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Metaheuristic Approaches for Energy Optimization in Wireless Sensor Networks: A Systematic Review of Trends, Challenges, and Future Directions

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Abstract

Wireless Sensor Networks (WSNs) have become a foundational technology across diverse domains, ranging from critical healthcare monitoring to large-scale environmental management. However, the severe energy constraints of sensor nodes remain a persistent bottleneck, threatening both operational efficiency and network longevity. While metaheuristic algorithms offer promising solutions, existing reviews often focus on isolated network layers or rely on outdated datasets. Addressing this gap, this Systematic Literature Review (SLR) analyzes 48 primary studies published between 2019 and 2024, offering a holistic taxonomy that integrates routing and clustering optimizations. The findings reveal that Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) continue to dominate the field, each appearing in 23.5% of studies. However, a decisive shift is observed toward hybrid techniques such as Firefly–PSO and Grey Wolf Optimization variants which demonstrate enhanced adaptability in avoiding local optima, albeit at higher computational costs. Performance evaluations remain heavily simulation-driven, primarily focusing on energy consumption (31.2%), network lifetime (29.8%), and throughput (19.9%), while real-world validations in domains like Industrial IoT remain scarce. Furthermore, the review identifies emerging trends integrating Machine Learning, Edge Computing, and UAV-assisted routing into metaheuristic frameworks, signaling a transition toward more secure and multi-objective optimization strategies. This study concludes by highlighting critical open issues in fault tolerance, heterogeneous node management, and security-aware routing, providing a strategic roadmap for developing resilient, deployment-ready WSN solutions.

Keywords: Wireless Sensor Networks, Metaheuristics, Energy Optimization, Routing, Clustering, Hybrid Algorithms.

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1. Introduction

Wireless Sensor Networks (WSNs) have evolved from a futuristic concept into a ubiquitous reality, embedded in diverse environments ranging from forests and cities to oceans. Serving as the critical infrastructure of the digital age, WSNs facilitate applications spanning wildfire monitoring to industrial process management. However, a fundamental challenge remains: these networks are severely constrained by the limited energy of sensor nodes. These nodes are typically battery-powered and situated in hostile environments where replacement is difficult, if not impossible [1]. Consequently, energy depletion is not merely a technical inconvenience; in critical scenarios such as disaster management or healthcare, it can directly compromise system reliability and patient safety [2].

To address these energy constraints, metaheuristic algorithms have been widely explored, largely because traditional deterministic methods often fail to scale or adapt to dynamic, uncertain environments [3]. Ant Colony Optimization (ACO) based routing, for instance, has successfully extended network lifetime by 30.55% and reduced response time by 14.71% in forest fire detection systems [1]. Similarly, hybrid ACO models have achieved nearly 50% energy savings compared to classical variants [4]. Particle Swarm Optimization (PSO) has emerged as another dominant approach. Notably, the PSO-EEC variant [5] demonstrates substantial performance gains in high-density heterogeneous network scenarios. Quantifying network lifetime improvement as the percentage increase in operational rounds, the study reports a 238% gain relative to the MDCH-PSO protocol and a 71% gain compared to the HSA-PSO variant. Furthermore, PSO-EEC consistently outperforms other advanced protocols, such as MCHEOR and MOPSO, under these conditions. Furthermore, combining PSO with Bellman-Ford routing has demonstrated more stable Cluster Head (CH) selection and reduced overhead [6]. Recent advancements using hybrid Salp Swarm PSO have even pushed throughput to 580 kbps with packet delivery ratios exceeding 99.4% and delays as low as 12.3 ms [7]. These metrics represent significant technological leaps rather than minor incremental gains.

The diversity of metaheuristic applications in this domain is remarkable. Modified Grasshopper Optimization with Lévy flight has demonstrated resilience in CH selection under diverse conditions [3], while Firefly-PSO hybrids have improved the balance between energy efficiency and load distribution [8]. Multi-objective approaches, such as Golden Jackal Optimization, have managed to optimize energy and routing simultaneously, yielding lifetime increases exceeding 40% in certain trials [9], [10]. Other bio-inspired models, including the Grey Wolf Optimizer (GWO), Cuckoo Search, and Artificial Bee Colony (ABC), have proven effective in balancing energy consumption across heterogeneous WSNs [11], [12]. Notably, one study reported a 96.98% performance gain compared to existing dynamic multipath routing protocols [13]. These compelling figures reflect a research community deeply focused on maximizing the utility of limited battery resources.

Despite these promising achievements, critical gaps persist. Many protocols that excel in simulations often falter when exposed to the complex, unpredictable realities of real world deployments [14]. Furthermore, energy optimization is frequently treated in isolation, leaving essential factors such as latency, reliability, and fault tolerance as secondary considerations [15], [16]. Although Quality of Service (QoS) aware secure routing protocols have proven feasible, security is rarely integrated into energy-aware designs [17]. Moreover, no single algorithm dominates across all environments. While ACO excels in adaptive routing and PSO is superior in clustering, hybrid models while often outperforming both introduce higher computational overhead [18], [19]. Striking the right balance between efficiency and complexity remains a non-trivial, unsolved research puzzle.

Therefore, a systematic review of metaheuristic approaches for WSN energy optimization is both timely and necessary. The purpose of this study is twofold: first, to synthesize achievements across a spectrum of algorithms, from classical ACO and PSO to newer hybrids like Firefly-PSO, Golden Jackal, and chaotic GWO; and second, to identify blind spots requiring urgent attention. This review aims to go beyond a simple catalogue of improvements; it frames the broader question of how metaheuristics can evolve into adaptive, multi-objective frameworks capable of supporting sustainable WSN deployment in IoT-enabled environments. While the answer is complex, the trajectory is clear: metaheuristics will continue to play a central role in shaping intelligent, energy-aware sensor networks.

This study is motivated by several critical voids in the existing literature. First, while specific algorithmic variants have demonstrated exceptional performance gains particularly in simulation-based clustering protocols [5] these findings often remain as isolated empirical successes. Consequently, there is a distinct lack of comprehensive analysis that synthesizes these scattered performance breakthroughs into a coherent, evolutionary trend applicable to broader WSN deployments.

Second, the gap between theoretical advancement and practical reliability remains wide; for instance, while compression based routing has shown an 84% path reduction in simulations [20], evaluations in real-world deployments remain scarce. Third, the integration of emerging technologies such as machine learning, reinforcement learning, and IoT driven adaptive optimization with metaheuristics is still underdeveloped, despite early promise in bridging cross-domain intelligence [7], [15], [16].

Consequently, it is insufficient to merely celebrate performance ratios; it is crucial to interrogate the transferability, scalability, and robustness of these solutions. To this end, this Systematic Literature Review (SLR) provides a holistic overview of energy efficient techniques in WSNs relying on metaheuristic algorithms. To sharpen the focus, four research questions (RQs) are posed:

- RQ1: What are the prominent energy optimization techniques in WSNs that utilize metaheuristic algorithms?
- RQ2: What performance metrics are used to evaluate the energy efficiency of these metaheuristic-based techniques?
- RQ3: In which application domains have these WSNs been deployed, and how do these contexts impact system performance?
- RQ4: What are the recent advancements and emerging trends in metaheuristic algorithms for WSN energy optimization as highlighted in contemporary literature?

Based on these research questions, the main contributions of this study are summarized as follows:

1. Taxonomy Proposal: This study proposes a decision-oriented taxonomy categorizing metaheuristic-based energy optimization methods according to targeted network operations, including CH selection, clustering, routing, and hybrid mechanisms.
2. Integrated Synthesis: It presents a synthesis linking metaheuristic techniques, optimization objectives,

evaluation metrics, and application domains to facilitate clearer method selection and analysis.

3. Trend Identification: The review identifies recent methodological evolutions, specifically highlighting the increasing shift towards hybrid and multi-objective approaches.
4. Future Roadmap: The study outlines a concise, actionable research roadmap by consolidating open challenges and future opportunities derived from the systematic analysis.

The remainder of this paper is organized as follows: Section 2 describes the research methodology adopted for the SLR. Section 3 presents the results corresponding to RQ1–RQ4. Section 4 discusses the findings and their implications. Finally, Section 5 concludes the paper by summarizing the main contributions and outlining directions for future research.

1.1. Comparison with Existing Surveys

Although the literature on Wireless Sensor Networks (WSN) is extensive, existing reviews often address energy optimization in a fragmented manner, focusing on isolated network layers or relying on datasets that predate the recent surge in hybrid metaheuristic algorithms. To explicitly articulate the novelty and necessity of this study, we conducted a comparative analysis against eight prominent surveys in the field.

As detailed in Table 3, prior works generally exhibit three limitations:

- Scope Fragmentation: Many surveys focus exclusively on clustering [21], [22], [23] or node deployment [21], [24], ignoring the critical cross-layer dependency between clustering and routing.
- Narrow Algorithmic Focus: Recent reviews often restrict their scope to specific protocol families, such as LEACH successors [25], thereby missing the broader spectrum of modern swarm intelligence (e.g., Golden Jackal, Salp Swarm) that operate on non-hierarchical principles.
- Temporal Gaps: Comprehensive methodological reviews [22], [26] typically cover literature up to 2019 or 2020. Consequently, they fail to capture the paradigm shift towards multi-objective and hybrid optimization techniques that characterizes the 2021–2024 period.

In contrast, this Systematic Literature Review (SLR) bridges these gaps by offering a decision-oriented taxonomy that integrates Cluster Head (CH) selection, clustering formation, and routing into a unified energy optimization framework. Furthermore, it focuses strictly on the most recent high-impact studies (2019–2024), providing distinctive insights into the trade-offs between computational complexity and network longevity in IoT-enabled environments.

