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Machine Learning and Bio-Inspired Deep Learning Approaches for Energy-Efficient and Secure Clustering and Routing in Wireless Sensor Networks:A Survey

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Abstract
Wireless Sensor Networks (WSNs) remain constrained by the finite battery energy of their constituent nodes, which makes energy-aware clustering and routing the central design problem of the field. Since the introduction of the Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol, a large body of research has sought to improve cluster-head (CH) election and multi-hop routing along four broad lines: (1) geometry- and threshold-based unequal clustering to counter the "hotspot" or energy-hole problem near the base station; (2) machine-learning and metaheuristic CH election using k-means, fuzzy logic, particle swarm optimization (PSO), genetic algorithms (GA), and artificial neural networks; (3) bio-inspired swarm-intelligence routing using Ant Colony Optimization (ACO), the Grey Wolf Optimizer (GWO), and hybrid combinations of these and other nature-inspired metaheuristics; and (4) reinforcement learning (RL) and deep learning approaches, including tabular Q-learning, Deep Q-Networks (DQN), Long Short-Term Memory (LSTM) energy prediction, and autoencoder-based anomaly detection for security. This survey reviews and synthesizes 71 peer-reviewed and preprint sources across these four lines, organizes them into a coherent taxonomy, and builds comparative tables of their clustering/routing mechanisms, evaluation scale, and reported performance gains. The review is deliberately structured to support a three-phase enhancement of an existing Energy-Efficient Machine-Learning-based Clustering and Routing (EEMLCR) protocol: a hotspot-aware adaptive CH scheduling phase, a bio-inspired ACO-GWO multi-objective routing phase, and a unified deep-learning phase combining LSTM-based proactive energy prediction, DQN-based routing, and autoencoder/trust-based security. The survey concludes by identifying three concrete gaps in the existing literature — the absence of a threshold-driven, TDMA-integrated hotspot recovery mechanism; the lack of a systematic ACO-explores/GWO-exploits routing pipeline validated at scale; and the absence of a single framework unifying proactive LSTM prediction, DQN routing, and trust-cross-validated anomaly detection — that motivate the proposed enhancements.

Keywords: wireless sensor networks; cluster-head election; energy-hole problem; hotspot mitigation; ant colony optimization; grey wolf optimizer; reinforcement learning; deep Q-network; LSTM; autoencoder; trust management; intrusion detection.

1. Introduction

A Wireless Sensor Network (WSN) consists of a large number of small, battery-powered sensor nodes deployed over a region of interest to sense, process, and forward physical measurements toward one or more base stations (BS). Because each node typically carries a non-rechargeable, energy-constrained battery and radio transmission dominates a node's energy budget, the central engineering problem of WSN protocol design is to organize the network topology and its routing paths so that energy consumption is both minimized and balanced across nodes. If a small subset of nodes is forced to relay disproportionately more traffic than the rest of the network, those nodes deplete their batteries early, the network fragments, and the effective coverage and lifetime of the deployment collapse well before the average node has exhausted its energy.

Clustering is the dominant architectural response to this problem. Nodes are grouped into clusters, each managed by a cluster head (CH) that aggregates and forwards data on behalf of its members, which lets ordinary member nodes transmit only over short intra-cluster distances while the comparatively energy-expensive long-range or multi-hop transmission burden is concentrated in, and rotated among, the cluster heads. The seminal Low-Energy Adaptive Clustering Hierarchy (LEACH) protocol formalized this idea and established randomized CH rotation as the baseline energy-balancing mechanism (Heinzelman et al., 2000). Three decades of follow-on

research have progressively replaced LEACH's purely probabilistic CH election with (a) geometry-aware unequal clustering that explicitly compensates for the disproportionate relay burden carried by cluster heads near the base station, (b) machine-learning and metaheuristic optimization techniques that select cluster heads according to multi-factor fitness functions, (c) bio-inspired swarm-intelligence routing that discovers energy- and load-balanced multi-hop paths among cluster heads, and, most recently, (d) reinforcement-learning and deep-learning techniques that let the network learn and even anticipate energy-aware routing and clustering decisions rather than reacting to them after the fact.

This survey reviews that literature in support of a proposed three-phase enhancement of an existing protocol referred to as EEMLCR (Energy-Efficient Machine-Learning-based Clustering and Routing), which currently combines K-means clustering with tabular Q-learning routing. The motivating proposal identifies three specific weaknesses in this baseline: (1) EEMLCR's centroid-based K-means clustering ignores the hotspot problem, whereby cluster heads positioned close to the base station relay traffic for multiple hops and drain faster than peripheral nodes, collapsing the network prematurely; (2) EEMLCR's tabular Q-learning routing does not scale gracefully, because the state-action space explodes and convergence slows once the network grows past a few hundred nodes; and (3) EEMLCR's Q-table is fundamentally reactive rather than predictive, and offers no mechanism for detecting compromised or malicious nodes. The three enhancement phases — HS-EEMLCR (hotspot-aware adaptive CH scheduling), BIO-EEMLCR (bio-inspired ACO-GWO multi-objective routing), and DL-SEEMLCR (a unified deep-learning framework combining LSTM energy prediction, DQN routing, and autoencoder-based security) — map directly onto four distinct bodies of prior work, which this survey organizes as follows: Section 2 reviews foundational clustering and hierarchical routing protocols; Section 3 reviews the hotspot/energy-hole problem and unequal-clustering countermeasures; Section 4 reviews machine-learning and metaheuristic cluster-head election (k-means, fuzzy logic, PSO, GA, and neural approaches); Section 5 reviews bio-inspired multi-objective routing based on ACO, GWO, and their hybrids; Section 6 reviews reinforcement-learning and deep-reinforcement-learning routing; Section 7 reviews predictive (LSTM) and security-aware (autoencoder, trust-based, and ML-intrusion-detection) deep learning applied to WSNs; Section 8 synthesizes the reviewed literature into comparative tables; Section 9 identifies concrete research gaps and positions the proposed three-phase enhancement against them; and Section 10 concludes.

2. Foundational Clustering And Hierarchical Routing Protocols

The clustering paradigm for WSNs was established by four protocols that remain the baseline against which nearly all subsequent work is benchmarked. LEACH (Heinzelman et al., 2000) elects cluster heads through a distributed, round-based probabilistic threshold: each node generates a random number each round and becomes a cluster head if that number falls below a threshold computed from the desired fraction of cluster heads and the round history, which guarantees every node eventually serves as CH and so distributes energy load stochastically over time. Non-cluster-head nodes join the nearest cluster head and transmit only over a short single hop, while cluster heads aggregate their members' data and transmit it directly to the base station. Simulation results in the original paper showed up to an eight-fold reduction in energy dissipation relative to direct transmission and static clustering. LEACH's central weakness — motivating almost all follow-on work reviewed in this survey — is that its CH election is purely probabilistic and ignores each node's actual residual energy, position relative to the base station, or local node density, so a low-energy node can be elected CH purely by chance while badly-placed cluster heads can create highly uneven cluster sizes.

HEED (Hybrid Energy-Efficient Distributed clustering) addressed part of this weakness by making CH election primarily a function of residual energy, with a secondary intra-cluster communication-cost parameter (such as node degree or average minimum reachability power) used to break ties and improve the balance of cluster sizes (Younis & Fahmy, 2004). HEED's election process is designed to terminate in a constant number of iterations independent of network diameter, and it guarantees full connectivity with only linear message overhead — properties that made it a common baseline for later energy-aware clustering research, and one directly extended by the K-means-based and fuzzy-logic-based cluster-head selection schemes reviewed in Section 4. PEGASIS (Power-Efficient Gathering in Sensor Information Systems) took a different architectural approach, replacing clusters entirely with a single greedy nearest-neighbor chain along which nodes pass fused data to a single rotating leader that alone communicates with the base station (Lindsey & Raghavendra, 2002); the authors reported PEGASIS sustaining roughly two to three times as many communication rounds before node death as LEACH, at the cost of higher end-to-end latency for distant nodes on the chain. TEEN (Threshold-sensitive Energy-Efficient sensor Network protocol) targeted reactive, event-driven sensing rather than periodic monitoring, introducing a hard threshold (an absolute sensed value that triggers a transmission) and a soft threshold (the minimum change in sensed value required before a node retransmits), which sharply reduces redundant transmissions in applications where the sensed phenomenon changes slowly (Manjeshwar& Agrawal, 2001).

Two broader surveys frame how this family of protocols has since been organized and evaluated. Al-Karaki and Kamal (2004) classify WSN routing protocols along two orthogonal axes — network structure (flat, hierarchical, or location-based) and protocol operation (multipath, query-based, negotiation-based, QoS-based, or coherent-based) — and catalog the energy-accuracy and overhead trade-offs inherent to each category, a taxonomy still widely used to position new protocols. Sabor et al. (2017) narrow the focus specifically to hierarchical (clustering) routing for mobile WSNs, building a twelve-criterion taxonomy (network architecture, clustering attributes, energy model, mobility handling, and so on) and comparing protocols on delay, energy efficiency, and scalability. Table 1 summarizes the four foundational protocols on the dimensions most relevant to the hotspot problem and the machine-learning enhancements discussed later in this survey.

Table 1. Foundational WSN clustering and routing protocols.

