is uniformly superior across all scenarios.

The six identified gaps remain the most important limitations of the field. In particular, weak security integration, limited physical validation, uncertain large-scale scalability, incomplete Pareto analysis, poor cross-domain transferability, and insufficient hardware awareness all constrain the practical value of current optimization claims.

The future-direction analysis suggests several promising research directions, including federated learning, edge-fog-cloud orchestration, secure AI, quantum-inspired optimization, transfer learning, and hardware-aware model compression. These directions are relevant because they address multiple identified gaps simultaneously, but they remain at different levels of maturity and require stronger empirical validation before firm deployment recommendations can be made.

A systems-level perspective is increasingly necessary. Future progress will likely depend less on isolated algorithmic refinement and more on integrating physical-layer assumptions, MAC behavior, routing logic, hardware constraints, and QoS requirements into coherent evaluation frameworks. Equally important is a shift from MATLAB-dominant evidence toward hardware-in-the-loop and testbed-based benchmarking, which is necessary for more credible deployment-oriented conclusions.

More broadly, the findings of this review are relevant to IoT sensing infrastructure beyond WSN routing alone. They indicate that algorithm choice is increasingly coupled to hardware capability, data availability, and security requirements, and that future routing frameworks are likely to be evaluated as part of larger edge-intelligence ecosystems rather than as isolated network-layer modules.

The review highlights progress in WSN energy optimization, but the strongest reported gains remain constrained by methodological heterogeneity, limited statistical reporting, and insufficient real-world validation. The most important next step for the field is therefore stronger evidence quality, clearer deployment-oriented benchmarking, and closer alignment between optimization design and realistic hardware conditions.

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