2. Research Methodology

A Systematic Literature Review (SLR) operates not merely as a procedural checklist, but as a disciplined methodology designed to identify, evaluate, and synthesize relevant research with clarity and precision [27]. The ultimate objective is to transcend scattered empirical findings and construct a comprehensive, balanced understanding of the state of the art within a specific domain. In the context of this study, that domain while specific is critical: energy-efficient strategies in Wireless Sensor Networks (WSNs) empowered by metaheuristic algorithms.

This review is guided by a set of carefully defined research questions focusing on four key themes: energy consumption optimization, performance metrics, application domains, and algorithmic innovations. Each question is framed to explore not only technical specifications but also the extent to which metaheuristics can push the operational limits of resource-constrained networks. This deliberate framing ensures that the review avoids becoming a mere catalogue of algorithms, instead providing a contextualized analysis of the field.

To achieve this, we adopted a structured SLR protocol consisting of six interconnected stages. These stages function as a cycle of refinement rather than a purely mechanical sequence, where each step informs the next:

1. Formulation of Research Questions: Establishing precise questions to define the review's boundaries and prevent scope drift.
2. Literature Search: Conducting systematic searches across multiple digital libraries using tailored keywords and boolean logic to ensure both breadth and relevance.
3. Primary Research Selection: Applying strict inclusion and exclusion criteria to filter studies, ensuring a balance between rigorous selection and comprehensive coverage.
4. Data Extraction: Systematically recording data regarding optimization techniques, evaluation metrics, application domains, and emerging algorithmic trends.
5. Assessment of Research Quality: Evaluating the methodological soundness, reproducibility, and contextual relevance of each study to ensure that only high-quality evidence is synthesized.
6. Data Synthesis: Integrating findings to identify convergences, contradictions, and research gaps, thereby answering the research questions with coherence.

This six-step protocol is illustrated in Figure 1. While the figure depicts a logical sequence, the actual process involved iterative refinement, where earlier stages were revisited whenever ambiguities arose in the literature. This iterative approach is essential to scholarly rigor, ensuring that the review remains transparent, comprehensive, and firmly aligned with the study's initial objectives.

2.1. Research questions

The initial phase of this SLR involved the precise formulation of Research Questions (RQs). Well defined RQs are critical to ensuring that the review remains focused and does not devolve into a disjointed collection of findings. They serve as the guiding mechanism that aligns the study with its specific objectives and addresses the broader analytical needs of the research community.

To ensure methodological rigor, the formulation of these RQs was guided by the Population, Intervention, Comparison, Outcomes, and Context (PICOC) framework [27]. The selection of PICOC was strategic; it provides a structured lens through which diverse studies can be synthesized into coherent lines of enquiry. By clearly defining elements such as the population (WSNs), intervention (metaheuristic algorithms), and outcomes (energy optimization, performance, and longevity), the framework anchors the review in concrete dimensions. This structural consistency is particularly vital in the WSN domain, where metric heterogeneity often complicates direct comparisons between studies.

Table 1 summarizes the specific PICOC criteria applied in this study. Derived from these criteria, four distinct RQs were formulated to drive the investigative process. These questions are not merely mechanical; they are designed to probe the literature with precision, enabling a critical assessment that distinguishes robust empirical evidence from theoretical assertions. Table 2 presents the finalized RQs alongside their specific research objectives.

Table 1: Summarizes the PICOC criteria used

Element	Description
Population	Wireless Sensor Networks (WSNs) requiring energy-efficient solutions.
Intervention	Metaheuristic algorithms applied to optimize energy efficiency in WSNs
Comparison	Comparison of metaheuristic techniques with traditional optimization methods or among themselves
Outcomes	Improved energy efficiency, extended network lifetime, and enhanced system performance.
Context	Applications of WSNs across various domains, including agriculture, healthcare, IoT, and smart cities

Table 2: Research Question & Objective

RQ	Research Question	Objective
RQ1	What energy optimization techniques in WSNs have utilized metaheuristic algorithms?	To identify and categorize energy-efficient techniques leveraging metaheuristics.
RQ2	What performance metrics are used to evaluate the energy efficiency of metaheuristic-based techniques in WSNs?	To explore and analyze the key metrics used to assess energy efficiency.
RQ3	In which application domains have WSNs been implemented, and how do these applications impact system performance?	To investigate the domains where WSNs are applied and their effect on system efficiency.
RQ4	What are the recent advancements in metaheuristic algorithms for energy optimization in WSNs?	To review the latest trends and developments in metaheuristic algorithms.

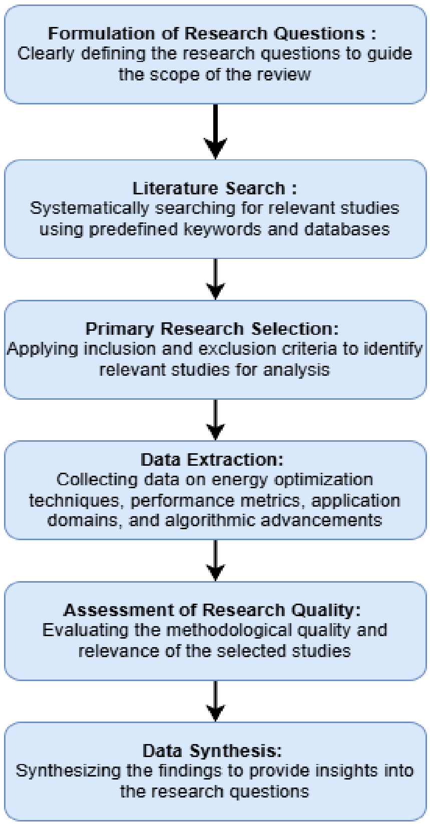

Figure 1: Systematic literature review protocol

2.2. Literature search strategy

To ensure comprehensive coverage of high-impact research, the primary literature search was conducted using the Scopus database (https://www.scopus.com/). Scopus was selected for its extensive indexing of reputable publishers, including IEEE, ScienceDirect, and Springer, which guarantees a baseline of peer-reviewed quality. Consistent with the PICOC framework defined in the previous section, the search criteria were developed to align strictly with the study's objectives.

To target studies focusing on energy-efficient techniques in Wireless Sensor Networks (WSNs) via metaheuristic algorithms, the following Boolean search string was formulated:

("wireless sensor network" OR "WSN") AND ("metaheuristic" OR "genetic algorithm" OR "particle swarm optimization" OR "ant colony optimization" OR "hybrid metaheuristics") AND ("energy optimization" OR "energy efficiency" OR "energy-aware") AND ("performance metrics" OR "network lifetime" OR "energy consumption") AND ("application" OR "use case" OR "domain")

This search string was strategically constructed to intersect distinct research dimensions:

- Context: Energy optimization within WSN architectures.
- Intervention: The utilization of specific metaheuristic and hybrid approaches.
- Evaluation: Key performance indicators such as energy consumption, network lifetime, and throughput.
- Scope: The application of these systems in diverse domains, including IoT, agriculture, healthcare, and smart cities.

To maintain currency and relevance, the search was temporally restricted to articles published between 2019 and 2024. This timeframe ensures that the review captures the most recent technological advancements and algorithmic trends. Following the initial retrieval, studies were subjected to rigorous screening based on predefined inclusion and exclusion criteria, ensuring that only high-quality and pertinent research was synthesized in this review.

2.3. Study Selection

The identification of primary studies followed a rigorous, multi stage screening protocol designed to ensure both the relevance and quality of the selected literature. As illustrated in Figure 2, the process initiated with the retrieval of 384 candidate articles through the application of the predefined search string.

In the initial phase, inclusion and exclusion criteria were systematically applied to eliminate studies falling outside the review's scope. This preliminary filtering narrowed the corpus to 200 articles. Subsequently, a screening of titles and abstracts was conducted to efficiently exclude papers that lacked immediate topical relevance or alignment with the study's objectives.

The remaining articles underwent a comprehensive full-text review. During this stage, each paper was critically appraised for methodological robustness, data clarity, and consistency with the overarching research aims. This meticulous evaluation process resulted in the final selection of 48 primary studies that fully satisfied all criteria.

To ensure data integrity and facilitate organization, the selected articles were catalogued using the Zotero reference management platform. This structured workflow ensures that the final body of literature constitutes a representative and high-quality evidence base, sufficiently comprehensive to address the formulated research questions.

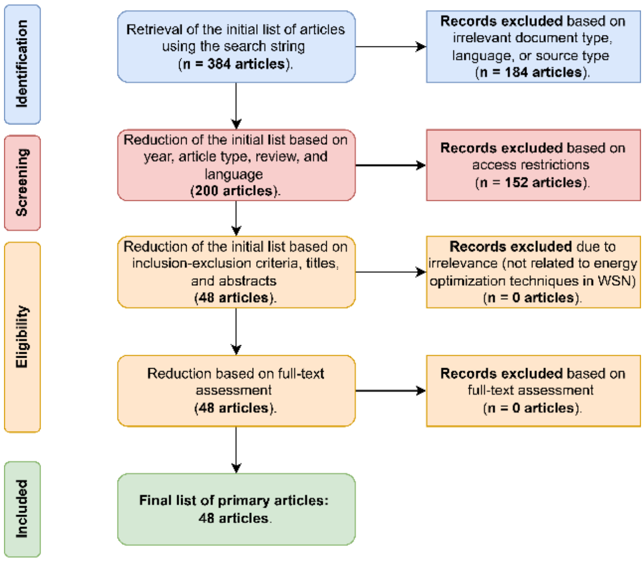

Figure 2: Primary studies selection steps

2.4. Data extraction

Following the study selection, data extraction was performed on the final set of primary studies to systematically gather the information required to address the established Research Questions (RQs). To maintain consistency and completeness across the review, this process adhered to a standardized extraction protocol, as summarized in Table 4.