Protocol	**CH Election Basis**	**Topology**	**Key Limitation Addressed by Later Work**
LEACH (Heinzelman et al., 2000)	Random probabilistic threshold	Single-hop clusters	Ignores residual energy and BS distance in CH choice
HEED (Younis & Fahmy, 2004)	Residual energy + intra-cluster cost	Single-hop clusters	Cluster-size imbalance persists; no hotspot compensation
PEGASIS (Lindsey & Raghavendra, 2002)	Chain leader rotation	Linear chain	High latency; single point of failure on the chain
TEEN (Manjeshwar& Agrawal, 2001)	Hierarchical + threshold-triggered	Single/multi-hop clusters	Not suited to continuous (non-event-driven) monitoring

3. The Hotspot / Energy-Hole Problem And Unequal Clustering

The hotspot (or energy-hole) problem arises because, in a multi-hop clustered WSN, cluster heads positioned closer to the base station must relay not only their own cluster's aggregated data but also the forwarded traffic of every cluster farther away. Liu et al. (2010) formalized this effect using a corona-based (concentric-ring) network model and showed analytically that, under equal-radius clustering, the innermost coronas nearest the base station are guaranteed to deplete their energy first regardless of how evenly initial energy is distributed, because their traffic load scales with the total network size rather than local cluster size alone; they proposed an unequal cluster-radius scheme in which clusters closer to the base station are deliberately kept smaller, which reduces each such cluster head's own sensing/aggregation burden and leaves more of its energy budget available for relaying. This unequal-clustering principle became the standard countermeasure and was refined by several subsequent protocols. Yu et al. (2011) proposed EADUC, a distributed unequal-clustering protocol in which each candidate cluster head's competition radius is adjusted according to a combination of its residual energy and its distance to the base station, achieving balanced energy consumption and full coverage with low computational overhead. Singh et al. (2018) combined fixed unequal grid-based clustering with a mobile data-mule that physically collects data from cluster heads, jointly optimizing cluster-head selection and rotation timing to sustain over 3,000 operational rounds in their simulations. Jasim et al. (2021) proposed EEUCB, which forms unequal clusters based on distance to the base station and additionally introduces a double cluster-head architecture (a primary and a secondary head sharing the intra-cluster and relay load) combined with sleep/awake scheduling; the authors report network-lifetime improvements of 57.75%, 19.63%, 14.7%, and 13.06% over LEACH, F-LEACH, EEFUC, and UDCH respectively. Chauhan and Soni (2021) proposed EAUCA, which similarly forms smaller clusters nearer the base station but additionally separates the relay-node role from the cluster-head role, so that no single node bears both the aggregation and multi-hop-relay burden simultaneously — a separation of concerns directly analogous to the TDMA-based sleep-slot recovery mechanism used to protect flagged hotspot nodes in the HS-EEMLCR phase this survey supports.

More recent unequal-clustering work has incorporated metaheuristic optimization directly into the radius/fitness computation. Alsolai et al. (2023) proposed ITSA-UCHSE, which uses an improved Tuna Swarm Algorithm with chaotic-map initialization and a fitness function combining residual energy and distance to produce variable cluster sizes, reporting improved energy consumption, network lifetime, and alive-node counts relative to competing unequal-clustering baselines. Khalaf et al. (2022) reviewed equal, unequal, and hybrid clustering

approaches for heterogeneous WSNs specifically through the lens of the hotspot problem, concluding that while dynamic unequal clustering (combined with residual-energy-based relay selection) meaningfully reduces — but does not eliminate — premature energy depletion near the base station, and identifying the hotspot problem as an open research challenge rather than a solved one. Prince et al. (2025) took a different structural approach with EEMCR, grouping fixed square-shaped clusters into larger "mega-clusters" with dual-level data aggregation specifically to counter hotspot-induced premature death near the base station, reporting lifetime improvements of up to 34.5% over comparison protocols across deployments of 600–1,200 nodes. Finally, Pantazis et al. (2009) analyzed TDMA-based sleep/wake scheduling as a general energy-conservation mechanism, developing analytical models showing that strategically scheduling nodes into sleep slots substantially extends network lifetime while preserving connectivity and data-delivery reliability — the same mechanism used in HS-EEMLCR's proposal to place flagged, energy-depleted hotspot nodes into recovery sleep slots rather than excluding them permanently.

Notably, the reviewed literature converges on unequal, geometry- or distance-based cluster sizing as the dominant hotspot countermeasure, but almost uniformly determines cluster geometry once at network setup or re-clusters on a fixed periodic schedule, rather than continuously monitoring per-round residual energy against an explicit threshold and dynamically excluding flagged nodes from CH eligibility mid-operation — the specific mechanism (a hotspot threshold θ_hot applied after every simulation round) proposed for HS-EEMLCR. This distinction is developed further in Section 9.

4. Machine Learning And Metaheuristic-Based Cluster-Head Election

A second and largely parallel line of research replaces LEACH's random threshold, or HEED's simple residual-energy-plus-tiebreaker rule, with cluster-head election governed by k-means/k-means++ partitioning, fuzzy-logic inference, swarm/evolutionary metaheuristic optimization, or trained neural networks. This section reviews each in turn, since EEMLCR's baseline uses K-means clustering (with K-means++ specifically proposed for the DL-SEEMLCR phase) and its Phase 1 hotspot-aware rotation modifies exactly this class of mechanism by adding a residual-energy/BS-proximity penalty term to what is otherwise a distance/centroid-based election.

4.1 K-means and K-means++ Based Clustering:

K-means partitions nodes into clusters purely by geometric proximity to iteratively updated centroids, which is computationally cheap but, used naively, ignores energy entirely and can produce clusters whose "cluster head" (the node nearest the centroid) has already exhausted much of its battery. Several recent papers address this by layering an energy- or structure-aware post-processing step onto standard k-means. Zeng et al. (2024) proposed KMSC, which divides the network into symmetric angular sectors around the sink and applies k-means within a sector only once its node count exceeds a defined threshold, then selects the cluster head via a weighted function of residual energy and intra-cluster distance combined with a hybrid single-hop/multi-hop forwarding scheme; simulations showed KMSC improving first-, half-, and last-node-death metrics over EECPK-means and LSC. Juwaied and Jackowska-Strumillo (2024) proposed DEC-KM, augmenting the Deterministic Energy-efficient Clustering protocol with a k-means recentering step to reduce intra-cluster distances, followed by heuristic reselection favoring high-energy nodes near cluster centroids and the base station, with MATLAB simulations on 50–200 node heterogeneous networks showing reduced total energy consumption and extended stability relative to standard DEC. Wu et al. (2022) proposed DCK-LEACH, which uses the Canopy algorithm to automatically determine cluster count and initial k-means centers (removing the need to manually tune k), and additionally designates both a primary cluster head (selected by residual energy and centroid proximity) and a vice cluster head (selected by residual energy and base-station distance) per cluster to explicitly share the communication load — a dual-head design conceptually related to EEUCB's double cluster-head scheme reviewed in Section 3. Periyasamy et al. (2016) proposed a modified k-means (Mk-means) scheme that elects three rotating cluster heads per cluster rather than one, combined with energy thresholds and node blacklisting, and reported requiring far fewer re-clustering cycles (about 17 versus 55) than standard k-means while substantially extending first-node-death time relative to LEACH, HEED, ECRA, and SECA. Yoon et al. (2024) proposed IK-MACHES, combining improved k-means with a mobility-aware, multi-factor scored cluster-head election (residual energy, base-station distance, centroid distance, and node mobility) targeted specifically at mobile/autonomous-vehicle WSN deployments.

4.2 Fuzzy-Logic-Based Clustering

Fuzzy-logic clustering replaces hard energy/distance thresholds with linguistic membership functions, letting a cluster-head-eligibility score be computed smoothly from multiple imprecise inputs simultaneously. Zhang et al.

(2017) proposed EEDCF, which uses Takagi-Sugeno-Kang fuzzy inference (avoiding the extra defuzzification step required by the more common Mamdani model) over three inputs — a node's own residual energy, its node degree, and its neighbors' average residual energy — computed entirely locally; by explicitly accounting for neighbor energy, EEDCF is presented as directly mitigating the hotspot problem near cluster heads, and simulations on 100- and 150-node networks showed it extending both network lifetime and total data delivered compared to DFLC and EADEEG. El Alami and Najid (2016) proposed EEFL-CH, a LEACH extension that uses fuzzy logic over residual energy, an "expected efficiency" measure, and proximity to the base station to replace LEACH's probabilistic threshold outright, reporting reduced energy consumption and extended network lifespan. Sennan et al. (2024) proposed FHHO, which embeds fuzzy logic inside the Harris Hawks Optimization metaheuristic to jointly balance maximizing residual energy against minimizing sink distance when selecting cluster heads in IoT-based WSNs; MATLAB simulations reported FHHO improving network lifespan by 18–44% and throughput by 5–20% over PSO-ECHS, FIGWO, and GWO-C baselines, illustrating that fuzzy-logic scoring and swarm-metaheuristic optimization are frequently combined rather than treated as mutually exclusive design choices.

4.3 Swarm and Evolutionary Metaheuristic Clustering (PSO, GA)

Particle Swarm Optimization (PSO) and Genetic Algorithms (GA) treat cluster-head selection as a global optimization problem over a fitness function combining energy, distance, and degree terms, searched via a population of candidate solutions rather than a single greedy or threshold-based rule. Kuila and Jana (2014) proposed a widely cited two-part PSO framework: a PSO-based clustering technique balancing intra-cluster distance and residual energy for cluster-head selection, and a separate PSO-based multi-hop routing scheme among cluster heads formulated as a constrained optimization problem — establishing the now-common pattern of using one metaheuristic for clustering and (potentially a different) one for inter-cluster routing, which the proposed BIO-EEMLCR phase adopts explicitly with ACO for path discovery and GWO for path selection. Rawat and Chauhan (2021) proposed PSO-EEC, applying PSO with a fitness function combining energy ratio, node-to-cluster-head distance, and node degree for cluster-head selection, and a second PSO pass for multi-hop relay-node selection, reporting network-lifetime improvements of 71–238% and stability-period improvements of 126–396% over MDCH-PSO, MCHEOR, MOPSO, and HSA-PSO. On the genetic-algorithm side, Kaedi et al. (2022) proposed a 2-level genetic algorithm that jointly optimizes cluster-head selection and inter-cluster routing paths within a single evolutionary process — rather than solving the two subproblems sequentially, as most clustering-then-routing protocols (including the baseline EEMLCR) do — specifically to avoid locally optimal cluster/route combinations produced by sequential optimization. Verma et al. (2019) proposed a genetic-algorithm-based cluster-head selection scheme evaluated under both single-sink and multiple-sink configurations for heterogeneous WSNs, extending GA-based clustering beyond the single-BS assumption common in most of the surveyed literature.

4.4 Neural-Network and Hybrid Metaheuristic Clustering

A smaller but growing body of work applies trained neural networks or multi-algorithm hybrids directly to cluster-head classification. Senturk (2025) trained an artificial neural network to classify candidate cluster heads in place of LEACH's probabilistic threshold, reporting over 85% classification accuracy and cluster-head determination 83.28% faster than standard LEACH — evidence that a trained model can replace, rather than merely re-weight, the underlying election rule, foreshadowing the DQN-based routing replacement proposed for DL-SEEMLCR. Goel et al. (2026) proposed WIFNCP, built on a hybrid combining Whale Optimization, the INFO algorithm, fusion-fission optimization, and the naked mole-rat algorithm to select cluster heads favoring higher residual energy, combined with dual-hop inter-cluster routing; benchmarked against ten existing protocols including LEACH, SEP-E, HCR, and ERP, WIFNCP is reported to extend stability-period lifetime by up to 90%. This trend toward combining three or more metaheuristics into a single election/routing pipeline is a direct precedent for the ACO-GWO hybridization proposed for BIO-EEMLCR, discussed next. Table 2 compares the machine-learning and metaheuristic clustering approaches reviewed in this section.

Table 2. Machine-learning and metaheuristic cluster-head election approaches.

Approach (Source)	Election Mechanism	Inputs to Fitness/Score	Reported Gain vs. Baseline
KMSC (Zeng et al., 2024)	Sector k-means + weighted score	Residual energy, intra-cluster distance	Improved node-death metrics vs. EECPK-means, LSC
DCK-LEACH (Wu et al., 2022)	Canopy-seeded k-means, dual CH	Residual energy, centroid & BS	Extended lifetime vs. LEACH, RCH-LEACH,

		distance	K-LEACH
EEDCF (Zhang et al., 2017)	TSK fuzzy inference	Own/neighbor energy, node degree	Extended lifetime & data delivered vs. DFLC, EADEEG
FHHO (Sennan et al., 2024)	Fuzzy + Harris Hawks Optimization	Residual energy, sink distance	+18–44% lifespan, +5–20% throughput vs. PSO-ECHS, GWO-C
PSO-EEC (Rawat & Chauhan, 2021)	PSO fitness function	Energy ratio, distance, node degree	+71–238% lifetime vs. MDCH-PSO, MOPSO
2-level GA (Kaedi et al., 2022)	Joint GA over CH + routing	Combined clustering + routing fitness	Avoids locally-optimal sequential solutions
ANN-LEACH (Senturk, 2025)	Trained neural classifier	Learned from labeled CH examples	>85% accuracy, 83.28% faster election
WIFNCP (Goel et al., 2026)	Whale+INFO+fission-fusion+NMR hybrid	Residual energy weighting	Up to +90% stability-period lifetime

5. Bio-Inspired Multi-Objective Routing: Aco, Gwo, And Hybrid Approaches

Once cluster heads are elected, a second optimization problem remains: choosing energy-, load-, and reliability-balanced multi-hop paths among cluster heads toward the base station. Swarm-intelligence metaheuristics — most prominently Ant Colony Optimization (ACO) and the Grey Wolf Optimizer (GWO) — have become the dominant tool for this inter-cluster routing problem, and their combination is the specific mechanism proposed for the BIO-EEMLCR phase, in which ACO is used to explore and discover candidate multi-hop paths via pheromone trails (with pheromone evaporation acting as a proxy for energy cost) and GWO is then used to exploit that candidate set by selecting the globally optimal next hop under a multi-objective fitness function combining residual energy, hop count, and distance-to-BS ratio.

5.1 Ant Colony Optimization (ACO) Based Routing

ACO routing simulates artificial ants that probabilistically construct paths and deposit pheromone proportional to path quality, with evaporation causing poor paths to be forgotten over time — a mechanism naturally suited to representing energy cost, since a path through low-energy relays can be made to evaporate faster. Jeba Anandh and Baburaj (2020) proposed RACO, a hierarchical ACO routing protocol in which ant agents select minimally congested, energy-efficient paths between outer- and inner-layer nodes, explicitly estimating neighboring cluster-heads' forwarding capacity from residual energy to balance load and reduce cluster-head overload — directly addressing the same near-BS overload dynamic that produces the hotspot problem. Tawfeek et al. (2025) proposed MACOA, a modified ACO combining a multi-objective heuristic (energy, reliability, bandwidth, and distance), an adaptive pheromone-decay mechanism tied to node energy and link reliability, and a dynamic exploration-exploitation schedule; NS-3 simulations against GA, PSO, ABC, deep RL, and E-RARP baselines across 100–300 node networks showed MACOA extending network lifetime by roughly 25% over GA and 6% over PSO while retaining 6–15% more residual energy, and — notably — outperforming a deep-RL baseline on this metric, suggesting swarm and learning-based routing are not strictly ordered in performance and are worth combining rather than treating as substitutes. Han et al. (2024) improved ACO routing for IoT-connected WSNs by incorporating node positioning (reference/anchor points) directly into the transfer-probability and pheromone-update rules, reporting improvements in energy consumption, transmission delay, dead-node count, and throughput. Sun et al. (2017) proposed a lighter-weight enhancement to the ACO heuristic and pheromone-update mechanism specifically to better account for node energy and path quality during route selection. Security has also been folded directly into ACO routing: Sun et al. (2019) proposed SRPMA, a multi-objective ACO protocol that optimizes path residual energy and a per-node trust value simultaneously, reporting improved resistance to blackhole attacks compared to prior methods — though later literature notes SRPMA considers only energy and trust (not distance or hop count) in path generation, a limitation the BIO-EEMLCR fitness function (which explicitly includes hop count and BS-distance ratio) is designed to avoid.

5.2 Grey Wolf Optimizer (GWO) Based Routing and Clustering

GWO models the leadership hierarchy and cooperative hunting behavior of grey wolves (alpha, beta, delta, and omega wolves) to balance exploration and exploitation during optimization, and has been applied to WSN cluster-head selection, inter-cluster routing, or both. Al-Aboody and Al-Raweshidy (2016) presented one of the earliest and most-cited applications of GWO to heterogeneous WSN clustering and routing, motivating a large number of follow-on GWO-based protocols. Zhao et al. (2020) proposed HMGWO, a three-phase protocol

combining heterogeneity-aware initial cluster selection, a modified GWO with dynamically updated weighting coefficients, and iterative cluster-set refinement; simulations reported network-lifetime improvements of 55.7%, 31.9%, 46.3%, and 27.0% over SEP, DEEC, M-SEP, and FIGWO respectively. Sennan et al. (2026) proposed MOGWO, using fuzzy logic to score candidate cluster heads on residual energy, neighbor count, and base-station distance within a multi-objective GWO framework — closely mirroring the residual-energy/hop-count/BS-distance-ratio fitness function proposed for BIO-EEMLCR — and reported MATLAB simulations (300 nodes) showing 10–20% lifetime extension, 5–10% reduced communication overhead, and 2–10% higher packet delivery ratio over LEACH, IFFOA, SHO-CH, and SHO-OBL. Dinesh and Santhosh Kumar (2024) proposed GWO-SMSLO, combining GWO cluster-head selection with a modified Sea Lion Optimization algorithm for route selection and layering in elliptic-curve cryptography for security, reporting a 12% reduction in energy consumption, 8% increase in packet delivery ratio, and 15% lifetime extension in NS3-based validation alongside resistance to multiple attack types. Kaddi et al. (2024) proposed EOAMRCL, a centralized cross-layer protocol combining GWO clustering, a minimal-energy routing phase, and an enhanced CSMA/CA MAC layer with sleep/wake scheduling, reporting improvements in lifetime, energy consumption, collision rate, and throughput over EEUC, DWEHC, and CGA-GWO. Rahmani et al. (2025) proposed GWFCCV, combining GWO with Fuzzy C-Means clustering and multi-criteria decision-making (CRITIC weighting with Fuzzy VIKOR ranking) to select cluster heads and routes for WSN-IoT, reporting lifetime improvements of 5.43–23.26% over EACMRP-MS, FEEC-IIR, and FRLDG. A recent methodological survey by Shokouhifar et al. (2026) specifically reviews and categorizes the GWO-based cluster-routing literature, confirming that fitness-function formulation and hybridization strategy (rather than GWO's base mechanics alone) are the primary axes along which these protocols now differentiate themselves — consistent with the pattern observed across C6–C10 above.

5.3 Hybrid ACO-GWO and Other Hybrid Bio-Inspired Routing

Direct hybridization of ACO and GWO — rather than choosing one or the other — has emerged specifically to combine ACO's strong global exploration behavior with GWO's stronger exploitation/convergence behavior. Widians et al. (2024) proposed a general-purpose hybrid ACO-GWO metaheuristic explicitly designed to balance exploration and exploitation better than either algorithm alone, testing it against the CEC 2014 benchmark suite (unimodal, multimodal, and hybrid functions) and reporting improved performance on several test cases, while also noting that combining two algorithmic frameworks increases computational cost relative to either alone — a trade-off the BIO-EEMLCR design accepts explicitly in exchange for the claimed faster convergence and fault-tolerant multi-path discovery. Although this particular study benchmarks the hybrid on generic optimization problems rather than WSN routing directly, it provides the clearest available evidence for the underlying premise of the BIO-EEMLCR design — that pairing an exploration-oriented swarm algorithm (ACO) with an exploitation-oriented one (GWO) outperforms either alone — and its exploration/exploitation framing maps directly onto BIO-EEMLCR's stated division of labor ("ACO explores, GWO exploits").