The extracted data were organized into four primary dimensions, directly aligning with the study's objectives:

- Optimization Strategies: Analyzing how energy optimization is implemented in WSNs via specific metaheuristic algorithms.

- Performance Metrics: Identifying key evaluation indicators, such as energy consumption, network lifetime, throughput, and latency.
- Application Domains: Categorizing deployment contexts, including the Internet of Things (IoT), precision agriculture, healthcare, and smart cities.
- Algorithmic Innovations: Documenting recent advancements, including novel designs, hybrid optimization models, and integrations with emerging technologies.

This structured categorization ensured that every extracted data point maintained a direct lineage to a specific research question. Consequently, this rigorous organization laid a robust foundation for the subsequent synthesis phase, facilitating a targeted and coherent analysis of the literature.

2.4. Research quality assessment and data synthesis

To ensure a holistic evaluation, the data extraction encompassed both qualitative dimensions (interpreting algorithmic effectiveness and framing) and quantitative metrics (usage frequency and performance indicators). Given the significant heterogeneity in experimental setups across the literature, a narrative synthesis approach was adopted. This method integrates diverse outcomes into a coherent framework, supported by data visualizations to elucidate patterns that statistical aggregation alone cannot capture. Furthermore, the review prioritized research quality specifically methodological rigor and reproducibility to mitigate the impact of varying reporting standards. This reflective stance ensured that evidentiary quality, rather than mere publication volume, governed the synthesis.

The analysis reveals a steady upward trajectory in research output, as illustrated in Figure 3, which peaked in 2023 with 13 articles dedicated to WSN energy optimization. Geographically, India leads with over 30 affiliations, followed closely by China, while contributions from other nations remain comparatively limited. This distribution reflects distinct socio-economic drivers: India's research focuses on scalable, low-cost solutions, whereas China's output aligns with state-led investments in IoT and smart city infrastructure.

These regional priorities directly influence the research agenda and algorithmic selection. In terms of dissemination, IEEE, Springer, and Elsevier serve as the primary publication venues. Collectively, these findings indicate a vibrant yet geographically concentrated domain, highlighting an urgent need for broader global participation and standardized experimental reporting to ensure the field's maturity.

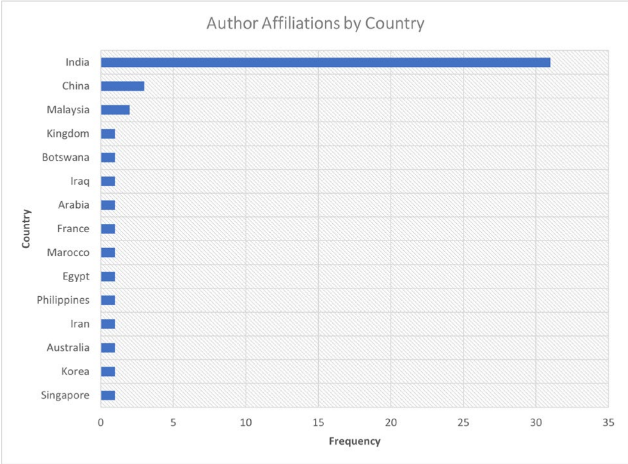

Figure 3a: Paper distribution country

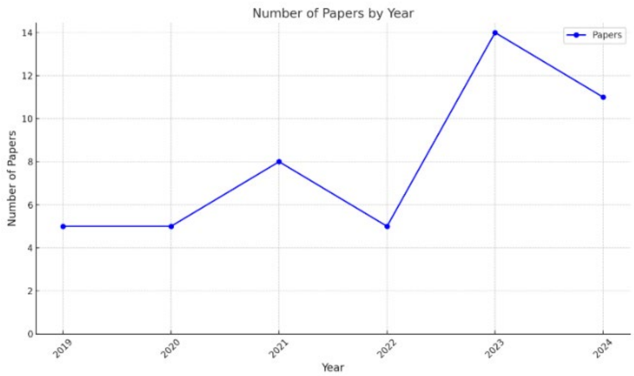

Figure 3b: Paper distribution year

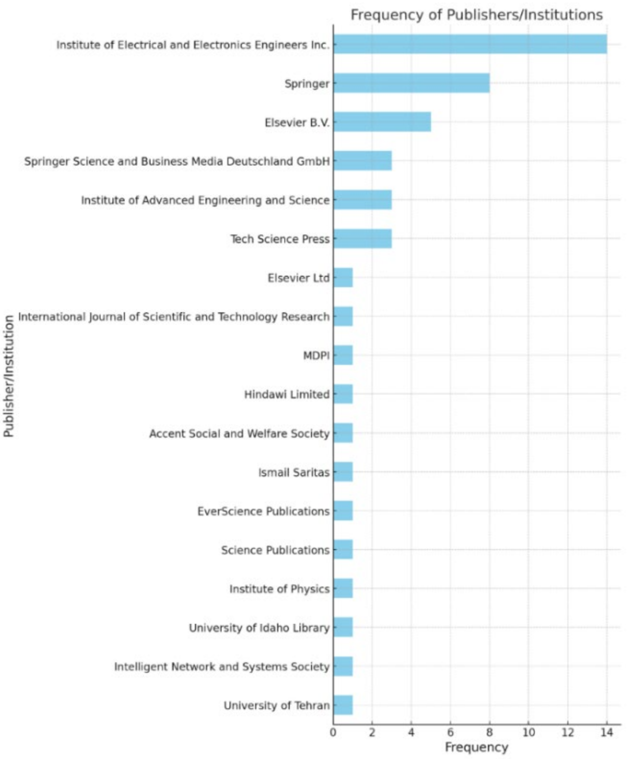

Figure 3c: Paper distribution of publishers institution

Table 3: Comparison with existing surveys

Ref. & Year	**Scope & Primary Focus**	**Time Span**	**Primary Studies**	**Taxonomy / Key Limitation**	**Distinctive Insights of Current Work**
Shahraki et al. (2020) [26]	Clustering Objectives. Focuses on clustering goals (coverage, connectivity).	2008–2019	>100	Limitation: Focuses on objectives rather than specific metaheuristic interventions; data predates the "hybrid algorithm" surge.	Focuses specifically on Metaheuristic Interventions with updated data (2019–2024).
Yadav & Mahapatra (2021) [28]	Hierarchical Routing. Focuses on clustering and security.	2012–2020	~50	Limitation: Heavily biased towards LEACH variants and security, lacking depth on modern swarm intelligence.	Integrates Routing and Clustering evenly, without limiting scope to hierarchical structures.
Raj et al. (2022) [22]	CH Selection. Exclusive focus on Cluster Head selection/formation.	2012–2020	143	Limitation: Covers only the setup phase, ignoring the data transmission (routing) phase essential for total energy analysis.	Covers the full energy chain: from CH Selection to Multi-hop Routing.
Hussain et al. (2024) [25]	LEACH Successors. Specific review of LEACH protocol variants.	2018–2023	40	Limitation: Narrow scope (LEACH only); ignores non-LEACH bio-inspired algorithms (e.g., WOA, GWO).	Broad Scope: Analyzes diverse bio-inspired algorithms beyond th LEACH family.
Singh et al. (2021) [24]	Nature-inspired Coverage. Focuses on Optimal Coverage/Deployment.	2010–2020	90	Limitation: Addresses *Node Placement* (initialization), not operational energy efficiency (active routing).	Focuses on Operational Energy Efficiency (dynamic network phase).
Gheisari et al. (2020) [23]	Clustering Algorithms. Trends and challenges in clustering.	2014–2019	40	Limitation: Dataset is outdated; taxonomy misses recent "Hybrid Metaheuristic" trends.	Updates the research roadmap wit Hybrid Optimization trends from 2021–2024.
Swetha et al. (2019) [21]	Node Placement. Strategies for sensor deployment.	2002–2018	30	Limitation: Focuses on static deployment; uses the oldest dataset among compared surveys.	Analyzes Dynamic Energy Management and adaptability in changing environments.
This Work (2025)	Energy Optimization (Routing + Clustering) via Metaheuristics	2019–2024	48	Taxonomy: Integrated (CH Selection, Clustering, Routing).	Contribution: Synthesizes Cross-layer Optimization and links algorithms to IoT/Smart City domains.

Table 4: Outlines the data extraction properties and their alignment with the research questions.

Property	**Description**	**Research Question (RQ)**
Optimization Technique	The metaheuristic algorithms and techniques used for energy optimization in WSNs (e.g., PSO, GA, ACO, hybrid models).	RQ1 : What energy optimization techniques in WSNs have utilized metaheuristic algorithms?
Performance Metrics	Key metrics used to evaluate energy efficiency (e.g., energy consumption, network lifetime, throughput).	RQ2: What performance metrics are used to evaluate the energy efficiency of metaheuristic-based techniques in WSNs?
Application Domain	The fields or domains where WSNs are applied (e.g., IoT, agriculture, healthcare, smart cities).	RQ3 : In which application domains have WSNs been implemented, and how do these applications impact system performance?
Recent Advancements	Recent trends and innovations in metaheuristic algorithms for energy optimization.	RQ4 : What are the recent advancements in metaheuristic algorithms for energy optimization in WSNs?