Whale Optimization Algorithm (WOA)-based routing represents a parallel hybridization trend worth reviewing for comparison. Bali et al. (2022) proposed an adaptive WOA (AWOA) for multi-objective cluster-head selection followed by fuzzy-inference-based supercluster-head selection, and an oppositional variant (OWOA) using quasi-oppositional-based learning to improve convergence, reporting that OWOA outperforms conventional PSO, GA, and standard WOA on delay, delivery ratio, energy consumption, lifetime, and throughput. Kumar et al. (2024) proposed WAOA, explicitly combining WOA for cluster-head selection (via a multi-objective fitness function over residual energy, inter-node and CH-to-sink distances, node degree, and centrality) with ACO for multi-hop routing path discovery — structurally the closest published analogue to the BIO-EEMLCR ACO-GWO design, differing mainly in which metaheuristic is paired with ACO. Tested across center/remote base-station placements and homogeneous/heterogeneous energy scenarios, WAOA outperformed MOORP, MMABC, and AZEBR by 5.78–18.52% in network lifetime, keeping 142 of 150 nodes alive at 12,000 rounds versus total node death for the baselines — direct evidence that combining ACO's path discovery with a second exploitation-oriented metaheuristic yields large, measurable network-lifetime gains at the scale (hundreds of nodes, thousands of rounds) relevant to BIO-EEMLCR's proposed evaluation up to 800 nodes. Jadhav and Shankar (2017) proposed WOA-C, a simpler single-metaheuristic baseline using WOA alone for cluster-head selection via a fitness function based on a node's own residual energy plus its neighbors' summed energy, reporting improved residual energy retention and stability relative to LEACH. Table 3 compares the bio-inspired routing approaches reviewed in this section.

Table 3. Bio-inspired swarm-intelligence routing approaches.

Approach (Source)	Algorithm(s) Combined	Fitness/Objective Inputs	Evaluation Scale	Reported Gain
RACO (Jeba	ACO	Congestion, energy	Not specified	Reduced CH overload,

Anandh & Baburaj, 2020)				extended lifetime
MACOA (Tawfeek et al., 2025)	Modified ACO	Energy, reliability, bandwidth, distance	100–300 nodes (NS-3)	+25% lifetime vs. GA, +6% vs. PSO
SRPMA (Sun et al., 2019)	Multi-objective ACO	Path energy + node trust	Not specified	Improved blackhole resistance
HMGWO (Zhao et al., 2020)	Modified GWO	Heterogeneity, energy, distance	Not specified	+27–56% lifetime vs. SEP, DEEC, FIGWO
MOGWO (Sennan et al., 2026)	Fuzzy + GWO	Energy, neighbor count, BS distance	300 nodes (MATLAB)	+10–20% lifetime, +2–10% PDR
GWO-SMSLO (Dinesh & Kumar, 2024)	GWO + Sea Lion Optimization	Energy, route security (ECC)	NS3	+15% lifetime, +8% PDR, -15% delay
Hybrid ACO-GWO (Widians et al., 2024)	ACO + GWO	CEC2014 benchmark functions	Benchmark suite	Improved exploration/exploitation balance
WAOA (Kumar et al., 2024)	WOA + ACO	Energy, distance, degree, centrality	150 nodes, 12,000 rounds	+5.8–18.5% lifetime vs. MOORP, MMABC
OWOA (Bali et al., 2022)	Oppositional WOA + fuzzy	Multi-objective (delay, energy, etc.)	Not specified	Outperforms PSO, GA, standard WOA

6. Reinforcement Learning And Deep Reinforcement Learning For Wsn Routing

A distinct and more recent line of research treats routing as a sequential decision problem learned via reinforcement learning (RL), in which each node (or a centralized controller) learns a routing policy from reward feedback — typically a function of energy consumed, delay incurred, or delivery success — rather than following a fixed heuristic or metaheuristic-optimized rule computed once per round. EEMLCR's existing routing layer uses tabular Q-learning, and the proposed DL-SEEMLCR phase replaces this tabular approach with a Deep Q-Network specifically because, as network size grows, the state-action space of a tabular Q-table grows intractably large and slows convergence — a scalability limitation this section traces through the literature.

6.1 Tabular Q-Learning Based Routing

Liang et al. (2008) presented one of the earliest multi-agent reinforcement-learning routing protocols for WSNs, in which each node acts as an independent learning agent adapting its next-hop decisions based on reward feedback, establishing the foundational precedent for treating WSN routing as a distributed RL problem. Yun and Yoo (2021) proposed a Q-learning-based routing protocol that jointly considers data-aggregation opportunities and energy efficiency, letting nodes learn routing policies that favor paths enabling redundant-data aggregation while conserving energy. Keum and Ko (2022) proposed MC-TIRP for mission-critical WSNs, combining AOMDV-based multipath discovery filtered by trust evaluation — local trust from packet-forwarding ratio, expected transmission time, and energy, combined with global path trust updated via Q-learning rewards; OPNET simulations with 100 nodes showed MC-TIRP sustaining roughly 70% packet delivery ratio (versus below 50% for AOTDV, TQR, and ATRP) even at 30% malicious-node density, with sub-50ms delay maintained up to 40% malicious nodes. Obi et al. (2021) proposed LACQRP, a centralized, sink-based approach that first generates the set of feasible routing paths via an "All Minimum Spanning Trees" algorithm and then applies Q-learning to select routes maximizing network lifetime — illustrating that tabular Q-learning has been applied at both fully distributed (per-node agent) and fully centralized (sink-computed) granularities.

Across this body of work, tabular Q-learning routing is consistently evaluated on networks of roughly 100–300 nodes; none of the reviewed tabular-Q-learning papers report evaluation beyond a few hundred nodes, which is consistent with — and lends independent support to — the claim motivating DL-SEEMLCR that tabular Q-learning's state-action space becomes increasingly unmanageable, and its convergence increasingly slow, as network size grows past roughly 400 nodes.

6.2 Deep Q-Networks and Deep Reinforcement Learning Routing

Deep reinforcement learning replaces the explicit Q-table with a neural network that approximates the Q-function over a continuous or high-dimensional state space, avoiding tabular blow-up and, as several of the

papers below demonstrate, allowing routing policies to be evaluated at substantially larger network scales than tabular Q-learning. Bhimshetty and Ikechukwu (2024) proposed EEDQN, using a Deep Q-Network to select transmission paths based on intermediary nodes' residual energy; Python simulations on 120 nodes over 11,250 m² showed EEDQN outperforming LEACH and fuzzy-c-means baselines while consuming only 1.1 J/round. Hu et al. (2024) proposed DeepNR, combining deep neural networks with Q-learning to jointly optimize energy efficiency and security, evaluated on 500 MICAz sensor nodes and reporting roughly 30% lifespan gain, 25% throughput increase, and 20% security improvement over LEACH, PEGASIS, and DEEC — directly evidencing that DQN-style routing scales to network sizes an order of magnitude larger than the tabular-Q-learning studies in Section 6.1, and that energy and security objectives can be optimized jointly within a single DRL framework, exactly as DL-SEEMLCR proposes to do by feeding trust scores into the DQN's state space. Suresh S. et al. (2023) proposed a DRL routing approach using a double cluster-pairing method to find low-latency, low-power paths for IoT-enabled WSNs. Yang et al. (2024) proposed WOAD3QN-RP, combining the Whale Optimization Algorithm with a Dueling Double DQN to jointly select cluster heads and routing paths, using swarm intelligence to guide the DRL agent's exploration — a hybrid pattern structurally analogous to BIO-EEMLCR's ACO/GWO exploration-exploitation pairing but applied to guide a DQN rather than in place of one. Manogaran et al. (2025) combined federated learning with an Adaptive Double Deep Q-Learning routing strategy (ADDQL), letting distributed nodes learn privacy-preserving routing policies without centralizing raw data, and reported improved energy consumption, delay, packet delivery ratio, and scalability. Liu (2026) proposed QPSODRL, combining entropy-guided quantum particle swarm optimization for cluster formation with DRL-based route optimization, reporting improvements in lifetime, load balancing, throughput, and energy consumption over four state-of-the-art baselines. Ghamry and Shukry (2024) proposed a DRL framework that partitions IoT-enabled WSNs into unequal clusters based on current data load, multi-objectively balancing energy efficiency, delay, and lifetime — directly combining the unequal-clustering hotspot countermeasure from Section 3 with DRL-based routing. Finally, Gupta et al. (2026) proposed a DRL routing framework for military WSNs integrating trust management and lightweight cryptography, reporting roughly 20% improved routing efficiency and 99.46% intrusion-detection accuracy, providing the closest single-paper precedent for DL-SEEMLCR's combination of DQN routing with a trust/security layer feeding into the same state space. Table 4 compares the RL and DRL routing approaches reviewed in this section, ordered by evaluated network scale.

Table 4. Reinforcement-learning and deep-reinforcement-learning routing approaches.

Approach (Source)	RL Method	Network Scale Evaluated	Security-Aware?	Reported Gain
Multi-agent RL (Liang et al., 2008)	Tabular Q-learning	Not specified	No	Foundational distributed-agent design
MC-TIRP (Keum & Ko, 2022)	Tabular Q-learning + trust	100 nodes	Yes	~70% PDR at 30% malicious nodes
LACQRP (Obi et al., 2021)	Centralized Q-learning	Not specified	No	Lifetime-maximizing path selection
EEDQN (Bhimshetty& Ikechukwu, 2024)	DQN	120 nodes	No	1.1 J/round, outperforms LEACH
DeepNR (Hu et al., 2024)	DNN + Q-learning	500 nodes	Yes	+30% lifespan, +25% throughput, +20% security
WOAD3QN-RP (Yang et al., 2024)	WOA-guided Dueling Double DQN	Not specified	No	Improved routing efficiency & lifetime
ADDQL (Manogaran et al., 2025)	Federated Double DQN	Not specified	No (privacy-preserving)	Improved energy, delay, PDR, scalability
Adaptive DRL (Gupta et al., 2026)	DQN + trust + crypto	Not specified	Yes	+20% routing efficiency, 99.46% IDS accuracy

7. Predictive And Security-Aware Deep Learning In Wsns

The DL-SEEMLCR phase adds two further deep-learning components beyond DQN routing: an LSTM network trained on Phase 1/2 energy-consumption time series to predict per-node depletion ahead of time, enabling proactive rather than reactive cluster-head rotation; and an autoencoder-based anomaly detector, cross-validated with a lightweight neighbor-consensus trust score, to flag compromised nodes exhibiting black-hole, sinkhole, or selective-forwarding behavior before they are excluded from cluster-head election and routing. This section reviews the literature underlying each component.

7.1 LSTM-Based Energy and Traffic Prediction

Shu et al. (2019) proposed a dual-prediction data-reduction scheme in which a lightweight LMS adaptive filter runs locally on resource-constrained sensor nodes while a more powerful LSTM model runs at the sink, with both predicting sensed values so that data is transmitted only when the node-side and sink-side predictions diverge beyond a threshold — a split-computation pattern (lightweight prediction at the node, heavier LSTM prediction centrally) directly relevant to where DL-SEEMLCR's own LSTM energy predictor should be situated relative to per-node resource constraints. Mohanty et al. (2020) proposed an LSTM-based distributed data-mining model aimed at reducing redundant data transmission and improving overall WSN energy efficiency, applying LSTM's capacity to model temporal dependencies in sensor/energy time series to a broader data-reduction objective than depletion forecasting alone. Neither paper predicts per-node energy depletion specifically several rounds ahead for the purpose of proactive cluster-head rotation — the specific mechanism proposed for DL-SEEMLCR — indicating that, while LSTM-based time-series prediction is well established for WSN data volume/traffic reduction, its application to proactive, rotation-triggering energy-depletion forecasting is comparatively underexplored, a gap discussed further in Section 9.

7.2 Autoencoder-Based Anomaly Detection

Autoencoders learn a compressed representation of normal node behavior (traffic patterns, energy-usage patterns) and flag high reconstruction error as anomalous, which suits WSN security because it requires no labeled attack data and can be trained on each node's own historical baseline. Luo and Nagarajan (2018) proposed a distributed anomaly-detection architecture in which lightweight autoencoder neural networks run locally on sensor nodes for real-time flagging while heavier learning/refinement occurs at the cloud; testing on a real indoor WSN over four months showed high detection accuracy and low false-alarm rate with computational complexity suitable for resource-constrained devices — directly supporting the feasibility of running an autoencoder anomaly detector alongside DL-SEEMLCR's DQN router without prohibitive overhead. Subhan et al. (2026) conducted a taxonomy-driven meta-synthesis of autoencoder-based self-supervised WSN anomaly detection, organizing the literature along learning objective, architecture, data context, and evaluation protocol, and finding that self-supervised learning integrated with autoencoders improves robustness over purely reconstruction-driven baselines in heterogeneous, dynamic WSNs, while flagging persistent deployment barriers around scalability, interpretability, and energy/memory overhead — barriers directly relevant to whether DL-SEEMLCR's autoencoder can run continuously alongside its DQN and LSTM components within typical sensor-node or edge-gateway resource budgets. Haque and Soliman (2025) developed a hybrid detection framework pairing a Transformer-based autoencoder with Isolation Forest and XGBoost to distinguish sensor malfunctions from network intrusions using adaptive thresholding, reporting roughly 95% accuracy with high recall on emulated forest-monitoring data from 15 sensor nodes — demonstrating that autoencoder-based detection is increasingly combined with complementary classical ML models (Isolation Forest, XGBoost) rather than deployed alone, a pattern DL-SEEMLCR's proposal echoes by cross-validating autoencoder flags with a separate trust score rather than acting on reconstruction error alone. Haque et al. (2024) provide a broader survey of supervised, unsupervised, and semi-supervised machine-learning techniques (including but not limited to autoencoders) for detecting anomalies in noisy, unreliable WSN sensor data, comparing reported performance metrics across approaches and identifying open challenges for future WSN anomaly-detection systems.

7.3 Trust-Based Security and Machine-Learning Intrusion Detection

A closely related line of work addresses the same black-hole, sinkhole, and selective-forwarding threats through explicit trust modeling rather than (or alongside) anomaly detection, providing the specific neighbor-consensus cross-validation mechanism DL-SEEMLCR proposes to reduce false positives from transient energy dips or packet loss. Roy et al. (2008) proposed one of the earliest dynamic trust-management schemes for WSNs, computing trust values from observed node behavior over time to detect and isolate nodes participating in sinkhole and black-hole attacks, establishing trust accumulation (rather than static cryptographic authentication alone) as a foundational defense mechanism against routing-layer attacks. Sharma and Bharti (2025) proposed a

two-phase trust-based detection approach for decentralized WSNs — first identifying potential malicious nodes, then confirming actual attackers attempting to intercept data — with NS2-based evaluation showing improved throughput, reduced packet loss, and lower delay compared to existing sinkhole-detection techniques. Khan et al. (2024) introduced a delta-threshold-based trust model combining direct and indirect trust with a forgetting-curve mechanism to counter black-hole attacks in RPL-based, resource-constrained green IoT networks, evaluating nodes on energy, unselfishness, honesty, and dishonesty metrics and reporting higher detection rates and lower false-positive rates than existing schemes — directly analogous to the false-positive-reduction goal of DL-SEEMLCR's neighbor-consensus trust cross-validation step. Zhukabayeva et al. (2025) developed a real-time WSN detection methodology for wormhole and sinkhole attacks using a 3-sigma-rule-based anomaly-detection mechanism over a ZigBee/GSM-GPRS architecture, reporting that wormhole attacks measurably reduced hop counts while increasing delay, and sinkhole attacks caused a 27% traffic-concentration increase at malicious nodes, with both attack types detected successfully in real time. Lai et al. (2022) proposed a correlation-based detection method exploiting spatial/temporal correlation among neighboring sensor readings to identify malicious nodes without relying purely on trust accumulation, offering a lightweight complement to trust-management schemes.

Finally, a cluster of recent papers applies classical machine-learning classifiers directly to WSN intrusion-detection datasets, typically addressing the severe class imbalance inherent in attack-traffic data. Pandey et al. (2025) combined Tabu Search metaheuristic optimization with Random Forest classification to automatically tune hyperparameters for WSN intrusion detection, reporting up to 99.67% accuracy on the WSN-DS dataset and improved detection of Blackhole/Gray-Hole attack variants. Talukder et al. (2024) proposed MLSTL-WSN, combining machine-learning classifiers with SMOTE-Tomek Link resampling to address class imbalance, reporting 99.78% accuracy for binary classification and 99.92% for multiclass classification on the 374,661-record WSN-DS dataset. Talukder et al. (2025) extended this with a hybrid pipeline combining KMeans-SMOTE for class balancing, PCA for dimensionality reduction, and Random Forest classification, reporting 99.94% accuracy/F1 on WSN-DS and 99.97% on TON-IoT while remaining computationally efficient for resource-limited networks. Collectively, this body of work demonstrates that classical ML classifiers, when paired with appropriate resampling and dimensionality-reduction preprocessing, achieve very high detection accuracy on benchmark WSN intrusion datasets — evidence supporting the feasibility of DL-SEEMLCR's lighter-weight autoencoder-plus-trust-score approach as a computationally cheaper, node-deployable alternative to full classifier retraining. Table 5 compares the security-focused approaches reviewed in this section.

Table 5. Security-focused deep-learning, trust-based, and ML intrusion-detection approaches for WSNs.

Approach (Source)	Detection Mechanism	Threats Addressed	Reported Performance
Distributed AE (Luo & Nagarajan, 2018)	Node-local + cloud autoencoder	General anomalies	High accuracy, low false-alarm, low overhead
Transformer-AE+IF+XGBoost (Haque & Soliman, 2025)	Autoencoder + Isolation Forest + XGBoost	Malfunction vs. intrusion	~95% accuracy, high recall
Dynamic Trust Mgmt (Roy et al., 2008)	Behavioral trust accumulation	Sinkhole, black hole	Foundational trust-based isolation
Trust-based isolation (Sharma & Bharti, 2025)	Two-phase trust detection	Sinkhole	Improved throughput, lower delay/loss
ORM (Khan et al., 2024)	Direct+indirect trust, forgetting curve	Black hole (RPL/IoT)	Higher detection rate, lower false positives
3-sigma real-time (Zhukabayeva et al., 2025)	Statistical anomaly rule	Wormhole, sinkhole	Real-time detection of both attack types
Correlation detection (Lai et al., 2022)	Spatial/temporal correlation	General malicious nodes	Lightweight complement to trust models
Tabu+RF (Pandey et al., 2025)	Tabu search-optimized Random Forest	Blackhole/Gray-hole (WSN-DS)	Up to 99.67% accuracy
MLSTL-WSN (Talukder et al., 2024)	SMOTE-Tomek + ML classifiers	DoS-type attacks (WSN-DS)	99.78–99.92% accuracy
Hybrid KMeans-SMOTE+PCA+RF (Talukder et al., 2025)	Balancing + PCA + Random Forest	Multiple (WSN-DS, TON-IoT)	99.94–99.97% accuracy/F1

8. Comparative Synthesis

Read together, the four lines of research surveyed here trace a coherent evolutionary path. LEACH-era protocols (Section 2) established randomized, energy-agnostic CH rotation as a baseline; unequal-clustering work (Section 3) recognized that CH rotation alone does not balance the disproportionate relay burden carried near the base station, and countered it primarily through static or periodically-recomputed geometric cluster sizing; machine-learning and metaheuristic clustering (Section 4) replaced probabilistic or purely geometric CH election with fitness functions that explicitly weigh residual energy, distance, and node degree, computed via k-means, fuzzy logic, PSO, GA, or trained neural networks; bio-inspired swarm routing (Section 5) extended multi-factor optimization from cluster-head selection to the harder problem of multi-hop inter-cluster path selection, increasingly through hybrids that explicitly pair an exploration-oriented algorithm with an exploitation-oriented one; and reinforcement-learning and deep-learning approaches (Sections 6–7) represent the most recent shift, from route selection computed once per round via a fitness function toward routing (and now prediction and security) policies that are learned, and in the case of DQN-based approaches, that scale to substantially larger networks than tabular Q-learning permits.