3. Results and analysis

3.1. [RQ1] Energy optimization techniques in WSNs have increasingly leveraged metaheuristic algorithms to achieve enhanced efficiency and performance

3.1.1 Routing Protocols in WSN: Concepts, Structures, and Classifications

In Wireless Sensor Networks (WSNs), routing extends beyond simple data forwarding; it entails the strategic orchestration of communication paths to optimize scarce energy, limited bandwidth, and computational resources. Consequently, routing protocols must simultaneously satisfy three conflicting objectives: conserving energy, preserving network coverage, and meeting Quality of Service (QoS) demands, such as low latency and reliable throughput. This requirement is critical in time-sensitive deployments like healthcare monitoring, where transmission delays or premature node failures can directly compromise patient safety [7].

Routing protocols are generally classified into three distinct dimensions. From a structural perspective, they are categorized as flat-based (where all nodes act as peers), hierarchical-based (where nodes are grouped into clusters with assigned leaders), or location-based (utilizing geographic data for path selection) [29]. From an operational perspective, protocols may be proactive (periodic updates), reactive (on-demand discovery), or hybrid [30]. Finally, regarding optimization objectives, algorithms are tailored for specific goals, ranging from energy maximization and QoS compliance [31] to multipath schemes designed for fault tolerance and reliability [17]. In practice, these categories often overlap, as modern algorithms increasingly integrate multiple criteria to address the complex interplay of network constraints.

Clustering-based routing exemplifies this architectural complexity. In this approach, the network is partitioned into clusters, each managed by a Cluster Head (CH) responsible for data collection, aggregation, and transmission to the sink. By minimizing high-energy long-distance transmissions, hierarchical clustering significantly reduces power consumption and extends system lifetime. As illustrated in Figure 4, intra-cluster communication is kept short-range and energy-efficient, while inter-cluster routing is optimized for load balancing. Meta-heuristic optimizations play a pivotal role in this mechanism, primarily by enhancing the intelligence of CH selection and enabling dynamic adaptation of routing paths.

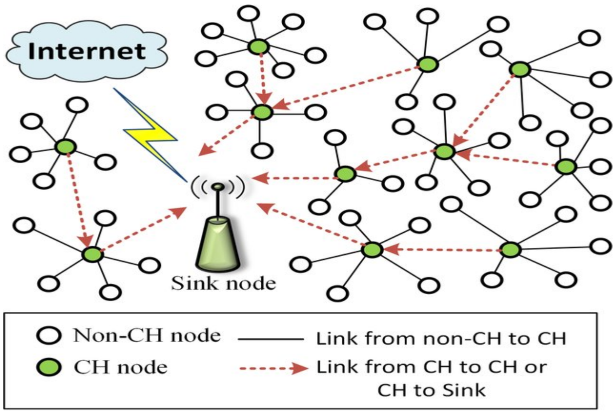

Figure 4: The routing process

For instance, Gundeboyina et al. [17] [16] proposed the Energy- and Distance-aware Multi-Objective Firebug Swarm Optimization (ED-MOFSO) protocol, which identifies optimal routes by evaluating both residual energy and inter-node distances. By employing a composite fitness function that integrates available energy with hop count, the algorithm ensures that routing decisions are both energy-efficient and topology-aware. Furthermore, prior to route initiation, Cluster Heads (CHs) are selected based on their proximity to the base station and energy reserves. Performance evaluations demonstrate measurable gains in delay, throughput, overhead, and Packet Delivery Ratio (PDR), illustrating the effective transition of metaheuristic strategies from theoretical concepts to tangible energy savings.

In a parallel development, Jeba Anandh et al. [32] explored a dynamic ant-inspired protocol where control packets function as artificial agents. These agents traverse the network to discover paths, depositing pheromone trails that are dynamically updated based on node energy levels and traffic load. Over time, optimal paths are reinforced through pheromone accumulation, guiding data along sustainable routes. The protocol's hierarchical structure, which directs data from outer tiers inward, effectively reduces bottlenecks and balances traffic. The primary strength of this scheme lies in its adaptivity; it reacts in real-time to dynamic network conditions, redistributing loads to extend node lifetime.

Complementing these approaches, Nayyar et al. [33] introduced the Improved Energy-Efficient Multipath Ant-based Routing Protocol (IEEMARP). By integrating multipath routing with ant colony heuristics and lightweight memory management, IEEMARP minimizes redundant storage while ensuring robustness. Comparative simulations reveal that it outperforms classical protocols such as Basic ACO, DSDV, and DSR by approximately 10% in terms of energy efficiency, throughput, packet delivery, and end-to-end delay. While a 10% improvement may appear incremental, in energy constrained WSNs, such gains translate into significant extensions in operational time. This underscores a critical reality: marginal increases in algorithmic efficiency often yield disproportionately large practical benefits in sensor network longevity.

Collectively, these studies highlight the diversity of routing innovations within the WSN domain. Whether utilizing swarm intelligence, multi-objective fitness functions, or hybrid mechanisms that balance exploration and exploitation, the unifying principle remains consistent: routing is not merely a path discovery problem but a complex challenge of energy-aware orchestration, where the survival of individual nodes contributes directly to the sustainability of the entire network.

3.1.2 Clustering Techniques in Wireless Sensor Networks

Clustering constitutes a fundamental strategy in Wireless Sensor Networks (WSNs), designed to enhance communication efficiency and maximize network longevity. in this hierarchical architecture, sensor nodes are organized into groups, each governed by a Cluster Head (CH). The CH functions as a local coordinator, responsible for data aggregation to eliminate redundancy before relaying the refined information to the Base Station (BS). By minimizing direct, long-range transmissions from individual nodes, this layered structure significantly mitigates communication overhead and conserves critical energy resources.

As illustrated in Figure 5, the cluster-based architecture streamlines data flow: CHs manage local sensing coverage and act as the primary gateway to the BS. This setup not only reduces congestion and coverage gaps but also improves scalability. However, the efficacy of clustering depends heavily on the underlying algorithms for cluster formation and CH selection. These approaches are generally categorized into three primary taxonomies: classical protocols, optimization-based techniques, and machine learning-oriented solutions.

Classical methods, such as the Low-Energy Adaptive Clustering Hierarchy (LEACH) and Hybrid Energy-Efficient Distributed Clustering (HEED), offer simplicity and baseline energy awareness. However, their performance is often compromised in large-scale deployments or heterogeneous environments, where static parameters fail to adapt to dynamic network conditions [34]. Consequently, research has shifted toward optimization-based techniques, particularly those utilizing metaheuristics like Particle Swarm Optimization (PSO). These methods seek near-optimal cluster configurations by dynamically minimizing energy consumption while maintaining robust connectivity [5]. More recently, machine learning approaches, including fuzzy logic and adaptive neural networks, have further enhanced system flexibility, enabling real-time responses to topological changes.

Despite these advancements, clustering implementation faces persistent challenges, such as the "energy hole" problem caused by uneven load distribution among CHs and the stringent latency requirements of time-sensitive applications. Therefore, selecting an appropriate technique requires a careful trade-off analysis tailored to specific use cases, ranging from environmental monitoring to mission-critical IoT healthcare. To provide a clear landscape of the current state-of-the-art, Table 8 presents the distribution of reviewed papers categorized by technique, evaluation metric, and algorithmic focus.

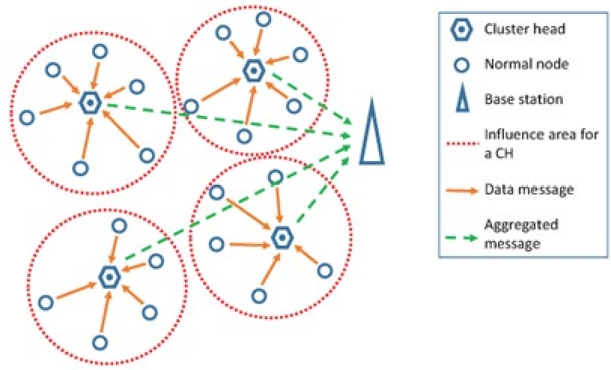

Figure 5: Cluster-based architecture

The distribution of metaheuristic algorithms for energy optimization in Wireless Sensor Networks (WSNs) reveals a distinct hierarchy in research focus. Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) have established themselves as the dominant paradigms, collectively representing 47% of the reviewed studies (23.5% each). This prevalence indicates their adaptability and long-proven effectiveness in complex routing and clustering tasks [1], [20]. Such dominance is empirically justified; for instance, advanced PSO-based implementations have demonstrated substantial extensions in network longevity compared to other metaheuristic benchmarks, including MDCH-PSO and MOPSO variants, particularly within high-density simulation environments. [5], while ACO models have achieved energy reductions of nearly 50% compared to traditional deterministic protocols [4]. Conversely, emerging algorithms such as Grey Wolf Optimization (GWO) and Artificial Bee Colony (ABC) currently account for approximately 3% each, reflecting a growing but selective interest in alternative swarm-based strategies [11], [12].

Beyond these dominant pillars, the landscape diversifies significantly in the intermediate tier. Algorithms such as Cuckoo Search (CS), Genetic Algorithms (GA), Simulated Annealing (SA), and specific clustering-centric models like LEACH each contribute approximately 2.9% to the literature. These methods are frequently deployed in specialized or hybrid configurations where standard protocols exhibit limitations [9], [35]. While their individual adoption rates may appear marginal, they often serve as critical testbeds for experimental designs aimed at addressing niche constraints. At the periphery of current research, smaller shares of approximately 1% are attributed to methods such as Jaya Optimization (JO), League Championship Particle Swarm Optimization (LCPSO), and the Bat Optimization Algorithm (BOA). These entries signify an active exploration phase within the community, where novel mechanisms are investigated to overcome specific local optima issues inherent in established techniques.