A cross-cutting observation is that hotspot mitigation, cluster-head-election optimization, and routing optimization have almost always been studied in isolation from one another and from security: none of the 71 reviewed sources combines a real-time, threshold-triggered hotspot detector, a bio-inspired multi-objective router evaluated past 500 nodes, a proactive LSTM energy predictor, a DQN router, and an autoencoder/trust-based security layer within a single evaluated framework. Individual pairwise combinations exist — Ghamry and Shukry (2024) combine unequal clustering with DRL routing; Gupta et al. (2026) combine DQN routing with trust and cryptography; Sennan et al. (2024) combine fuzzy logic with a bio-inspired metaheuristic; Yang et al. (2024) combine a bio-inspired metaheuristic with a DQN variant — but no single reviewed protocol spans all three of the proposed EEMLCR phases' component techniques simultaneously. This observation directly motivates the phased, additive design (HS-EEMLCR → BIO-EEMLCR → DL-SEEMLCR) reviewed in Section 9, in which each phase's component techniques are individually well-precedented in the literature reviewed above, but their specific combination and the scale at which the combination is proposed to be evaluated is not.

9. Research Gaps And Positioning Of The Proposed Enhancements

Three specific gaps emerge from the literature reviewed above, each corresponding to one of the three proposed EEMLCR enhancement phases.

Gap 1 — Hotspot mitigation is predominantly static rather than round-by-round adaptive. Every unequal-clustering countermeasure reviewed in Section 3 (Liu et al., 2010; Yu et al., 2011; Singh et al., 2018; Jasim et al., 2021; Chauhan & Soni, 2021; Alsolai et al., 2023; Prince et al., 2025) determines cluster geometry either once at deployment or on a fixed re-clustering schedule, based on distance-to-base-station and/or residual energy at the time of (re-)clustering. None of these protocols continuously monitors each node's residual energy against an explicit round-by-round threshold and dynamically excludes flagged nodes from CH eligibility mid-operation while placing them into a recovery mechanism, as HS-EEMLCR's hotspot threshold θ_hot and TDMA-based sleep-slot recovery propose to do. The closest precedents are Pantazis et al.'s (2009) TDMA sleep-scheduling analysis, which is not tied to a hotspot-specific triggering threshold, and Chauhan and Soni's (2021) EAUCA, which separates relay and CH roles but does not use a per-round adaptive threshold. HS-EEMLCR's combination of (a) a per-round, per-node hotspot threshold applied after simulation, and (b) TDMA-based sleep-slot recovery specifically for flagged nodes, and (c) a penalty term (combining residual energy and BS proximity) added to an otherwise K-means/centroid-based CH rotation, therefore represents a genuinely under-explored adaptive refinement of the unequal-clustering literature rather than a restatement of it.

Gap 2 — Systematic ACO-explores/GWO-exploits hybridization for WSN routing, validated at scale against Q-learning-family baselines, is largely unaddressed. Section 5 shows that ACO-based routing (Section 5.1) and GWO-based routing/clustering (Section 5.2) have each been extensively studied, and that hybrid bio-inspired routing exists in related but distinct forms — a generic ACO-GWO hybrid benchmarked only on synthetic optimization functions rather than WSN routing (Widians et al., 2024), and WOA-ACO hybrids that pair ACO with a different exploitation-oriented metaheuristic (Kumar et al., 2024; Yang et al., 2024). No reviewed source pairs ACO (using pheromone evaporation explicitly as an energy-cost proxy) with GWO (using a multi-objective fitness of residual energy, hop count, and distance-to-BS ratio) for WSN inter-cluster routing specifically, nor evaluates such a pairing against Q-probabilistic and Q-learning-family baselines at the 800-node scale BIO-EEMLCR proposes — a scale beyond nearly every metaheuristic-routing study reviewed in

Section 5, most of which evaluate at 100–500 nodes. BIO-EEMLCR's specific fitness formulation and evaluation scale therefore fill a concrete and identifiable gap rather than duplicating an existing hybrid.

Gap 3 — No reviewed framework unifies proactive LSTM energy prediction, DQN routing, and trust-cross-validated autoencoder security within a single evaluated system. Section 6.2 shows DQN-based routing is well established and increasingly combined with trust/security (Hu et al., 2024; Gupta et al., 2026) or with unequal clustering (Ghamry&Shukry, 2024), and Section 7 shows LSTM-based prediction (Shu et al., 2019; Mohanty et al., 2020) and autoencoder-based anomaly detection (Luo & Nagarajan, 2018; Subhan et al., 2026; Haque & Soliman, 2025) are each independently well established, with trust-based cross-validation similarly well precedented for reducing false positives (Khan et al., 2024). However, none of the reviewed LSTM papers forecasts per-node energy depletion specifically to trigger proactive CH rotation ahead of node death, as opposed to reducing redundant data transmission generally; and no reviewed paper feeds both LSTM-derived CH-eligibility weighting and autoencoder/trust-derived security scores into a single DQN's state space, as DL-SEEMLCR proposes. Gupta et al.'s (2026) DQN-plus-trust-plus-cryptography framework is the closest existing precedent, but it does not incorporate a predictive LSTM component or K-means++-based clustering, and reports evaluation in a military-WSN context distinct from DL-SEEMLCR's general clustering/routing setting. DL-SEEMLCR's proposed unification of prediction, routing, and trust-cross-validated security within one state space therefore addresses a gap that is visible only once the LSTM-prediction, DQN-routing, and autoencoder/trust-security literatures are read together, as this survey has done.

10. Conclusion

This survey reviewed 71 sources spanning foundational WSN clustering protocols, hotspot/energy-hole mitigation via unequal clustering, machine-learning and metaheuristic cluster-head election, bio-inspired swarm-intelligence routing, reinforcement-learning and deep-reinforcement-learning routing, and predictive/security-aware deep learning for WSNs. The reviewed literature shows a clear historical progression — from LEACH's randomized, energy-agnostic clustering, through increasingly multi-factor and optimization-driven CH election and routing, to today's learning-based and predictive approaches — and demonstrates that each individual technique proposed for the three-phase EEMLCR enhancement (adaptive hotspot-threshold clustering with TDMA recovery; ACO-GWO hybrid multi-objective routing; and a unified LSTM-DQN-autoencoder deep-learning framework) is grounded in a substantial body of directly related prior work. At the same time, the comparative synthesis in Section 8 and the gap analysis in Section 9 show that no single reviewed protocol combines round-by-round adaptive hotspot detection, an ACO-explores/GWO-exploits routing pipeline validated at network scales up to 800 nodes, and a unified predictive-plus-security deep-learning layer within one evaluated system. The proposed HS-EEMLCR, BIO-EEMLCR, and DL-SEEMLCR phases therefore each occupy a specific, identifiable position relative to the existing literature: extensions and novel combinations of well-established component techniques, rather than restatements of any single prior protocol, and the survey's comparative tables (Tables 1–5) and gap analysis provide a structured basis for benchmarking each phase's reported results against the closest existing precedents identified above.

References

1. Al-Aboody, N. A., & Al-Raweshidy, H. S. (2016). Grey wolf optimization-based energy-efficient routing protocol for heterogeneous wireless sensor networks. In 2016 4th International Symposium on Computational and Business Intelligence (ISCBI). IEEE. https://doi.org/10.1109/ISCBI.2016.7743266

2. Al-Karaki, J. N., & Kamal, A. E. (2004). Routing techniques in wireless sensor networks: A survey. IEEE Wireless Communications, 11(6), 6–28. https://doi.org/10.1109/MWC.2004.1368893

3. Alsolai, H., Maashi, M., Saeed, M. K., Mohamed, A., Assiri, M., Abdelbagi, S., Drar, S., &Abdelmageed, A. A. (2023). Leveraging metaheuristic unequal clustering for hotspot elimination in energy-aware wireless sensor networks. Sensors, 23(5), Article 2636. https://doi.org/10.3390/s23052636

4. Bali, H., Gill, A., Choudhary, A., Anand, D., Alharithi, F. S., Aldossary, S. M., & Vidal Mazón, J. L. (2022). Multi-objective energy efficient adaptive whale optimization based routing for wireless sensor network. Energies, 15(14), Article 5237. https://doi.org/10.3390/en15145237

5. Bhimshetty, S., & Ikechukwu, A. V. (2024). Energy-efficient deep Q-network: Reinforcement learning for efficient routing protocol in wireless internet of things. Indonesian Journal of Electrical Engineering and Computer Science, 33(2), 971–980. https://doi.org/10.11591/ijeecs.v33.i2.pp971-980

6. Chauhan, V., & Soni, S. (2021). Energy aware unequal clustering algorithm with multi-hop routing via low degree relay nodes for wireless sensor networks. Journal of Ambient Intelligence and Humanized Computing, 12(2), 2469–2482. https://doi.org/10.1007/s12652-020-02385-1

7. Dinesh, K., & Santhosh Kumar, S. V. N. (2024). GWO-SMSLO: Grey wolf optimization based clustering with secured modified Sea Lion optimization routing algorithm in wireless sensor networks. Peer-to-Peer Networking and Applications, 17(2), 585–611. https://doi.org/10.1007/s12083-023-01603-9

8. El Alami, H., & Najid, A. (2016). Energy-efficient fuzzy logic cluster head selection in wireless sensor networks. In 2016 International Conference on Information Technology for Organizations Development (IT4OD) (pp. 1–7). IEEE. https://doi.org/10.1109/IT4OD.2016.7479300

9. Ghamry, W. K., &Shukry, S. (2024). Multi-objective intelligent clustering routing schema for internet of things enabled wireless sensor networks using deep reinforcement learning. Cluster Computing, 27(4), 4941–4961. https://doi.org/10.1007/s10586-023-04218-0

10. Goel, S., Sharma, K. P., Mittal, N., Mittal, V., Khafaga, D. S., Aldakheel, E. A., &Abouhawwash, M. (2026). Energy efficient clustering protocol in wireless sensor networks using an adaptive hybrid optimization algorithm. Scientific Reports, 16(1), Article 6300. https://doi.org/10.1038/s41598-026-36957-6

11. Gupta, R., Gupta, S. K., Singh, S. B., Kumar, R., & Muthukkumar, R. (2026). Adaptive deep reinforcement learning–based secure routing for wireless sensor networks. Scientific Reports. https://doi.org/10.1038/s41598-026-62519-x

12. Han, H., Tang, J., & Jing, Z. (2024). Wireless sensor network routing optimization based on improved ant colony algorithm in the Internet of Things. Heliyon, 10(1), Article e23577. https://doi.org/10.1016/j.heliyon.2023.e23577

13. Haque, A., Chowdhury, N.-U.-R., Soliman, H., Hossen, M. S., Fatima, T., & Ahmed, I. (2024). Wireless sensor networks anomaly detection using machine learning: A survey. In Intelligent Systems and Applications: Proceedings of IntelliSys 2023 (Lecture Notes in Networks and Systems, Vol. 824, pp. 491–506). Springer. https://doi.org/10.1007/978-3-031-47715-7_34

14. Haque, A., & Soliman, H. (2025). A transformer-based autoencoder with isolation forest and XGBoost for malfunction and intrusion detection in wireless sensor networks for forest fire prediction. Future Internet, 17(4), Article 164. https://doi.org/10.3390/fi17040164

15. Heinzelman, W. R., Chandrakasan, A. P., & Balakrishnan, H. (2000). Energy-efficient communication protocol for wireless microsensor networks. In Proceedings of the 33rd Annual Hawaii International Conference on System Sciences (Vol. 1, p. 10). IEEE. https://doi.org/10.1109/HICSS.2000.926982

16. Hu, L., Han, C., Wang, X., Zhu, H., & Ouyang, J. (2024). Security enhancement for deep reinforcement learning-based strategy in energy-efficient wireless sensor networks. Sensors, 24(6), Article 1993. https://doi.org/10.3390/s24061993

17. Jadhav, A. R., & Shankar, T. (2017). Whale optimization based energy-efficient cluster head selection algorithm for wireless sensor networks. arXiv. https://arxiv.org/abs/1711.09389

18. Jasim, A. A., Idris, M. Y. I., Azzuhri, S. R. B., Issa, N. R., Rahman, M. T., &Khyasudeen, M. F. B. (2021). Energy-efficient wireless sensor network with an unequal clustering protocol based on a balanced energy method (EEUCB). Sensors, 21(3), Article 784. https://doi.org/10.3390/s21030784

19. Jeba Anandh, S., & Baburaj, E. (2020). Energy efficient routing technique for wireless sensor networks using ant-colony optimization. Wireless Personal Communications, 114(4), 3419–3433. https://doi.org/10.1007/s11277-020-07539-0

20. Juwaied, A., & Jackowska-Strumillo, L. (2024). Improving performance of cluster heads selection in DEC protocol using K-means algorithm for WSN. Sensors, 24(19), Article 6303. https://doi.org/10.3390/s24196303

21. Kaddi, M., Omari, M., Salameh, K., &Alnoman, A. (2024). Energy-efficient clustering in wireless sensor networks using grey wolf optimization and enhanced CSMA/CA. Sensors, 24(16), Article 5234. https://doi.org/10.3390/s24165234

22. Kaedi, M., Bohlooli, A., &Pakrooh, R. (2022). Simultaneous optimization of cluster head selection and inter-cluster routing in wireless sensor networks using a 2-level genetic algorithm. Applied Soft Computing, 128, Article 109444. https://doi.org/10.1016/j.asoc.2022.109444

23. Keum, D., & Ko, Y.-B. (2022). Trust-based intelligent routing protocol with Q-learning for mission-critical wireless sensor networks. Sensors, 22(11), Article 3975. https://doi.org/10.3390/s22113975

24. Khalaf, O. I., Tavera Romero, C. A., Hassan, S., & Iqbal, M. T. (2022). Mitigating hotspot issues in heterogeneous wireless sensor networks. Journal of Sensors, 2022, Article 7909472. https://doi.org/10.1155/2022/7909472

25. Khan, M. A., Rais, R. N. B., Khalid, O., & Ahmad, S. (2024). Trust-based optimized reporting for detection and prevention of black hole attacks in low-power and lossy green IoT networks. Sensors, 24(6), Article 1775. https://doi.org/10.3390/s24061775

26. Kuila, P., & Jana, P. K. (2014). Energy efficient clustering and routing algorithms for wireless sensor networks: Particle swarm optimization approach. Engineering Applications of Artificial Intelligence, 33, 127–140. https://doi.org/10.1016/j.engappai.2014.04.009

27. Kumar, N., Singh, K., & Lloret, J. (2024). WAOA: A hybrid whale-ant optimization algorithm for energy-efficient routing in wireless sensor networks. Computer Networks, 254, Article 110845. https://doi.org/10.1016/j.comnet.2024.110845

28. Lai, Y., Tong, L., Liu, J., Wang, Y., Tang, T., Zhao, Z., & Qin, H. (2022). Identifying malicious nodes in wireless sensor networks based on correlation detection. Computers & Security, 113, Article 102540. https://doi.org/10.1016/j.cose.2021.102540

29. Liang, X., Balasingham, I., & Byun, S.-S. (2008). A multi-agent reinforcement learning based routing protocol for wireless sensor networks. In 2008 5th IEEE International Symposium on Wireless Communication Systems (ISWCS) (pp. 552–557). IEEE. https://doi.org/10.1109/ISWCS.2008.4726117

30. Lindsey, S., & Raghavendra, C. S. (2002). PEGASIS: Power-efficient gathering in sensor information systems. In Proceedings, IEEE Aerospace Conference (Vol. 3, pp. 3-1125–3-1130). IEEE. https://doi.org/10.1109/AERO.2002.1035242

31. Liu, A.-F., Wu, X.-Y., Chen, Z.-G., & Gui, W.-H. (2010). Research on the energy hole problem based on unequal cluster-radius for wireless sensor networks. Computer Communications, 33(3), 302–321. https://doi.org/10.1016/j.comcom.2009.09.008

32. Liu, G. (2026). QPSODRL: An improved quantum particle swarm optimization and deep reinforcement learning based intelligent clustering and routing protocol for wireless sensor networks. Scientific Reports, 16(1), Article 5526. https://doi.org/10.1038/s41598-026-35365-0

33. Luo, T., & Nagarajan, S. G. (2018). Distributed anomaly detection using autoencoder neural networks in WSN for IoT. In 2018 IEEE International Conference on Communications (ICC). IEEE. https://doi.org/10.1109/ICC.2018.8422402

34. Manjeshwar, A., & Agrawal, D. P. (2001). TEEN: A routing protocol for enhanced efficiency in wireless sensor networks. In Proceedings 15th International Parallel and Distributed Processing Symposium (IPDPS 2001) (pp. 2009–2015). IEEE. https://doi.org/10.1109/IPDPS.2001.925197

35. Manogaran, N., Raphael, M. T. M., Raja, R., Jayakumar, A. K., Nandagopal, M., Balusamy, B., & Ghinea, G. (2025). Developing a novel adaptive double deep Q-learning-based routing strategy for IoT-based wireless sensor network with federated learning. Sensors, 25(10), Article 3084. https://doi.org/10.3390/s25103084

36. Mohanty, S. N., Lydia, E. L., Elhoseny, M., Al Otaibi, M. M. G., & Shankar, K. (2020). Deep learning with LSTM based distributed data mining model for energy efficient wireless sensor networks. Physical Communication, 40. https://doi.org/10.1016/j.phycom.2020.101097

37. Obi, E., Mammeri, Z., &Ochia, O. E. (2021). A lifetime-aware centralized routing protocol for wireless sensor networks using reinforcement learning. In 2021 17th International Conference on Wireless and Mobile Computing, Networking and Communications (WiMob) (pp. 363–368). IEEE. https://doi.org/10.1109/WiMob52687.2021.9606390

38. Pandey, V. K., Prakash, S., Gupta, T. K., Sinha, P., Yang, T., Rathore, R. S., Wang, L., Tahir, S., & Bakhsh, S. T. (2025). Enhancing intrusion detection in wireless sensor networks using a Tabu search based optimized random forest. Scientific Reports, 15(1), Article 18634. https://doi.org/10.1038/s41598-025-03498-3

39. Pantazis, N. A., Vergados, D. J., Vergados, D. D., & Douligeris, C. (2009). Energy efficiency in wireless sensor networks using sleep mode TDMA scheduling. Ad Hoc Networks, 7(2), 322–343. https://doi.org/10.1016/j.adhoc.2008.03.006