The overall distribution, as illustrated in Figure 6, underscores a dual reality in the field. First, established algorithms like ACO and PSO remain the technological backbone of WSN optimization, consistently delivering measurable improvements in energy efficiency, throughput, and delay metrics. Second, the incremental rise of alternative approaches whether GWO, ABC, or hybridized versions of lesser-known algorithms suggests that the domain is still evolving. This trend indicates that WSN energy optimization is not a settled problem but a continuous trajectory of refinement. To provide a structured overview of this landscape, the algorithms identified in the literature are organized under the taxonomy of optimization techniques, as depicted in Figure 10.

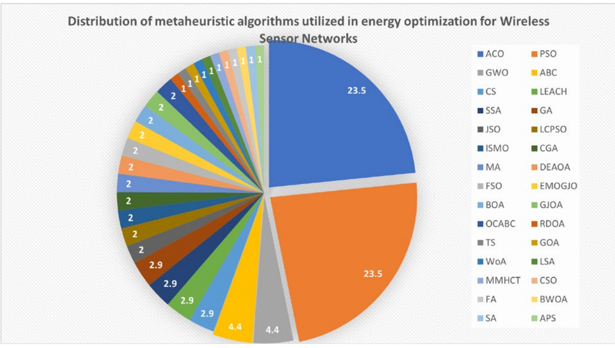

Figure 6: Distribution of metaheuristic algorithms utilized in energy optimization for Wireless Sensor Networks (WSNs)

3.2. [RQ2] Key performance metrics for evaluating metaheuristic-based energy efficiency in WSNs

The distribution of performance metrics, as illustrated in Figure 7, elucidates the prevailing priorities within the WSN research community. Energy consumption dominates the evaluation landscape, featuring in 31.2% of the reviewed studies. This prevalence is anticipated, given that energy constitutes the fundamental operational constraint governing network longevity [4], [5]. Closely related, the lifetime of live nodes is utilized in 29.8% of studies, underscoring that preserving node functionality is not merely a statistical objective but a prerequisite for maintaining network connectivity and preventing topology fragmentation [9], [20].

Complementing these energy-centric parameters, throughput (19.9%) and Packet Delivery Ratio (PDR) (11.3%) highlight the critical dimension of reliability. While throughput quantifies the volume of successful data transmission, PDR assesses the consistency of packet arrival. Although these metrics appear less frequently than energy parameters, their significance remains profound; an energy-efficient network that fails to deliver data reliably lacks practical utility, regardless of its operational duration [7], [14].

Conversely, end-to-end delay (2%) remains underrepresented despite its criticality in latency-sensitive applications, such as disaster management and healthcare monitoring, where millisecond-level delays can directly compromise safety [36]. Other auxiliary metrics, including computation time, communication overhead, and coverage area, each account for approximately 1%, offering niche insights into algorithmic complexity and spatial resilience. Most notably, security-related metrics—specifically resilience against Denial-of-Service (DoS) attacks—comprise only 1% of the literature. This scarcity exposes a significant vulnerability in current methodologies, particularly for IoT-enabled WSNs where attacks on resource-constrained nodes can compromise entire system integrity.

Synthesizing the evidence from Table 8 and Figure 7, a clear hierarchical pattern emerges: researchers overwhelmingly prioritize energy conservation and lifetime extension, while delay, overhead, and security are often treated as secondary considerations. However, the evolving demands of modern WSN applications necessitate a paradigm shift. The forthcoming challenge is not merely to optimize energy, but to design holistic evaluation frameworks that integrate reliability, latency, and security. Ultimately, while energy efficiency is foundational, it must not be pursued at the expense of system dependability and secure operation.

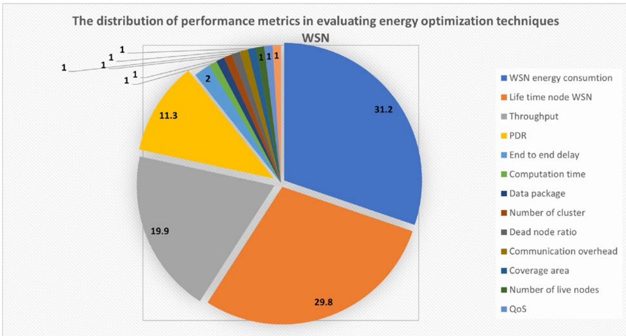

Figure 7: The distribution of performance metrics in evaluating energy optimization techniques WSN

3.3. [RQ3] Application Domains of WSNs and Their Impact on System Efficiency

As illustrated in Figure 8, the deployment of Wireless Sensor Networks (WSNs) permeates diverse sectors, with healthcare emerging as the predominant domain, accounting for 24.8% of the reviewed studies. This prominence underscores the critical integration of WSNs in patient monitoring, remote diagnostics, and real-time vital sign tracking—technologies that have fundamentally reshaped telemedicine architectures [30][37]. Agriculture follows closely at 20%, where WSNs serve as the technological foundation for precision farming, soil assessment, and automated irrigation, thereby minimizing resource wastage and optimizing yield [9]. Meanwhile, military applications constitute 16.8%, prioritizing persistent surveillance, reconnaissance, and target tracking, which highlights the strategic value of distributed sensing in mission-critical operations [33].

In the intermediate tier, environmental monitoring represents 14.4% of the applications, encompassing forest fire detection, flood risk management, and biodiversity conservation [32], [38]. Concurrently, smart city implementations and industrial adoption each capture 9.6% of the landscape. The former leverages WSNs for urban efficiency such as traffic control and waste management while the latter focuses on industrial automation and process reliability [14], [35].

Specific niche applications further demonstrate the versatility of the technology. Disaster management (4.8%) and early warning systems (3.2%) illustrate the role of WSNs in hazard detection, ranging from seismic activity to volcanic monitoring. The remaining distribution includes transportation (2.4%) and specialized security or sub-agricultural systems (approx. 1% each), confirming that even specialized sectors derive value from WSN deployment [13].

Collectively, this distribution evidences a technology that is both versatile and scalable. The dominance of healthcare and agriculture reflects an alignment with fundamental human needs, while military and environmental monitoring are driven by strategic and ecological imperatives. Ultimately, these trends indicate that WSNs have evolved beyond niche experimental deployments to become the ubiquitous backbone of intelligent, resilient, and sustainable systems.

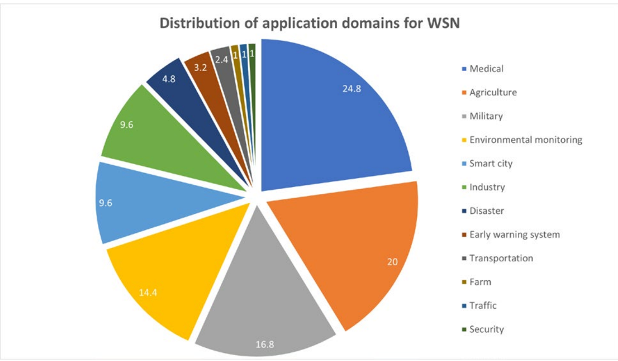

Figure 8: Distribution of application domains for WSN

3.4. [RQ4] Recent Trends and Advancements in Metaheuristic Algorithms

Recent developments in metaheuristic algorithms for Wireless Sensor Networks (WSNs) are principally driven by two operational imperatives: minimizing energy consumption and sustaining high-performance metrics. Among the reviewed studies, Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) maintain a dominant position, each utilized in 16% of the cases [1][20]. This prevalence is not coincidental but empirically substantiated; ACO has consistently demonstrated the capacity to reduce energy usage by approximately 50% compared to classical routing schemes [4], whereas PSO-based protocols, such as the PSO-EEC variant [5], have demonstrated substantial extensions in network lifetime compared to advanced benchmarks like MDCH-PSO and MOPSO, particularly in high-density simulation environments. These robust empirical outcomes justify the enduring research focus on these foundational algorithms.

In contrast, emerging techniques such as Grey Wolf Optimization (GWO) and Artificial Bee Colony (ABC) appear less frequently, each accounting for 3% of the literature. However, their adoption signifies a strategic shift toward alternatives better suited for specific constraints, such as heterogeneous WSN environments or security-aware deployments [11][12]. Beyond these, specialized methods including Cuckoo Search (CS), Genetic Algorithms (GA), and various hybrid metaheuristics surface in smaller proportions. These algorithms function as experimental testbeds where unconventional strategies are rigorously evaluated to address niche optimization challenges [9][42].

As illustrated in Figure 9, the selection of objective functions closely aligns with these algorithmic preferences. Maximizing residual energy remains the predominant objective, accounting for 46.7% of studies, which underscores that node survival is central to the research agenda. Inter-node distance (22.2%) is also prioritized as a critical factor for lowering transmission costs and stabilizing connectivity. Meanwhile, objectives focused on optimal clustering (6.7%) and routing efficiency (4.4%) represent ongoing efforts to refine topology control and streamline communication paths [26][36]. Recently, optimization criteria have expanded beyond the traditional energy–distance paradigm to include trust management for secure data exchange, multi-hop path optimization for resilience, and load balancing for equitable resource utilization.

Synthesizing this evidence suggests that the field is simultaneously stable and evolving. While ACO and PSO remain the technological workhorses trusted for consistent improvements, the diversification into hybrid models and multi-objective formulations signals a drive toward algorithmic innovation. Researchers are moving beyond incremental gains to probe for breakthroughs that address complex requirements. This trajectory is particularly relevant for critical domains such as healthcare and environmental monitoring, where reliability, latency, and security are as pivotal as energy conservation. Figure 9 encapsulates this dynamic landscape, where established algorithms coexist with innovative newcomers to push WSN research toward broader operational horizons.

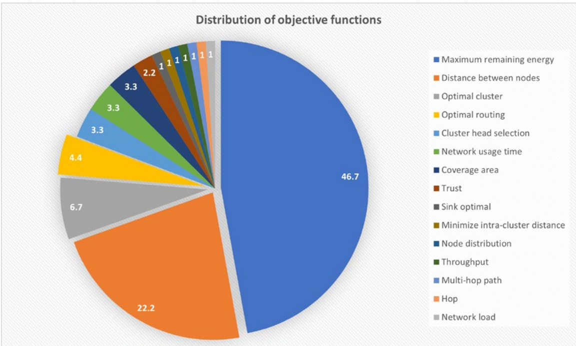

Figure 9: Distribution of objective functions

4. Results and analysis

4.1. Synthesis of Key Findings: Trends, Insights, and Opportunities Metaheuristic Algorithms

The empirical findings of this review confirm that Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO) remain the dominant approaches in Wireless Sensor Networks (WSNs). Collectively, they appear in a significant portion of the reviewed studies, spanning references [1], [3], [4], [5], [6], [8], [14], [18], [19], [20], [32], [33], [38], [39], [40], [41]. This prevalence is not coincidental but stems from their proven efficacy. Inspired by ant foraging behavior, ACO excels at identifying optimal communication paths and minimizing routing energy costs. Similarly, PSO, leveraging swarm movement dynamics, dynamically tunes network parameters to extend operational lifetime often exceeding baseline protocols by more than 200% [12]. Consequently, these two methods have established themselves as the foundational pillars of WSN optimization.

However, the algorithmic landscape is evolving. Alternatives such as Grey Wolf Optimization (GWO) [11] [42][43] and Artificial Bee Colony (ABC) [12][15][44] are gaining traction, each representing approximately 3% of the literature. GWO emulates the social hierarchy and hunting mechanism of wolf packs to balance exploration and exploitation, whereas ABC simulates the foraging behavior of honeybees to optimize resource allocation and data flow. The distinct advantage of these emerging methods lies in their ability to mitigate inherent weaknesses in ACO and PSO, particularly regarding premature convergence and high computational overhead. This capability is especially critical for large-scale, heterogeneous deployments where scalability and fairness are as pivotal as raw efficiency.

Recent empirical studies substantiate this trend toward diversification. Qabouche (2023) introduced the Energy-Efficient and Coverage-Aware Grey Wolf Optimizer (EEC-GWO), which refines Cluster Head (CH) selection by integrating node density and inter-node distance into its fitness function. This approach resulted in improved coverage ratios, elimination of blind spots, and enhanced adaptability in heterogeneous networks [11]. In parallel, Wang et al. (2020) proposed an enhanced ABC-based clustering protocol that utilizes energy levels and node density to optimize CH tasks, coupled with a polling control scheme to alleviate CH energy burdens. The outcomes are tangible: the protocol achieved higher throughput, balanced energy consumption, and extended network lifetimes, proving particularly effective in reliability-critical scenarios [12].

A comprehensive synthesis of these algorithmic enhancements and their performance impacts is presented in Table 7. This summary highlights how established techniques like ACO and PSO coexist with emerging alternatives, collectively pushing the boundaries of WSN optimization in new, more adaptive directions.

4.2. Strengths and Limitations of Existing Research

Wireless Sensor Networks (WSNs) occupy a central position in contemporary research due to their critical versatility in healthcare, environmental monitoring, and the industrial Internet of Things (IoT). However, persistent challenges continue to impede their widespread real-world adoption. While deterministic algorithms were historically employed to address these issues, recent studies [45] highlight that evolutionary approaches offer superior adaptability for solving the NP-hard routing problems inherent in dynamic WSN environments. A primary bottleneck is the heavy reliance on simulation-based evaluations [8] [41] [46]. While simulations serve as valuable initial testbeds, they rarely capture stochastic real-world phenomena such as node mobility, fluctuating energy availability, or environmental heterogeneity [47] [48]. This disconnect explains the frequent operational failure of protocols that demonstrate theoretical efficacy but lack robustness in physical deployments.

Energy efficiency constitutes the cardinal design objective in WSNs, yet structural inefficiencies such as premature convergence, suboptimal Cluster Head (CH) selection, and the "energy hole" problem continue to precipitate energy hotspots and premature node depletion [49]. Furthermore, clustering protocols designed to adapt to network dynamics often remain rigid in practice, failing to accommodate heterogeneous environments where node capacities vary significantly [50] [51]. Consequently, this inability to adapt leads to inefficient resource utilization and critically reduced network longevity.

A further limitation lies in the inadequate application of multi-objective optimization. While protocols such as LEACH or ACO-based routing successfully extend network lifetime, they often do so at the detriment of Quality of Service (QoS) or security [52][53]. The optimization of a single metric frequently compromises others. This trade-off is particularly precarious in mission-critical contexts, such as remote healthcare or disaster response, where system reliability cannot be sacrificed for marginal energy gains.

Beyond algorithmic constraints, practical deployment imposes distinct physical and operational challenges. Conventional architectures relying on fixed sink placement or single-hop routing hinder scalability in large-scale networks. Conversely, emerging solutions like UAV-assisted WSNs face regulatory and hardware limitations. Moreover, clustering algorithms that neglect dynamic CH placement risk inducing imbalanced energy consumption and coverage holes. A critical, yet often under-discussed issue, is spatiotemporal data correlation; ignoring this factor results in redundant transmissions and inefficient data fusion, thereby aggravating energy drain.

Collectively, these findings indicate that while WSN research has advanced significantly, substantial gaps persist. The field requires adaptive algorithms responsive to environmental volatility, multi-objective frameworks that balance conflicting trade-offs, and holistic designs that account for node-level constraints. Table 5 [54] synthesizes these unresolved challenges and outlines strategic directions for future exploration.

Table 5: A brief evaluation of the advantages and disadvantages of existing approaches in previous research

Category	Key Limitation	Examples	Impact
Simulation Reliance	Over-reliance on simulation environments, failing to capture real-world complexities	Node mobility, environmental dynamics	Limits real-world applicability and validation
Energy Efficiency	Premature convergence, unbalanced energy consumption, hotspot issues	LEACH, PSO-based protocols	Early node failure, reduced network lifetime
Dynamic Adaptability	Static configurations, limited support for heterogeneous networks	Static sink placement, single-hop routing	Inefficient performance in dynamic environments
Multi-objective Trade-offs	Challenges balancing energy efficiency, QoS, and security	ACO, hybrid PSO-GWO	Trade-offs affect holistic optimization
Computational Complexity	High complexity in hybrid algorithms, limiting real-time application	PSO-ACO, HFAPSO	Increases resource usage, delays decision-making
Scalability and Coverage	Fixed CH placement, limited handling of large-scale deployments	LEACH, static routing	Inefficient clustering, reduced coverage

4.3. Emerging Trends in Wireless Sensor Networks: Advancements and Future Directions

Recent advancements in Wireless Sensor Networks (WSNs) demonstrate a decisive paradigm shift toward energy efficiency, scalability, and adaptability. A primary driver of this momentum is the evolution of hybrid metaheuristic algorithms notably PSO, ACO, and GWO which refine Cluster Head (CH) selection to optimize the trade-off between energy consumption and network longevity [55]. These contributions represent substantial operational enhancements rather than mere incremental improvements; superior clustering directly correlates with prolonged nodal survival and stabilized connectivity within energy-constrained environments.

Scalability, historically a limiting factor in WSN deployment, is currently being revolutionized through the integration of mobile sinks and UAV-assisted routing. UAVs possess the capability to reposition dynamically, thereby maintaining node connectivity and minimizing redundant transmissions [56]. This adaptability is of significant practical utility, particularly in scenarios characterized by node mobility or stochastic environmental shifts [57].

Concurrently, advancements in data fusion and compression techniques are proving critical. By embedding Recurrent Neural Networks (RNNs) or grey prediction models into clustering and routing architectures, researchers have successfully mitigated transmission overhead while preserving data fidelity [58] [59]. The outcome is a dual advantage: significant reduction in energy depletion coupled with the delivery of more accurate, timely information.

A parallel methodological evolution is the adoption of multi-objective optimization frameworks. Protocols such as ODMRP-ACO and IEEMARP are designed to simultaneously target energy efficiency, Quality of Service (QoS), and security metrics, including packet delivery ratio, latency, and reliability. Similarly, recent hybrid approaches like the HPSO-based routing design by Selvan et al. [60] have successfully integrated trust metrics and congestion control into the optimization process, ensuring that energy efficiency does not compromise network security. These frameworks are indispensable for real-time or mission-critical deployments, where the optimization of one metric cannot be achieved at the expense of system integrity [61].

Beyond protocol design, the convergence of IoT and WSNs is fundamentally transforming the field. The edge computing paradigm shifts data processing closer to the source nodes, effectively reducing latency and conserving bandwidth, while blockchain integration ensures secure and trustworthy data exchanges [62]. When synergistic with energy harvesting, duty cycling, and predictive modeling, these technologies transition WSNs from experimental prototypes into sustainable, robust infrastructures ready for large-scale deployment [63].