40. Periyasamy, S., Khara, S., & Thangavelu, S. (2016). Balanced cluster head selection based on modified k-means in a distributed wireless sensor network. International Journal of Distributed Sensor Networks, 12(3). https://doi.org/10.1155/2016/5040475

41. Prince, B., Kumar, P., & Singh, S. K. (2025). Multi-level clustering and prediction based energy efficient routing protocol to eliminate hotspot problem in wireless sensor networks. Scientific Reports, 15(1), Article 1122. https://doi.org/10.1038/s41598-024-84596-6

42. Rahmani, A. M., Haider, A., Ali, S., Mohammadi, M., Mehranzadeh, A., Khoshvaght, P., & Hosseinzadeh, M. (2025). A routing approach based on combination of gray wolf clustering and fuzzy clustering and using multi-criteria decision making approaches for WSN-IoT. Computers and Electrical Engineering, 122, Article 109946. https://doi.org/10.1016/j.compeleceng.2024.109946

43. Rawat, P., & Chauhan, S. (2021). Particle swarm optimization-based energy efficient clustering protocol in wireless sensor network. Neural Computing and Applications, 33(21), 14147–14165. https://doi.org/10.1007/s00521-021-06059-7

44. Roy, S. D., Singh, S. A., Choudhury, S., & Debnath, N. C. (2008). Countering sinkhole and black hole attacks on sensor networks using dynamic trust management. In 2008 IEEE Symposium on Computers and Communications (pp. 537–542). IEEE. https://doi.org/10.1109/ISCC.2008.4625768

45. Sennan, S., Ramasubbareddy, S., Dhanaraj, R. K., Nayyar, A., & Balusamy, B. (2024). Energy-efficient cluster head selection in wireless sensor networks-based internet of things (IoT) using fuzzy-based Harris hawks optimization. Telecommunication Systems, 87(1), 119–135. https://doi.org/10.1007/s11235-024-01176-9

46. Sennan, S., Sankar, S., Somula, R., Pandey, D., & Cho, Y. (2026). A multi-objective grey wolf optimization algorithm for energy-efficient cluster-based routing in IoT-enabled WSNs. Scientific Reports, 16, Article 179. https://doi.org/10.1038/s41598-025-28950-2

47. Senturk, A. (2025). Artificial neural networks–based LEACH algorithm for fast and efficient cluster head selection in wireless sensor networks. International Journal of Communication Systems, 38(3), Article e6127. https://doi.org/10.1002/dac.6127

48. Sharma, S., & Bharti, V. (2025). Trust based mechanism for the isolation of sink hole attack in wireless sensor networks. In Artificial Intelligence and Its Applications: Proceedings of ICAIA 2023 (Communications in Computer and Information Science, Vol. 2308, pp. 26–36). Springer. https://doi.org/10.1007/978-3-031-84394-5_3

49. Shokouhifar, M., Fanian, F., Hosseinzadeh, M., Smerat, A., Othman, K. M., Noorwali, A., & Zafar, E. Y. O. (2026). Grey wolf optimizer for cluster-based routing in wireless sensor networks: A methodological survey. Computer Modeling in Engineering & Sciences, 146(1). https://doi.org/10.32604/cmes.2026.073789

50. Shokouhifar, M., Fanian, F., Rafsanjani, M. K., Hosseinzadeh, M., &Mirjalili, S. (2024). AI-driven cluster-based routing protocols in WSNs: A survey of fuzzy heuristics, metaheuristics, and machine learning models. Computer Science Review, 54, Article 100684. https://doi.org/10.1016/j.cosrev.2024.100684

51. Shu, T., Chen, J., Bhargava, V. K., & de Silva, C. W. (2019). An energy-efficient dual prediction scheme using LMS filter and LSTM in wireless sensor networks for environment monitoring. IEEE Internet of Things Journal, 6(4), 6736–6747. https://doi.org/10.1109/JIOT.2019.2911295

52. Singh, S. K., Kumar, P., & Singh, J. P. (2018). An energy efficient protocol to mitigate hot spot problem using unequal clustering in WSN. Wireless Personal Communications, 101(2), 799–827. https://doi.org/10.1007/s11277-018-5716-3

53. Subhan, R. M., Lee, Y.-D., & Koo, I. (2026). Autoencoder-based self-supervised anomaly detection in wireless sensor networks: A taxonomy-driven meta-synthesis. Applied Sciences, 16(3), Article 1448. https://doi.org/10.3390/app16031448

54. Sun, Y., Dong, W., & Chen, Y. (2017). An improved routing algorithm based on ant colony optimization in wireless sensor networks. IEEE Communications Letters, 21(6), 1317–1320. https://doi.org/10.1109/LCOMM.2017.2672959

55. Sun, Z., Wei, M., Zhang, Z., & Qu, G. (2019). Secure routing protocol based on multi-objective ant-colony-optimization for wireless sensor networks. Applied Soft Computing, 77, 366–375. https://doi.org/10.1016/j.asoc.2019.01.034

56. Suresh S, S., Prabhu, V., & Parthasarathy, V. (2023). An intelligent data routing strategy based on deep reinforcement learning for IoT enabled WSNs. e-Prime: Advances in Electrical Engineering, Electronics and Energy, 6, Article 100298. https://doi.org/10.1016/j.prime.2023.100298

57. Talukder, M. A., Khalid, M., & Sultana, N. (2025). A hybrid machine learning model for intrusion detection in wireless sensor networks leveraging data balancing and dimensionality reduction. Scientific Reports, 15(1), Article 4617. https://doi.org/10.1038/s41598-025-87028-1

58. Talukder, M. A., Sharmin, S., Uddin, M. A., Islam, M. M., & Aryal, S. (2024). MLSTL-WSN: Machine learning-based intrusion detection using SMOTETomek in WSNs. International Journal of Information Security, 23(3), 2139–2158. https://doi.org/10.1007/s10207-024-00833-z

59. Tawfeek, M. A., Alrashdi, I., Alruwaili, M., Jamel, L., Elhady, G. F., & Elwahsh, H. (2025). Improving energy efficiency and routing reliability in wireless sensor networks using modified ant colony optimization. EURASIP Journal on Wireless Communications and Networking, 2025, Article 22. https://doi.org/10.1186/s13638-025-02449-w

60. Verma, S., Sood, N., & Sharma, A. K. (2019). Genetic algorithm-based optimized cluster head selection for single and multiple data sinks in heterogeneous wireless sensor network. Applied Soft Computing, 85, Article 105788. https://doi.org/10.1016/j.asoc.2019.105788

61. Widians, J. A., Wardoyo, R., & Hartati, S. (2024). A hybrid ant colony and grey wolf optimization algorithm for exploitation-exploration balance. Emerging Science Journal, 8(4), 1642–1654. https://doi.org/10.28991/ESJ-2024-08-04-023

62. Wu, M., Li, Z., Chen, J., Min, Q., & Lu, T. (2022). A dual cluster-head energy-efficient routing algorithm based on canopy optimization and K-means for WSN. Sensors, 22(24), Article 9731. https://doi.org/10.3390/s22249731

63. Yang, X., Yan, J., Wang, D., Xu, Y., & Hua, G. (2024). WOAD3QN-RP: An intelligent routing protocol in wireless sensor networks—A swarm intelligence and deep reinforcement learning based approach. Expert Systems with Applications, 246, Article 123089. https://doi.org/10.1016/j.eswa.2023.123089

64. Yoon, C., Cho, S., & Lee, Y. (2024). Extending WSN lifetime with enhanced LEACH protocol in autonomous vehicle using improved K-means and advanced cluster configuration algorithms. Applied Sciences, 14(24), Article 11720. https://doi.org/10.3390/app142411720

65. Younis, O., & Fahmy, S. (2004). HEED: A hybrid, energy-efficient, distributed clustering approach for ad hoc sensor networks. IEEE Transactions on Mobile Computing, 3(4), 366–379. https://doi.org/10.1109/TMC.2004.41

66. Yu, J., Qi, Y., Wang, G., Guo, Q., & Gu, X. (2011). An energy-aware distributed unequal clustering protocol for wireless sensor networks. International Journal of Distributed Sensor Networks, 7(1), Article 202145. https://doi.org/10.1155/2011/202145

67. Yun, W.-K., & Yoo, S.-J. (2021). Q-learning-based data-aggregation-aware energy-efficient routing protocol for wireless sensor networks. IEEE Access, 9, 10737–10750. https://doi.org/10.1109/ACCESS.2021.3051360

68. Zeng, B., Li, S., & Gao, X. (2024). Threshold-driven K-means sector clustering algorithm for wireless sensor networks. EURASIP Journal on Wireless Communications and Networking, 2024(1), Article 68. https://doi.org/10.1186/s13638-024-02403-2

69. Zhang, Y., Wang, J., Han, D., Wu, H., & Zhou, R. (2017). Fuzzy-logic based distributed energy-efficient clustering algorithm for wireless sensor networks. Sensors, 17(7), Article 1554. https://doi.org/10.3390/s17071554

70. Zhao, X., Ren, S., Quan, H., & Gao, Q. (2020). Routing protocol for heterogeneous wireless sensor networks based on a modified grey wolf optimizer. Sensors, 20(3), Article 820. https://doi.org/10.3390/s20030820

71. CharpePrasanjeet Prabhakar, & Gaurav Tamrakar. (2025). Advanced Numerical Techniques for Solving High-Dimensional Integral Equations in Environmental Engineering Applications. *Journal of Applied Mathematical Models in Engineering*, *1*(4), 9–16.

72. Zhukabayeva, T., Zholshiyeva, L., Mardenov, Y., Buja, A., Khan, S., &Alnazzawi, N. (2025). Real-time detection and response to wormhole and sinkhole attacks in wireless sensor networks. Technologies, 13(8), Article 348. https://doi.org/10.3390/technologies13080348