In conclusion, the trajectory of WSN research is pivoting from abstract simulations toward intelligent, adaptive, and deployment-ready solutions. These innovations pave the way for resilient networks capable of supporting diverse applications, ranging from flood monitoring and patient tracking to industrial automation. A comprehensive synthesis of these future directions is presented in Table 6.

Table 6: Emerging trends in Wireless Sensor Networks

Trend	Example Algorithms	Applications
Energy Efficiency	PSO, GWO, ACO, ED-MOFSO	Urban monitoring, agriculture
Hybrid Algorithms	PSO-ACO, MIGJOA, ABC-GWO	Industrial IoT, disaster response
Dynamic Adaptability	UAV-assisted, mobile sink	Flood monitoring, wildfire detection
Data Fusion/Compression	RNN-based, Grey prediction	Environmental monitoring
QoS and Security	ODMRP-ACO, IEEMARP	Real-time health monitoring
Heterogeneous Networks	HWSN techniques, IoT-enabled	Smart cities, remote sensing
AI and Machine Learning	CNN, RNN, Reinforcement Learning	Predictive maintenance, anomaly detection, smart agriculture

4.4. Research Gaps in Wireless Sensor Networks (WSNs) Optimization

Despite substantial advancements in Wireless Sensor Network (WSN) research, achieving optimal energy efficiency, scalability, and real-world applicability remains a formidable challenge. While existing literature extensively addresses energy consumption and data transmission, it frequently overlooks the concurrent optimization of node heterogeneity, mobility, and Cluster Head (CH) selection within dynamic environments. Foundational protocols, such as LEACH, have been widely implemented but exhibit significant limitations in managing dynamic topologies and balancing energy distribution, often resulting in premature node failure and reduced network longevity [64]. Furthermore, the integration of clustering and routing mechanisms remains largely fragmented; this lack of cross-layer synergy restricts the potential for holistic improvements in both energy conservation and overall network performance [65].

The constraints of contemporary algorithms precipitate a critical need for methodologies tailored to heterogeneous WSNs. For instance, protocols like EECZ-SEP, which incorporate helper nodes, have demonstrated marked improvements in energy efficiency. However, their adaptability to dynamic, large-scale networks remains insufficiently explored. The absence of fully developed multi-hop and multi-layer architectures further impedes performance in practical deployments, where stochastic environmental factors significantly impact sensor reliability [66]. In parallel, while UAV-assisted data collection and bio-inspired algorithms offer promising enhancements, they are currently hindered by inherent constraints such as UAV energy budgets, obstacle avoidance, and environmental variability [67]. Moreover, ensuring security and scalability particularly within Industrial IoT (IIoT) contexts necessitates protocols capable of withstanding evolving cyber threats and accommodating increasing node densities.

Prospectively, the evolution of WSN capabilities necessitates the adoption of hybrid meta-heuristic algorithms, adaptive clustering mechanisms, and energy-aware routing protocols that respond effectively to heterogeneous and dynamic conditions. The critical frontier lies in integrating clustering and routing into a unified, adaptive framework supported by advanced machine learning and predictive analytics. Such integration enhances decision-making, maximizes energy efficiency, and fortifies system resilience in real-time applications [66]. Ultimately, these innovations possess the potential to bridge the persistent gap between theoretical simulation and practical deployment, thereby enabling robust, scalable WSN solutions for domains ranging from precision environmental monitoring to complex industrial automation.

5. Conclusion

This Systematic Literature Review (SLR) underscores the pivotal role of metaheuristic algorithms in enhancing the operational longevity and efficiency of Wireless Sensor Networks (WSNs). The synthesis of evidence confirms that established techniques, particularly Ant Colony Optimization (ACO) and Particle Swarm Optimization (PSO), constitute the cornerstone of current research. ACO remains dominant in optimizing routing paths and Cluster Head (CH) selection, while PSO excels in refining energy balance and coverage optimization. These contributions transcend theoretical improvements; they translate directly into empirically validated extensions of network lifetime and stability under varying load conditions.

However, the research landscape is evolving beyond these foundational algorithms. The emergence of Grey Wolf Optimization (GWO), Artificial Bee Colony (ABC), and hybrid metaheuristic schemes signals a strategic shift toward addressing complex, multi-dimensional trade-offs where single-objective algorithms often falter. The increasing adoption of these techniques reflects a growing community consensus: relying on singular methods is insufficient for dynamic, heterogeneous deployments. Instead, the focus is pivoting toward cross-layer optimization strategies that mitigate premature convergence and avoid local optima.

Despite this algorithmic progress, critical gaps persist. Security protocols and trust management mechanisms remain conspicuously underrepresented in energy optimization frameworks. Furthermore, the reliance on simulation-based validation continues to overshadow physical testbed implementations. This disconnect is particularly precarious for mission-critical domains such as healthcare and Industrial IoT, where energy depletion or routing instability is not merely a technical inefficiency but a potential cause of catastrophic failure endangering patient safety or critical infrastructure.

Prospectively, the trajectory of WSN research points toward adaptive and hybrid metaheuristics capable of integrating dynamic clustering, multi-objective routing, and resilience against heterogeneous node capacities.

The convergence of these algorithms with Machine Learning, predictive analytics, UAV-assisted data collection, Edge Computing, and Blockchain offers transformative opportunities to bridge the chasm between laboratory models and field-ready solutions. While some of these integrations are emerging, others remain theoretical concepts pending rigorous empirical validation.

Ultimately, achieving sustainable WSNs demands more than incremental algorithmic tuning. It requires the development of holistic frameworks that simultaneously balance Energy efficiency, Quality of Service (QoS), and Security within stochastic environments. If this research trajectory is sustained, WSNs will evolve from experimental networks into resilient, foundational infrastructures capable of supporting the rigorous demands of environmental monitoring, smart healthcare, and future smart cities.

Table 7: The basic principles of optimizing WSN

Algorithm	The basic principles of optimizing Wireless Sensor Networks (WSNs)
ACO	Routing Path Discovery: ACO generates ants at source nodes to explore optimal routes to sink nodes, considering energy consumption and delay [17]. Energy Efficiency: Updates pheromone values based on node quality, minimizing energy usage and extending network lifetime [13]. Performance in Multimedia Applications: ACO-based protocols, like EEABR, achieve higher throughput and better QoS compared to traditional protocols (e.g., DSDV, AODV) [13]. Energy-Aware Routing: EEABR exemplifies ACO's effectiveness in ensuring energy-conscious communication in WSNs [13]. Dynamic Adaptability: ACO adapts to network changes (e.g., node failures, traffic variations), ensuring reliable and efficient communication [13].
SO	Energy-Efficient Strategy: PSO is effective in optimizing Cluster Head (CH) selection to enhance network lifetime and reduce power consumption [68]. CH Optimization: Determines optimal CHs based on proximity to other nodes and residual energy, ensuring sustained network performance [68] [5]. Hybrid Approaches: Integration with algorithms like Improved LEACH (ILEACH) improves CH selection, enabling better load balancing and extended network lifespan [68]. Simulation Results: PSO-based models demonstrate significant improvements in WSN resilience and efficiency compared to traditional methods [68]. Low Computational Complexity: PSO's simplicity makes it suitable for real-time WSN applications requiring timely data transmission [69] .
GWO	Optimal CH Selection: GWO significantly improves network performance in terms of coverage, throughput, and energy consumption by optimizing Cluster Head (CH) selection [11]. Adaptive Nature: Dynamically adjusts search agent positions based on solution fitness, effectively addressing varying energy levels and communication distances in WSNs [8]. Objective Function: Combines parameters like intra-cluster distance, CH balancing factors, and residual energy to minimize energy consumption and maximize network lifetime [11]. Superior Performance: Outperforms other metaheuristic algorithms, such as PSO, in computational efficiency and energy-efficient clustering and routing [8]. Hybrid Approaches: Integrating GWO with other optimization techniques further enhances clustering and dynamic CH selection, improving network stability and longevity [11]. Exploration and Exploitation: Exhibits superior capabilities in balancing exploration and exploitation, making it a robust choice for energy-efficient routing in WSNs [11].
FSO	Efficient Clustering : FSO optimizes Cluster Head (CH) selection, reducing energy consumption for data transmission within the network. Optimal Routing : FSO's rapid identification capabilities enable the shortest and most energy-efficient routes between source nodes and the Base Station (BS), enhancing overall energy efficiency. Parameter Optimization : FSO algorithms balance exploration and exploitation of the solution space using tailored parameters, preventing unnecessary energy expenditure on suboptimal solutions. Independent Search Capability : Leveraging Hadamard manipulation, FSO performs independent searches across dimensions, effectively exploring potential energy-efficient network configurations. Reduced Overhead : FSO minimizes routing overhead, reducing control messages and computational demands, which directly saves network energy. Extended Network Lifetime: By optimizing clustering and routing, FSO reduces node energy consumption, prolonging operational lifespans and maintaining long-term network connectivity [16].

WOA	The Whale Optimization Algorithm (WOA) has been effectively applied in Wireless Sensor Networks (WSNs) to optimize Cluster Head (CH) selection by evaluating nodes based on energy levels and proximity to the base station, forming clusters that minimize transmission energy. In routing, WOA prioritizes nodes with high residual energy to reduce failure risks, accelerate data delivery, and extend network lifetime. Its energy-focused fitness functions ensure efficient operation with minimal waste, while multi-objective variants such as M-EBWOA have shown superior performance over traditional approaches like LEACH, HGWSFO, GA-PSO, and ECMOSSA. Simulation tools such as MATLAB support the design and validation of WOA-based methods, and future integration with advanced optimization techniques offers further potential for energy savings and longevity [37].

Figure 10: Taxonomy of the optimization technique

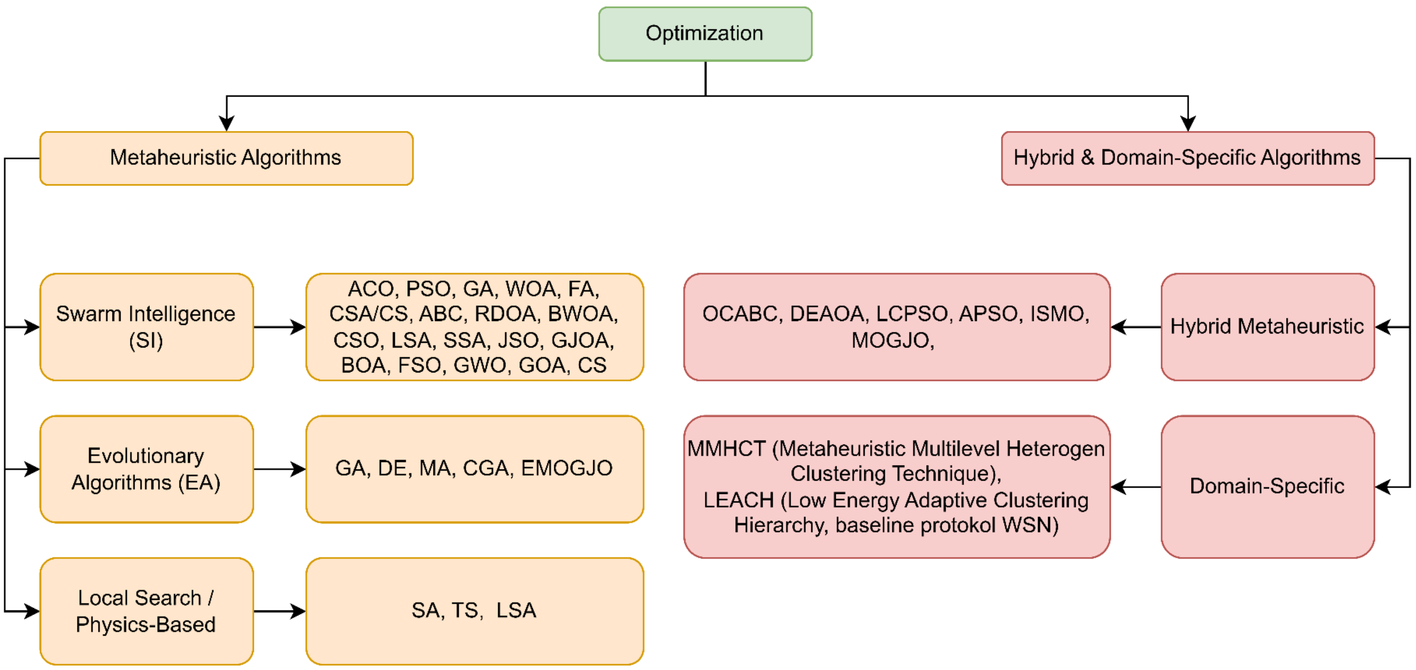

Table 8: Distribution of papers based on techniques, metrics, and algorithms

Paper (Year)	Algorithm optimization techniques		Optimization techniques		Performance Metrics					Application Domain							Algorithm
	Hybrid	Improve	Routing	Clustering	Energy consumption	Lifetime node	Throughput	PDR	End to end Delay	Medical	Agriculture	Military	Environmental monitoring	Smart city	Industry	Disaster	
2024 [20]		✔		✔	✔	✔	✔				✔		✔				CS, ACO
2024 [15]		✔		✔	✔		✔		✔	✔	✔			✔			ABC, PSO, CSO
2024 [44]	✔			✔	✔	✔	✔			✔	✔						ABC, ACO
2024 [9]		✔		✔	✔	✔	✔	✔								✔	GJOA
2024 [10]	✔		✔	✔								✔	✔				EMOGJO
2024 [35]		✔	✔	✔	✔	✔				✔	✔			✔			MA
2024 [43]	✔		✔	✔	✔	✔	✔			✔	✔			✔			CGA, GWO
2024 [70]		✔	✔	✔	✔	✔		✔			✔	✔					LCPSO
2024 [31]		✔	✔		✔	✔									✔		PSO
2024 [71]		✔		✔	✔	✔	✔			✔	✔						APSO
2024 [72]		✔		✔	✔	✔	✔			✔	✔		✔				LEACH
2023 [1]	✔		✔		✔	✔										✔	ACO, PSO
2023 [14]		✔		✔	✔	✔	✔				✔	✔	✔				PSO, OCABC
2023 [39]		✔	✔		✔	✔	✔	✔		✔	✔		✔				ACO
2023 [37]		✔		✔	✔	✔				✔	✔						BWOA
2023 [73]		✔	✔	✔	✔	✔	✔	✔		✔	✔						PSO
2023 [19]		✔		✔	✔	✔		✔	✔	✔	✔			✔			PSO
2023 [7]	✔		✔		✔		✔	✔					✔				ACO
2023 [42]	✔			✔	✔	✔						✔	✔				ACO, LEACH
2023 [36]		✔	✔		✔	✔	✔			✔		✔					SSA
2023 [11]		✔		✔	✔	✔	✔	✔		✔		✔	✔		✔		GWO
2023 [16]		✔	✔		✔	✔	✔	✔		✔		✔	✔				FSO
2023 [74]		✔	✔		✔	✔	✔	✔		✔	✔			✔			DEAOA
2023 [75]		✔	✔		✔	✔	✔	✔		✔		✔	✔				PSO
2022 [2]	✔		✔	✔	✔	✔	✔			✔			✔				PSO, GA
2022 [3]		✔	✔	✔	✔	✔							✔				GOA, WoA, ACO
2022 [18]	✔			✔	✔	✔		✔		✔	✔						PSO, LSA
2022 [38]	✔			✔	✔	✔				✔	✔						ACO, LEACH
2022 [46]		✔		✔	✔	✔		✔		✔	✔						JSO
2022 [76]		✔	✔	✔	✔	✔				✔	✔			✔			PSO, ACO
2022 [77]		✔	✔		✔					✔				✔			ISMO
2021 [78]		✔		✔	✔	✔	✔	✔		✔		✔					RDOA, SA

2021 [5]		✔		✔	✔	✔	✔	✔		✔		✔	✔				PSO
2021 [40]		✔		✔	✔	✔	✔			✔		✔				✔	PSO
2021 [79]	✔		✔	✔		✔	✔	✔		✔	✔			✔			BOA, ACO
2021 [80]		✔		✔	✔	✔						✔	✔			✔	MMHCT
2021 [17]		✔	✔		✔	✔	✔			✔	✔			✔			ACO
2020 [8]	✔			✔	✔	✔	✔				✔	✔	✔		✔		FA, PSO
2020 [6]		✔	✔	✔	✔	✔					✔	✔				✔	PSO
2020 [33]		✔	✔				✔	✔			✔	✔			✔		PSO, SSA
2020 [12]		✔		✔	✔	✔		✔		✔	✔			✔			ABC
2019 [41]		✔	✔		✔	✔	✔					✔	✔				ACO
2019 [4]		✔	✔		✔	✔				✔	✔						GWO, TS
2019 [13]		✔		✔	✔	✔		✔		✔			✔		✔		ACO
2019 [81]		✔	✔		✔	✔	✔			✔	✔			✔			ACO
2019 [82]		✔		✔	✔	✔	✔			✔	✔	✔					ACO, GS, PSO, CS

Ant Colony Optimization (ACO), Particle Swarm Optimization (PSO), Genetic Algorithm (GA), Whale Optimization Algorithm (WOA), Ant Colony Optimization algorithm (ACO), Firefly Algorithm (FA), Cuckoo Search Algorithm (CSA), Optimal Clustering Artificial Been Colony (OCABC), Red Deer Optimization Algorithm (RDOA), Black Widow Optimization Algorithm (BWOA), Cat Swarm Optimization (CSO), Metaheuristic Multilevel Heterogen Clustering Technique (MMHCT), Lightning Search Algorithm (LSA), Salp Swarm Algorithm (SSA), Tabu Search (TS), Low Energy Adaptive Clustering Hierarchy (LEACH), Squirrel Search Algorithm (SSA), Jellyfish Search Optimize (JSO), Golden Jackal Optimization Algorithm (GJOA), Butterfly Optimization Algorithm (BOA), Multi Objective Golden Jackal Optimization (MOGJO), Firebug Swarm Optimization (FSO), Differential Evolution with Arithmetic Optimization Algorithm (DEAOA), Memetic Algorithm (MA), Chaotic Genetic Algorithm (CGA), Improved Spider Monkey Optimization Algorithm (ISMO), Levy chaotic particle swarm optimization algorithm (LCPSO), Accelerated Particle Swarm Optimization Algorithm (ASPO), Algoritma cuckoo search (C

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Author Contributions.

R.H.: conceptualisation, investigation, editing, methodology, and writing the original draft; W.M.: research design, methodology, writing, reviewing, editing, and data analysis; S.S.: conceptualisation, data curation, writing, reviewing, and editing. All authors have read and agreed to the published version of this manuscript.

Conflicts of Interest.

The authors declare no conflicts of interest.

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